Proceedings of the

27th European Conference on Knowledge Management

Hosted by

Niccolò Cusano University, Italy

3-4 September 2026



Part 2

Marco Valeri

A conference managed by ACPI, UK

Proceedings of the

27th European Conference on Knowledge Management

ECKM 2026

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Volume 2

Edited by

Marco Valeri

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Volume 1 E-Book ISBN: 978-1-917204-86-6
Volume 2 E-Book ISBN: 978-1-917204-88-0
E-Book ISSN: 2048-8971
Volume 1 Print version ISBN: 978-1-917204-85-9
Volume 2 Print version ISBN: 978-1-917204-87-3
Print Version ISSN: 2048-8963

Published by Academic Conferences International Limited
Reading, UK
+44 (0) 118 324 6938
www.academic-conferences.org
info@academic-conferences.org

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About the 27th European Conference on Knowledge Management, 2026

The European Conference on Knowledge Management (ECKM) is a highly respected academic conference that has been held annually for 27 years, making it one of the longest-standing conferences in its field. ECKM provides an important platform for academics, researchers, practitioners, and industry leaders from around the world to exchange ideas, present research, and discuss developments in knowledge management (KM). The conference is dedicated to advancing the theory and practice of knowledge management across a wide range of sectors and disciplines.

The Proceedings of the 27th ECKM, 2026 includes academic research papers, PhD research papers and Master's research papers as well as work-in-progress papers, which have been presented and discussed at the conference. The proceedings are of an academic level appropriate to a research audience including graduates, post-graduates, doctoral and post-doctoral researchers. All papers have been double-blind peer reviewed by members of the Review Committee.

Aims and Scope

The primary aim of ECKM is to foster a deeper understanding of knowledge management processes, practices, and technologies, and to explore their impact on organizational effectiveness and innovation. The conference seeks to bridge the gap between theory and practice by encouraging the exchange of ideas between academics and practitioners. It also aims to promote interdisciplinary collaboration by bringing together experts from various fields such as business, information technology, education, and public administration.

ECKM's scope is broad, encompassing all aspects of knowledge management, from the creation and sharing of knowledge within organizations to the role of technology in enabling KM processes. The conference addresses both the strategic and operational dimensions of knowledge management, emphasising its importance in enhancing organizational learning, innovation, and competitive advantage.

Topics Covered

ECKM covers a wide range of topics related to knowledge management, reflecting the evolving nature of the field and its application in different contexts. The call for papers asked for contributions that considered the following topics. In addition, the committee welcomed papers on a number of specialist mini-tracks which can be seen at the end of this list.

Knowledge Creation and Sharing:

- Tacit and Explicit Knowledge
- Knowledge Sharing Practices.

Knowledge Management Systems and Technologies:

- KM Tools and Platforms

- Artificial Intelligence and KM
- Big Data and Knowledge Analytics.

Organizational Learning and Innovation:

- Learning Organizations
- Innovation Management
- Communities of Practice.

Strategic Knowledge Management:

- KM and Competitive Advantage
- Knowledge Strategy Development
- Intellectual Capital Management.

KM in Specific Contexts:

- KM in Public Administration
- KM in Education
- KM in Healthcare.

Knowledge Management and Organizational Culture:

- Cultural Barriers to KM
- Leadership and KM
- Change Management in KM Initiatives.

Ethics and Knowledge Management:

- Ethical Issues in KM
- Sustainability and KM.

Emerging Trends and Challenges in KM:

- Digital Transformation and KM
- Globalization and KM
- AI's role in KM
- The integration of KM with other business disciplines
- The evolving role of knowledge managers.

Mini Tracks

Experts in the field proposed mini tracks on the following topics. Papers accepted on these topics after the double-blind peer review process were presented as mini tracks at the conference and are also published in these proceedings.

- New Frontiers in Agentic AI, Knowledge Management for Strategic Forecasting in Learning Organizations
- Knowledge Management and Succession Planning in Family Business: Theory and Practices

- The Impacts of Generative AI on Individual, Group, and Organizational Knowledge Management
- Reclaiming Organizational Knowledge in an Age of Post-Truth Disruption

The programme from the 2026 conference can be downloaded from the publishing portal and full details about the conference can be seen from the conference website: https://www.academic-conferences.org/conferences/eckm/

ECKM 2026 Editorial

These proceedings represent the work of contributors to the 27th European Conference on Knowledge Management (ECKM 2026), hosted by Niccolò Cusano University, Italy on 3-4 September 2026. The Conference Chair is Professor Marco Valeri, from Niccolò Cusano University, Italy.

ECKM is now a well-established event on the academic research calendar and now in its 27th year the key aim remains the opportunity for participants to share ideas and meet the people who hold them. The scope of papers will ensure an interesting two days. The subjects covered illustrate the wide range of topics that fall into this important and ever-growing area of research.

The opening keynote presentation is given by Professor Nóra Obermayer, University of Pannonia, Hungary on the topic *InKNOWation: When Knowledge Becomes Innovation.* The Afternoon keynote will be given by Professor Sławomir Smyczek, University of Economics in Katowice, Poland, who will talk about *Models of Knowledge Diffusion in the Context of Internationalization and Building Networks of Professional Service Organizations*. The second day of the conference will open with an address by Professor Marina Dabić, University of Dubrovnik, Croatia, on the topic of *Future of Innovation: AI, Robots and the Role of Human Creativity.*

With an initial submission of 355 abstracts, after the double blind, peer review process there are 171 Academic research papers, 16 PhD research papers, 4 Masters Research papers, 4 Non-Academic papers and 3 work-in-progress papers published in these Conference Proceedings. These papers represent research from Armenia, Australia, Austria, Belgium, Brazil, Bulgaria, Canada, China, Croatia, Czech Republic, Egypt, Estonia, Finland, France, Germany, Hungary, India, Indonesia, Iran, Ireland, Israel, Italy, Japan, Jordan, Latvia, Lithuania, Malaysia, Mexico, Morocco, Nigeria, Northern Ireland, Norway, Poland, Portugal, România, Saudi Arabia, Slovakia, Slovenia, South Africa, Spain, Sweden, Switzerland, Taiwan (R.O.C.), Türkiye, UK, USA and Vietnam,

We hope you enjoy the conference.

Marco Valeri,
Niccolò Cusano University, Italy.

September 2026

Biographies of Chairs and Keynote Speakers

Conference Chair



Marco Valeri Associate Professor of Organizational Behavior at Niccolò Cusano University, Italy. His research areas include sustainability and green practices, strategy implementation, knowledge management, family business, crisis management, information technology, network analysis. He is member of several editorial boards of international tourism journals, reviewer and editor of several handbooks on entrepreneurship, tourism and hospitality management.

Keynote Speakers



Marina Dabić is a tenured Professor at the University of Dubrovnik, Croatia and the University of Ljubljana School of Economics and Business, Slovenia. She has authored over 270 Scopus- and WOS-indexed articles and edited 12 books published by Springer, Edward Elgar, Routledge, Wiley, Palgrave, and De Gruyter. Recognised for her outstanding contributions, Professor Dabić has been ranked among the top 2% of scientists in business and management for three years in a row by the prestigious Stanford list. She plays pivotal roles in various editorial capacities, serving as the Editor-in-Chief of Technology in Society (AJG 2*) and Associate Editor for Technological Forecasting and Social Change (AJG 3*) and Strategic Change (AJG 2). Additionally, she is a Senior editor for IEEE Transactions on Engineering Management, (AJG 3*) contributing significantly to the academic discourse in her field. She is a member of the editorial board of the Journal of Business Research, Journal of Business Logistics, Journal of Knowledge Management, Journal of Managerial Science, International Journal of Physical Distribution and Logistics Management, among others.



Nóra Obermayer is a Full Professor, Head of the Department of Management, and Vice-Dean for Development at the Faculty of Business and Economics, University of Pannonia, Hungary. She is the head of the Digitalisation and Knowledge Management (DKM) Research Group, which is part of the Multidisciplinary Centre of Research Excellence. She is the recipient of the Elsevier Scopus Young Researcher Award (Engineering category) and the Order of Merit of Hungary, Knight's Cross (Civil Division). Her research has been published in leading international peer-reviewed journals, including Scientometrics, European Management Journal, International and Multidisciplinary Journal of Social Sciences, Journal of Family Business Management, Kybernetes, and theCogent Social Sciences. She has gained international teaching experience through the Erasmus Teacher Mobility Program in the Netherlands, Finland, and Norway. Her research interests include knowledge management, social media, digitalisation, and Industry 4.0/5.0. She is a full member of the International Association for Knowledge Management (IAKM) and The New Club of Paris (NCP), and serves as Associate Editor of the Electronic Journal of Knowledge Management.



Sławomir Smyczek Full Professor of Marketing and Consumer Behaviour at the University of Economics in Katowice (Poland)

Mini Track Chairs



Dr. Liu Gang earned his Ph.D. from The Hong Kong Polytechnic University and is currently an associate professor at the Business School, Shenzhen Technology University. His research interests include knowledge management, organizational performance, innovation and entrepreneurship, and cross-cultural management. His work has been published in the Journal of Business Research, Industrial Management & Data Systems, Knowledge Management Research & Practice, and the European Conference on Knowledge Management. He serves on the committee of the European Conference on Knowledge Management and is co-editor of Management & Marketing and associate editor of the International Journal of Knowledge Management Studies.



Prof. Jacky F. L. Hong is Professor of Management and Head of the Department of Management and Marketing in the Faculty of Business Administration at the University of Macau. He received his PhD from Lancaster University. His research focuses on organizational learning and knowledge management in multinational corporations, with publications in Journal of Management Studies, Organization Studies, Journal of World Business, Management Learning, Journal of International Management, and International Business Review. He serves on the editorial review boards of Journal of World Business, Management Learning, and International Business Review.



Anna Maria Melina is Research fellow in Organization studies at University of Messina. Her research focuses on Knowledge Management, Family Business, Small & Medium Business, Generational Change and Healthcare System. She is a speaker in national and international conferences. She is the author and/or co-author of several publications, including books, articles, research reports and working papers.

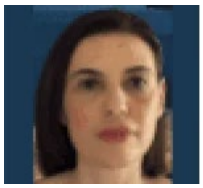


Prof. Dr. Mustafa SAĞSAN is currently serving as the Director of the Continuing Education Centre at the European University of Lefke, North Cyprus. He earned his Ph.D. in Management and Organization Science from Başkent University, Ankara, Türkiye, in 2008, and was subsequently promoted to Full Professor in 2017. Throughout his academic career, he has held several key administrative positions, including Rector, Director, Founding Chairperson, and Deputy Manager, across various universities. Prof. Sağsan has been actively engaged in

the field of Knowledge Management since 2002 and has authored over 150 scientific publications. In addition to his academic work, he is the creator and host of “Düşünce Nüansı” (Nuance of Thought) — the first television program in Northern Cyprus dedicated to scientific and philosophical discourse.



Dr Brenda van Wyk holds a PhD in Information Science, an M.Inf in Information and Knowledge Management and M.Ed. in Education Technology. She has published in various accredited journals and presented at national and international conferences on Higher Education, Research Management, AI Ethics and Literacy. She supervises and moderates postgraduate students on masters and doctoral level at UNISA, UCT and UP. Her research interests include, among others, Open Science, Learning Organizations, technology-assisted teaching and learning, digital scholarship, and Applied Ethics



Marzia Ventura Ph.D., is assistant Professor at Magna Graecia University of Catanzaro and she is member of Research Center “Economics and Management of Services”. The main topic of research is on human resource management, intellectual capital, corporate social responsibility, knowledge sharing in organizations.



Walter Vesperi is Research Fellow in Organization Theory and HRM at University of Palermo (IT). His research topics are on knowledge transfer, university entrepreneurship and agri-food sector. His publications appeared in academic journals and presented his research at several international conferences. Also he is member of editorial board of several International Journal.

ECKM Review Committee

ECKM is fortunate to have a significant number of international experts in the field willing to review papers. Care is taken to ensure that a fully double-blind peer review process is followed, and reviewers are not selected if they have any research or organisational connection to the author/s.

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Knowledge-based Smart City Management in the Context of Hofstede's Culture Dimensions

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Abstract: This study aims to examine the relationships between Hofstede's cultural dimensions and the adoption of knowledge-based solutions in city management. The cultural context of effective smart city management has been investigated based on a city's position in the global smart cities ranking (the IMD Smart City Index). Multiple regressions were used to identify the relationships between the independent variables (the values of the culture dimensions defined by Hofstede: power distance, individualism, masculinity, uncertainty avoidance, and long-term orientation) and the dependent variable – the value of the IMD Smart City Index. The IMD Smart City Index was chosen for its thematic relevance to the issue of adapting knowledge-based solutions in smart city management, as it reflects current results across several indicators that are priority indicators of the city's technological and innovative development. Smart cities were selected based on their rankings in the IMD Smart City Index. This study demonstrates that elevated levels of long-term orientation and individualism, coupled with low uncertainty avoidance, positively impact the adoption of knowledge-based city management. In contrast, the anticipated relationships between power distance and the adoption of smart city solutions, as well as between masculinity and their adoption, alongside effective knowledge-based smart city management, were not substantiated and warrant further examination. The proposed connections between specific dimensions of national culture and effective smart city management are pertinent to the cities featured in the IMD Smart City Index. The literature pays little attention to the cultural determinants of smart city management, particularly organisational and managerial solutions, during the transition from a classic city to a smart city. The paper explored the role of cultural factors in city management and urban development. The motivation for this study is to identify the relationship between Hofstede's cultural dimensions and the level of adaptation of knowledge-based solutions in city management and to examine their influence on a city's position in the global smart cities ranking. Future investigations should aim to explore additional variables that may affect the adoption of smart city solutions and the overall performance of city management.

Keywords: Smart city, Knowledge-based city management, Smart city solutions, Culture, Hofstede's culture dimensions

1. Introduction

A city today is a complex system characterised by many interconnected citizens, businesses, various modes of transportation, communication networks, services, and utilities. In their appearance, smart cities are the answer to this challenge. Smart cities were featured as an alternative to the traditional model, leveraging new technologies (especially ICTs) to address various challenges. It is believed that culture influences how people use information systems and accept and adopt information technology, thereby shaping knowledge-based smart city management.

National culture has long been considered a contextual factor influencing economic behaviour, including innovation and technology acceptance. The influence of cultural factors on new technology adoption has been recognised as a highly relevant field for exploration by many scientists. Notably, the transition from conventional urban environments to smart cities has not received adequate scholarly attention to the cultural determinants that underpin smart city management, particularly in terms of organisational and managerial solutions (Neves, 2025; Avis et al., 2025). Thus, this study aims to elucidate how cultural elements influence urban development and the broader discipline of city management.

The existing literature exhibits a notable deficiency in addressing the cultural determinants of smart city management, particularly regarding the organisational and managerial solutions required for transitioning from traditional urban frameworks to smart city paradigms. This paper critically examines the influence of cultural factors on urban management and development processes. The impetus for this study is to investigate the relationship between Hofstede's cultural dimensions and the extent of technological adoption in smart city management and the subsequent impact on a city's standing in global smart city rankings.

The motivation behind this study is to explore the relationship between Hofstede's cultural dimensions and the effective knowledge-based management of smart cities, as well as their influence on a city's standing in the global smart cities ranking.

This study aims to investigate the intricate relationships between Hofstede's cultural dimensions and the efficacy of smart city management, with a focus on a city's standing in the global smart cities ranking, as determined by the IMD Smart City Index.

The structure of the paper is as follows: after this introduction, the next section presents a literature review that includes a discussion of the research model and the development of hypotheses. The research methodology is elaborated upon in detail. Lastly, the research findings are presented and discussed, the implications examined, and the limitations and avenues for future research identified.

2. Literature Review

The concept of smart cities has undergone a significant evolution, initially characterised by the integration of advanced technologies such as sensors, high-speed internet infrastructure, and big data analytics platforms (Özdoğan et al., 2025; Audretsch et al., 2025). The contemporary city is a knowledge-based, smart city because its management requires the collection, processing, and use of large amounts of data.

The first dimension identified by Hofstede (1980), power distance, relates to the extent of accepted inequality among individuals within a given culture.

Power distance refers to the extent to which a society accepts formal power and status differences among its members. Hofstede (2011) posits that societies with diminished power distance are more inclined to adopt new technologies and foster innovative practices. In contrast, high levels of centralisation and formalisation tend to correlate negatively with the rates of innovation adoption. Nikolov and Krumova (2019) assert that power distance is a strong predictor, particularly in European nations, of specific aspects of e-governance in smart cities. Thus, the first hypothesis of this inquiry can be articulated as follows:

H1: *Knowledge-based smart city management is positively impacted by low power distance.*

This hypothesis posits that a reduced level of power distance can positively influence the efficacy of knowledge-based smart city management.

The constructs of individualism and collectivism represent a spectrum that reflects varying degrees to which societies endorse self-reliance over group integration (Hofstede, 1980).

In individualistic societies, individuals are encouraged to act autonomously, question authority, and take initiative, traits that align with entrepreneurship and knowledge creation. Individualism reflects the extent to which a society allows gratification and enjoyment while also facilitating them. There exists a positive correlation between individualism and technology acceptance (Escandon-Barbosa et al., 2022).

Furthermore, Masimba, Appiah, and Zuva (2019) have confirmed a significant positive relationship between individualistic orientations and technology adoption rates. These societies exhibit enhanced levels of innovation. Additional empirical evidence suggests that cultures classified as individualistic are more inclined to adopt technological innovations. A positive correlation is also identified between elevated individualism and indicators of innovation. Consequently, societies with stronger individualistic orientations are likely to exhibit greater innovation. Greater individualism among urban populations correlates with greater efficacy in managing smart cities. Individualism is posited to stimulate innovative thinking and personal accountability, both of which are essential attributes in the development and implementation of smart technologies and urban policies. As citizens engage more actively in their communities, their unique perspectives and contributions may yield more adaptive and responsive governance structures, ultimately resulting in improved outcomes for smart city initiatives. This relationship underscores the importance of cultivating individualistic values in fostering collaborative, technology-driven urban environments (Marchesani, 2023). Individuals in these societies feel empowered to voice their opinions, making them more inclined to innovate and embrace new concepts. Thus, individuals in individualistic cultures often exhibit self-reliance and independent thinking, which is anticipated to foster creativity and, by extension, heightened levels of innovation and the adoption of knowledge-based solutions (Dirsehan and Zoonen, 2022). In light of this comprehension, the second hypothesis posited in this study is articulated as follows:

H2: *Knowledge-based smart city management is positively affected by greater individualism.*

The dichotomy of masculinity versus femininity serves as a critical framework for understanding how various societies prioritise distinct values traditionally associated with gender. Feminine cultures place greater emphasis on relational dynamics. Research indicates that cultures with a feminine orientation are generally more supportive of the adoption of new technologies, as they are influenced by subjective norms and positive behavioural intentions (Neves et al., 2025).
On the other hand, Sunny, Patrick, and Rob (2019) attest that masculine societies may tend to have negative attitudes towards technological innovations. Masculinity alone may not serve as a definitive predictor of

technology acceptance, particularly concerning smart city initiatives (Okafor et al., 2023). Research by Meyer-Waarden et al. (2021) suggests that femininity moderates uncertainty avoidance, thereby enhancing trust in smart solutions that promote individuals' subjective well-being. Whereas masculinity often undermines collaboration and social openness, which are crucial for long-term innovation success (Prim et al., 2017).

In summary, Hofstede (2001) posits that organisations within masculine cultures are predominantly orientated towards performance recognition and rewards, alongside individual development, traits commonly associated with innovation. Therefore, this study proposes a positive correlation between masculinity and the propensity for innovation within smart city management contexts.

H3: *A higher level of masculinity has a positive influence on knowledge-based smart city management.*

Uncertainty avoidance is a critical cultural dimension that delineates the extent to which societies endeavour to mitigate unpredictability in their environments. The implementation of new technologies inherently entails a degree of uncertainty, particularly when their functionality is validated, but their economic viability remains contentious. This underscores the importance of economic risk as a primary concern in technology adoption.

Venkatesh and Zhang (2010) found that adopting new technology can engender uncertainty, culminating in heightened perceived stress and discomfort in cultures characterised by elevated uncertainty avoidance. Furthermore, research conducted by Mutambik (2024) identified uncertainty avoidance as a robust predictor of technology acceptance, particularly in the context of smart city initiatives. Supporting this premise, studies by Meyer-Warden et al. (2021) reveal that individuals originating from cultures with high uncertainty avoidance manifest heightened anxiety when confronted with transformative changes and the introduction of novel technologies, accompanied by an increased need for control.

Consequently, uncertainty avoidance emerges as a vital dimension that distinguishes societies by their propensity to embrace risk. According to Hofstede (2011), cultures marked by low levels of uncertainty avoidance exhibit a greater willingness to engage in risk-taking behaviours and to entertain divergent viewpoints, both of which are instrumental in fostering innovation and the adoption of new technologies. In contrast, societies characterised by high uncertainty avoidance exhibit a pronounced reluctance to experiment with unproven solutions in smart city initiatives. Risk-averse populations often require substantial assurances regarding privacy, security, and reliability before consenting to adopt such innovations. Therefore, the fourth hypothesis of this study can be articulated as follows:

H4: *A lower level of uncertainty avoidance positively impacts the effectiveness of knowledge-based smart city management.*

Long-term orientation represents a significant cultural dimension that encompasses a multifaceted understanding of temporal perspectives, integrating considerations of the past, present, and future. Cultures characterised by long-term orientation exhibit a societal time perspective influenced by enduring cognitive frameworks, wherein technology and situational evaluations are grounded in both present and prospective implications, rather than exclusively prioritising immediate, short-term outcomes (Tian et al., 2021). This dimension of long-term orientation pertains to the value a culture places on its traditions and the degree to which it emphasises historical and future considerations. Long-term orientation positively influences the functional, social, and emotional values attributed to emerging technologies, thereby fostering technology acceptance. Cultures with higher long-term orientation tend to be more receptive to adopting innovations and novel technologies. The rate of technology adoption is expected to be higher in nations with a lower long-term orientation than in those with a more pronounced one. Long-term orientation has been associated with innovation through a focus on future-oriented investment, persistence, and adaptive change. Furthermore, societies that score high on long-term orientation are inclined to invest significantly in sustainable, future-oriented smart city infrastructures, such as Internet of Things (IoT)-based environmental monitoring systems and predictive analytics. This propensity leads to a higher adoption rate of such solutions (Wang and Zhou, 2022). Accordingly, the following hypothesis emerges from this analysis:

H5: *A higher level of long-term orientation has a positive influence on knowledge-based smart city management.*

Culture significantly influences the management of smart cities, as demonstrated by numerous studies. This impact arises from culture's ability to foster either a conducive or a challenging environment for innovation. Smart cities should prioritise enhancing the quality of life alongside improving the efficiency and quality of services provided by government entities and businesses (Mutambik and Almuqrin, 2024).

3. Research Design and Methodology

Multiple regressions were employed to explore the relationship between the independent variables, cultural dimensions as defined by Hofstede, including power distance, individualism, masculinity, uncertainty avoidance, and long-term orientation (https://www.hofstede-insights.com/country-comparison-tool), and the dependent variable, which is the value of the IMD Smart City Index 2026. The IMD Smart City Index 2026 was chosen for its timeliness and thematic significance, as it captures current outcomes across several key indicators relevant to a city's development. Smart cities were selected based on their rankings within the IMD Smart City Index 2026 (https://www.imd.org/smart-city-observatory/home/).

The study makes use of the IMD Smart City Index 2026, which is the internationally accepted database released jointly by the International Institute of Management Development, along with the Singapore University of Technology and Design. The IMD Smart City Index is a vital tool for evaluating and enhancing the performance of cities worldwide in their journey toward becoming smarter and more sustainable. By assessing various dimensions of urban life, the index provides valuable insights that inform policy decisions, promote public accountability, and guide strategic planning. Through benchmarking, policy guidance, public accountability, and strategic planning, the IMD Smart City Index helps cities leverage technology to improve the quality of life for their residents and address the challenges of modern urbanisation. This index provides a more complete comparison of cities by ranking them not just on their economic performance but also by considering other important factors that influence their relative strengths (Ivaldi et al., 2026; Alshubiri, 2026).

The IMD Smart City Index is used widely by academics. It aims to measure how effectively a city uses technology and smart solutions to improve its citizens' quality of life and city management. It applies a combined weighting and scoring approach based on survey data collected from residents (Ruangwicha and Tuamsuk, 2026).

The IMD Smart City Index is a comprehensive tool developed to evaluate and rank cities worldwide based on their implementation of smart city initiatives. Created by the Institute for Management Development (IMD) in partnership with the Singapore University of Technology and Design, the index assesses various dimensions of urban life, providing valuable insights into how cities leverage technology to enhance the quality of life for their residents. The index covers multiple categories and indicators, reflecting the multifaceted nature of smart cities (Unal and Dursun, 2026).

Smart city performance is measured almost exclusively via citizens' views on the impacts of urban infrastructure and technology on their daily lives. The index captures the globe's smart cities based on the perceptions of their citizens regarding how they utilise technology to increase the quality of their lives. While a limited number of contextual indicators are included, the index is predominantly based on standardised perception-based measures collected from city residents. Based on the conceptual framework for the maturity of a smart city, the original IMD indicators were categorised into five domains representing major dimensions of the development of a city. Each set represents a certain dimension of the transformation of a city, which may be technology, infrastructure, environment, society, and economy, and comprises a set of perception indicators supplied by the citizens residing in the cities (Pavanini et al., 2026). The IMD Smart City Index relies on individuals' opinions collected through surveys. The perceptions of 120 residents for each city are assessed by the availability of infrastructure and technological services. Both are judged concerning five dimensions: health and safety, mobility, activities, opportunities, and governance. Weights of the five areas are not predetermined: respondents are asked to select five city priorities from 15 indicators. The weight of each category in the final calculation is adjusted based on the number of selected indicators that fall within that category. Thus, no indicator is thought to be the most influential on smartness in overall assessments. The final score for each city is calculated using weighted data from the past three years: the most recent year's weight is 3, and the least recent year's weight is 1 (Belizaire, 2026).

The IMD Smart City Index 2026 provides a holistic assessment of the world's 148 cities. Smart cities for this study were selected based on their rankings in the IMD Smart City Index 2026. The 49 cities with the highest ranking were included in the analysis. The following cities were taken into consideration: Zurich, Oslo, Geneva, London, Copenhagen, Dubai, Lausanne, Canberra, Singapore, Abu Dhabi, Helsinki, Seoul, Prague, Stockholm, Hamburg, Beijing, Amsterdam, Ljubljana, Munich, Shanghai, Hong Kong, Sydney, Auckland, Riyadh, Taipei City, Tallinn, Wellington, Vienna, Berlin, Bilbao, Warsaw, Vilnius, Hail, Doha, Boston, Tianjin, Madrid, Bratislava, Washington D.C., Zhuhai, Seattle, Luxembourg, Dusseldorf, Gothenburg, New York, Manchester, Riga, Toronto, and Dublin.

The top cities in the IMD Smart City Index 2026 overall have strong scores across all five categories. Not only do they make important economic contributions to the global economy, but they are also hubs of education and

business innovation, and they invest in the infrastructure necessary to maintain a high quality of life with a focus on the environment and effective governance.

4. Results and Discussion

Multiple regression analysis was employed to examine the relationship between Hofstede's cultural dimensions and the IMD Smart City Index 2026. The impact of cultural factors on the adoption of new technologies is increasingly recognised as a critical area of research. Studies that utilise and validate Hofstede's national culture dimensions demonstrate that these constructs are both relevant and significant, indicating that variations in national cultures significantly influence a wide range of organisational and individual behaviours and outcomes across different cities. The results of the regression analysis are presented in Table 1.

Table 1: The results of the regression analysis

Independent variables - national culture dimensions	**Standardized coefficients**	**t**	**Significance level**
	Beta		
Low power distance	0.083	0,372	0,640
Individualism	0.491	4,358	0,000
Masculinity	0.076	0,364	0,620
Low uncertainty avoidance	0.267	3,659	0,000
Long-term orientation	0.519	4,287	0,000
Dependent variable: the value of IMD Smart City Index 2026			
$R^2 = 0.831$, F = 29.167, significance level = 0.01.			

Source: own study based on https://www.imd.org/smart-city-observatory/home/ and https://www.hofstede-insights.com/country-comparison-tool.

The reliability assessment utilised in this study was Cronbach's alpha, which revealed that all research variables exceeded 0.8. This indicates a high level of internal consistency, suggesting that the measures employed are reliable and that the evaluation instrument is suitable for research purposes.

The findings indicate that the R-squared value was 0.831, demonstrating that the independent variables explain 83.1% of the variance in the adoption of smart city solutions, as measured by the IMD Smart City Index 2026. Furthermore, the linear relationship between Hofstede's cultural dimensions and the adoption of smart city solutions was statistically significant (F = 29.167, p = 0.01), thereby affirming the model's suitability for this study.

The following research hypotheses, listed below, demonstrate the relationship between Hofstede's cultural dimensions and the level of adaptation of knowledge-based solutions in city management and examine their influence on a city's position in the global smart cities ranking:

H1: *Knowledge-based smart city management is positively impacted by low power distance.*

H2: *Knowledge-based smart city management is positively affected by greater individualism.*

H3: *A higher level of masculinity has a positive influence on knowledge-based smart city management.*

H4: *A lower level of uncertainty avoidance positively impacts the effectiveness of knowledge-based smart city management.*

H5: *A higher level of long-term orientation has a positive influence on knowledge-based smart city management.*

Analysis of individual hypotheses yielded the following results: low power distance (beta = 0.083) did not establish a statistically significant relationship with the IMD Smart City Index 2026, as evidenced by a significance level of 0.640, which exceeds the 0.05 threshold; therefore, Hypothesis 1 is rejected.

Conversely, the significance level for individualism in the IMD Smart City Index 2026 was 0.000, well below 0.05, validating Hypothesis 2. The coefficient for individualism was notably substantial (beta = 0.491), thereby indicating that higher levels of individualism positively influence the adoption of innovative solutions.

Further analysis revealed that masculinity (beta = 0.076) did not demonstrate a statistically significant relationship with the adoption of smart city solutions, with a significance level of 0.620, leading to the rejection of Hypothesis 3. The significance level for low uncertainty avoidance in relation to the IMD Smart City Index 2026 was set at 0.000, thus confirming Hypothesis 4. The beta value for this variable is 0.267, suggesting that lower uncertainty avoidance is associated with a significant positive effect on the adoption of smart city solutions.

Moreover, the significance level for long-term orientation in relation to the adoption of smart city solutions was also 0.000, confirming Hypothesis 5. This test indicated that long-term orientation has the highest coefficient (beta = 0.519) among the cultural dimensions, indicating its predominant positive impact on the adoption of smart city solutions.

The outcomes of this investigation yield some unexpected insights. Notably, power distance and masculinity were found to be insignificant predictors in this model. In contrast, long-term orientation, individualism, and low uncertainty avoidance emerged as the three cultural dimensions that exhibited significant correlations. As hypothesised, long-term orientation positively influences the adoption of smart city solutions and the IMD Smart City Index 2026. Alongside this, both low uncertainty avoidance and individualism demonstrated significant and favourable effects on the adoption of smart city solutions. Consequently, hypotheses 1 and 3 are rejected, while hypotheses 2, 4, and 5 are confirmed.

These results offer a noteworthy discussion of the role of cultural dimensions in the adoption of smart city solutions. Specifically, the analysis reveals that power distance does not play a critical role in the adoption process, thereby challenging the expected impact of this cultural dimension on effective smart city management. Similarly, the masculinity dimension appears to be irrelevant in this context, suggesting that the values typical of masculine and feminine cultures exert an uncertain influence on the adoption of smart city solutions. For instance, while masculine values such as achievement and motivation may suggest a correlation to positive outcomes in innovation adoption, feminine cultures, characterised by values of equality and cooperation, may foster a more favourable environment for the acceptance of new technologies in urban management.

In terms of long-term orientation, the study affirms that cities in nations with higher levels of this dimension achieve higher scores on the IMD Smart City Index 2026. National cultures with a pronounced long-term orientation are generally more receptive to innovative ideas and solutions, demonstrating practical problem-solving skills that facilitate the adoption of new technologies in urban management. The hypothesised positive relationship between uncertainty avoidance and the IMD Smart City Index 2026 has also been substantiated; this finding posits that risk aversion, among other factors, may influence a culture's innovation capacity and readiness to implement modern technologies.

Finally, the confirmed positive association between high levels of individualism and the adoption of smart city solutions reinforces the assertion that more individualistic societies are predisposed to embracing innovative approaches in urban management.

Effective management in smart cities is profoundly influenced by both national and local cultural dimensions, notably individualism, uncertainty avoidance, and long-term orientation. These dimensions are fundamental in shaping organisational strategies and enhancing citizen engagement. A thorough understanding of these cultural factors enables policymakers and urban administrators to develop interventions that improve adoption rates and ensure equitable outcomes across diverse urban environments.

5. Conclusion

The findings of this study indicate that the adoption of smart city solutions is significantly influenced by cultural dimensions, specifically higher levels of individualism and long-term orientation, alongside a reduced level of uncertainty avoidance. However, the hypothesised relationships between masculinity and the adoption of smart city solutions, as well as the impact of low power distance, remain unsubstantiated and warrant further empirical investigation.

The main limitation of this study is the relatively small sample size of cities included in the analysis. Despite this limitation, the research has made progress towards achieving its primary research objective by substantiating that certain relationships between selected national culture dimensions and the adoption of smart city solutions are valid, as evidenced in the cities analysed within the context of the IMD Smart City Index. Conversely, the study raises pertinent questions about the relationship between masculinity and power distance and their respective influences on the adoption of smart city solutions, underscoring an urgent need for future scholarly

inquiry. One proposition for subsequent research is to expand the sample to encompass a broader range of national cultures and to analyse differing clusters of these cultures.

Individualism, uncertainty avoidance, and long-term orientation are key cultural dimensions that influence effective management in smart cities. These factors are essential for developing organisational strategies and encouraging public participation. Policymakers and city managers can create interventions that not only increase adoption rates but also foster equitable outcomes in a variety of urban settings by having a thorough understanding of these cultural factors.

Future investigations should aim to explore additional variables that may affect the adoption of smart city solutions and the overall performance of city management. Subsequent studies must strive to validate the findings by leveraging a larger sample. As the performance of smart cities cannot be fully elucidated through cultural dimensions alone, future research will also need to examine other elements that contribute to creating a conducive environment for enhancing smart city management. Additionally, as this study has illustrated, applicable technological solutions are present across the selected cities. A more comprehensive, diverse comparative analysis involving other urban areas would be beneficial for identifying broader trends in city management practices.

Ethics Declaration: This study utilised publicly available online data and did not involve direct interaction with participants. All data were anonymised, and no personally identifiable information was collected.

AI Declaration: No AI tools were used in the development of the paper. All work, including the analysis, interpretation and writing, was conducted solely by the author.

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Building Entrepreneurial Capacity in Universities Through Cross-Institutional Staff Training

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Abstract: Universities are increasingly expected to act as entrepreneurial and innovation-driven organisations, yet the development of entrepreneurial capacity among academic and professional staff remains uneven and fragmented. To address this issue, this study examines a cross-institutional knowledge management intervention designed to reduce fragmentation in university entrepreneurship support and strengthen staff capacity in innovation ecosystems. The study is situated within a five-university EIT HEI project and draws on needs-assessment data from all partner institutions, while the empirical evaluation focuses on two staff training cases implemented in Finland and the United Kingdom. Building on a multi-site needs assessment, semi-structured interviews and partner competence mapping were thematically analysed and formalised using a DACUM-based competence map that codifies three duty areas: (1) commercialisation of research and innovations, (2) student entrepreneurship support, and (3) innovative teaching methods in entrepreneurship. The resulting competence architecture specifies role-relevant tasks, required knowledge/skills/attitudes, supporting tools, and performance evidence, enabling transfer across heterogeneous academic and professional staff groups. The mapped competences were operationalised through blended local training and mentoring. In the two evaluated cases, training participation was associated with improved self-reported confidence in navigating entrepreneurship ecosystems, stronger cross-silo collaboration, and early spillover effects such as staff acting as ambassadors and strengthening links to external ecosystem actors. However, the study also identified challenges related to staff engagement, knowledge institutionalisation, and sustaining learning beyond project-based interventions. The findings suggest that structured competence mapping combined with multi-channel delivery can function as an effective KM design for eliciting, codifying, and scaling entrepreneurial support knowledge in higher education, while highlighting the need for stronger incentives and more systematic evaluation to sustain participation and evidence impact.

Keywords: Knowledge management, Competence mapping, DACUM, Higher education, Entrepreneurial ecosystems, Organizational learning, Capability building

1. Introduction

Over the past two decades, universities have been increasingly positioned as entrepreneurial and innovation-oriented organisations, expected to contribute not only through teaching and research but also through active engagement with industry and society (Etzkowitz & Leydesdorff, 2000, Guerrero et al., 2016). In practice, however, these activities do not always develop in a coordinated way.

In many institutions, entrepreneurship-related work is spread across different units: technology transfer offices, academic departments, and professional services, often with limited alignment between them (Siegel & Wright, 2015). As a result, expertise tends to remain localised, and opportunities for collaboration are not fully realised. This fragmentation is not only a structural issue but also a knowledge problem: relevant know-how exists, but it is unevenly distributed and not systematically shared.

This raises questions about how universities manage and mobilise knowledge internally. While higher education institutions are strong in knowledge creation, they are less effective when it comes to making that knowledge visible, transferable, and usable across contexts (Nonaka & Takeuchi, 1995, Dalkir, 2017). Much of the knowledge related to entrepreneurship support, for example, mentoring practices, ecosystem navigation, or funding strategies remains tacit and embedded in individual experience. Previous studies have shown that knowledge sharing in universities is often constrained by organisational silos and disciplinary boundaries (Fullwood et al., 2013), which further limits the scalability of such practices.

Efforts to address this have included the development of competence frameworks, most notably EntreComp, which conceptualises entrepreneurship as a set of knowledge, skills, and attitudes applicable across domains (Bacigalupo et al., 2016). These frameworks provide useful reference points, but they are typically broad and require adaptation to specific institutional roles. In parallel, approaches such as DACUM have been used in other contexts to map competences based on real work practices (Norton, 1997), although their use in higher education entrepreneurship remains relatively limited.

At the same time, staff development initiatives have increasingly focused on experiential learning formats (workshops, case-based activities, peer exchange) as a way to build entrepreneurial capability (Fayolle & Gailly, 2008). These approaches are effective at the individual level, but their impact often remains short-lived. Without mechanisms to connect learning to organisational processes, it becomes difficult to sustain change or embed new practices.

Taken together, this points to a gap between individual competence development and organisational knowledge use. What is missing are approaches that link competence mapping, training design, and knowledge management in a way that supports both learning and institutional integration, particularly in settings that involve multiple institutions.

This study addresses that gap by examining a cross-institutional intervention implemented within the CODEUNITED project, funded by the European Institute of Innovation and Technology Higher Education Initiative (EIT HEI). The intervention combines needs assessment, DACUM-based competence mapping, and multi-channel staff training across five European universities.

The aim is to explore how such an approach can support the development of entrepreneurial capacity among university staff and, at the same time, contribute to more structured knowledge processes within institutions. Specifically, the study looks at how competences are identified and formalised, how they are translated into training activities, and what kinds of outcomes and challenges emerge during implementation. Accordingly, the study is guided by the following research questions: 1) how does DACUM-based competence mapping support the codification and transfer of entrepreneurial knowledge within higher education institutions, 2) how do cross-institutional staff training interventions contribute to entrepreneurial capacity-building and organisational learning in universities?

2. Literature Review

Knowledge management (KM) in higher education builds on organisational KM theory, adapted to the distinctive structures of academic institutions. HEIs are regarded as knowledge organisations by nature, yet paradoxically resistant to formal KM adoption (Rowley, 2000, Quarchioni et al., 2020). Their knowledge is distributed across faculties, departments, and professional services, embedded in both explicit artefacts and tacit expertise (Al-Kurdi et al., 2018, Ramjeawon & Rowley, 2018).

Effective KM requires strategic embeddedness rather than ad hoc practice. Many HEIs lack formal KM strategies, dedicated roles, or performance frameworks, conditions consistently identified as structural barriers to effectiveness (Santos et al., 2024, Anatan & Bangun, 2024, Subedi, 2025). Alongside strategy, culture and leadership are critical enablers: trust, psychological safety, and collaborative norms facilitate voluntary knowledge sharing, while entrepreneurial and knowledge-oriented leadership strengthen the link between sharing, innovation, and intellectual capital (Fan & Beh, 2024, Basit et al., 2024, Ibarra-Cisneros et al., 2023).

At the organisational level, KM research highlights three interrelated mechanisms: knowledge codification (converting tacit expertise into explicit, reusable forms), knowledge transfer (moving and adapting knowledge across individuals, teams, and institutions), and institutional learning (embedding transferred knowledge in routines and organisational memory) (Nonaka & Takeuchi, 1995, Metaxiotis & Psarras, 2003, Castaneda et al., 2018). These mechanisms are especially relevant in entrepreneurial universities, where knowledge related to commercialisation, student support, mentoring, and ecosystem engagement tends to be practice-based and dispersed across multiple actors.

DACUM (Developing A Curriculum) competence mapping operationalises this codification-transfer-learning sequence by externalising tacit work knowledge into structured descriptions of duties, tasks, skills, knowledge requirements, tools, and performance indicators (Norton, 1997). The method is built around a facilitated workshop in which a panel of expert practitioners collaboratively analyse and articulate the full scope of a job or role. Rather than relying on external job analysts or pre-existing frameworks, DACUM centres the expertise of practitioners themselves, making the process particularly well suited to capturing contextually embedded, experience-based knowledge that resists easy formalisation. The primary output is a DACUM chart: a structured occupational profile that maps duties (broad areas of responsibility) onto specific tasks (discrete, observable units of work), together with the supporting knowledge, skills, attitudes, and tools required to perform them competently (Norton, 1997).

Each stage of the codification-transfer-learning sequence maps onto a distinct function of DACUM. First, DACUM supports knowledge codification by transforming tacit staff expertise into explicit competence descriptions, tasks, tools, and performance indicators that can be documented and communicated. Second, it supports knowledge transfer by rendering local practices understandable and reusable across departments, roles, and institutions. Third, DACUM supports institutional learning when the mapped competences are incorporated into staff development programmes, organisational routines, curricula, support services, or broader innovation ecosystem practices.

3. Methodology and Data

This study adopted a multi-phase mixed-methods design to investigate the development and implementation of a competence-based training intervention across higher education institutions. The methodology integrated qualitative needs assessment, competence mapping, and quantitative-qualitative evaluation of training delivery. The design followed a sequential exploratory logic, in which qualitative findings from interviews informed competence mapping and training design, which were subsequently evaluated using both quantitative and qualitative data. Such mixed-methods approaches are widely used in educational research to combine contextual depth with measurable outcomes (Jansen & van Leeuwen, 2020, Englund, 2025).

The research was conducted within the CODEUNITED project, a collaborative initiative involving five higher education institutions. The project strengthens university-oriented innovation ecosystems by embedding interdisciplinary entrepreneurship education through ecosystem mapping, inclusive training, and collaborative startup support. Multiple staff training programmes were organised in Autumn 2025 in each institution. Phase 1 implementation engaged 143 staff members (37 mentored) across all five partner universities. It is important to distinguish, however, between this broader project context and the empirical dataset on which the present study's analysis is based. This study focuses on two cases of staff training, organised in Finland and the UK, which constitute the core analytical dataset. The needs assessment phase drew on input from all five institutions, while the training evaluation data derive exclusively from these two cases (n=20 in total, see Table 1).

The study involved two groups of participants: project staff and training participants. Between August and October 2025, semi-structured interviews and group discussions were held with representatives of each institution's staff (both academic and support staff involved in entrepreneurship initiatives). Participants described their current programmes or support for entrepreneurship, relevant past projects and initiatives, expertise they could share, and needs for further development. These conversations explored existing practices, institutional capacity gaps, and future competence needs in three focus areas: research commercialisation and technology transfer, support for student entrepreneurship, and entrepreneurial teaching methods and staff development. In addition, each partner completed a competence mapping spreadsheet documenting specific expertise areas and key staff contacts. The qualitative transcripts were analysed to extract recurring themes regarding skill gaps and successful practices.

The participants of the training in the UK (n=11) responded to pre- and post-participation surveys assessing changes in confidence, applied entrepreneurial practice, and broader competence development using the EntreComp framework (Bacigalupo et al., 2016). The participants of the training in Finland filled in reflection diaries (n=3) or participated in semi-structured interviews (n=6).

Table 1: Summary of data sources, participants, and analytical methods

Phase	Data source	Participants	n	Analytical method
Needs assessment	Interviews & group discussions	Academic & support staff, all five institutions	8 group or individual interviews	Thematic analysis
Needs assessment	Competence mapping spreadsheet	Staff representatives, all five institutions	1 consolidated spreadsheet	Thematic analysis
Training evaluation (UK)	Pre- and post-surveys	Training participants	11	Descriptive statistics
Training evaluation (Finland)	Reflection diaries	Training participants	3	Thematic analysis
Training evaluation (Finland)	Semi-structured interviews	Training participants	6	Thematic analysis

Qualitative data (interviews, reflections, and discussions) were analysed using thematic analysis, involving iterative coding and the development of categories and themes to identify patterns in needs, experiences, and outcomes. Quantitative data from surveys were analysed using descriptive statistics to measure changes over time, particularly in pre-post comparisons.

4. Results

The results trace how entrepreneurial knowledge was identified, codified, transferred, and applied through the intervention. The analysis first examines how institutional needs and practices were translated into the DACUM competence framework, then considers how this framework informed training design and implementation. Finally, it assesses participant development, reported changes in practice, and implementation challenges. Together, the findings show how competence mapping and staff training functioned as KM mechanisms supporting knowledge sharing, absorptive capacity, boundary-spanning work, and organisational learning.

4.1 DACUM Competence Framework

The DACUM competence framework was a central outcome of the analysis, translating dispersed institutional needs and practices into a structured model for entrepreneurship capacity-building. From a KM perspective, it functioned as a knowledge codification mechanism by converting partly tacit staff expertise into explicit duties, tasks, knowledge, skills, attitudes, tools, and performance evidence. The framework is organised into three interrelated duty areas that reflect the core functions required to support innovation ecosystems within universities.

The first area focuses on strengthening the ability of staff to support the commercialisation of research outputs, bridging the gap between academic knowledge and market application. The second area emphasises the role of staff as facilitators and connectors within student entrepreneurship ecosystems, highlighting mentoring, coordination, and stakeholder engagement. The third area addresses the pedagogical dimension, focusing on the delivery of experiential and practice-oriented entrepreneurship education through innovative teaching methods.

Across these areas, the framework integrates knowledge, skills, attitudes, and performance-oriented outputs, making it both descriptive and actionable. It also created a shared vocabulary across institutions, supporting knowledge transfer between academic staff, professional services, and entrepreneurship support roles. In this sense, the framework operated as a boundary object that made locally embedded expertise understandable and reusable across organisational contexts.

Table 2: DACUM Competence Framework

Component	D1 – Commercialisation of Research	D2 – Student Entrepreneurship Support	D3 – Innovative Teaching Methods
Definition	Enabling academic staff and support personnel to translate research outputs into commercial value through patents, licenses, spin-outs, and funded innovation pathways.	Equipping staff to mentor, coach, and connect student entrepreneurs with resources, partners, and ecosystems locally and internationally.	Preparing educators to deliver experiential, challenge-based, and cross-disciplinary entrepreneurship education using modern pedagogical techniques.
Core Tasks	Manage IP and patenting processes, Identify commercial opportunities, Develop funding strategies, Prepare investor-ready pitches, Navigate technology transfer, Cultivate entrepreneurial mindset	Provide mentoring, Refer to ecosystem actors, Facilitate cross-departmental support, Support internationalization, Track outcomes	Design workshops, Organize challenges, Use serious games, Train-the-trainer, Integrate into curricula, Evaluate outcomes, Develop MOOC content
Knowledge	IP basics, TTO policies, licensing frameworks, innovation maturity levels	Institutional ecosystem, support services, startup visa/IP basics	Experiential learning theory, game-based learning, interdisciplinary pedagogy
Skills	Prior-art search, business model analysis, pitch preparation, negotiation	Coaching, active listening, ecosystem navigation, stakeholder engagement	Workshop facilitation, game moderation, curriculum design, rubric creation, digital content authoring

Component	D1 – Commercialisation of Research	D2 – Student Entrepreneurship Support	D3 – Innovative Teaching Methods
Attitudes	Proactivity, risk tolerance, openness to feedback, impact orientation	Empathy, inclusiveness, initiative, student-centredness	Creativity, learner-centeredness, adaptability, continuous improvement
Tools & Resources	Invention disclosure forms, NDA templates, BMC, FTO checklist, grant templates, pitch decks, TRL/IRL grids	Mentoring forms, CRM tools, partner lists, alumni registries, event templates	Design thinking templates, rubrics, game kits, teaching portfolios, MOOC platforms, self-efficacy scales
Performance Evidence	Patents filed, FTO notes, opportunity assessments, spin-out pathways, funding secured	Students mentored, referrals tracked, events held, cross-border ventures	Courses with entrepreneurial content, challenges delivered, MOOC modules published, learning impact measured

4.2 Training Programme Design and Implementation

The training programmes translated the DACUM duty areas into role-oriented learning activities. In KM terms, the programmes moved codified knowledge into situated learning environments where participants could interpret, adapt, and apply it to their own roles.

4.2.1 Startup Sprint (UK)

The Startup Sprint was organised in the UK, focused on the D2 competence area (Student Entrepreneurship Support) and was delivered to 11 non-academic staff members representing diverse roles within student and professional services. The programme adopted a blended learning format, combining four online sessions with three hybrid "Lunch and Learn" sessions. Its design was explicitly informed by DACUM-defined tasks associated with supporting early-stage student entrepreneurship, including facilitating venture development, identifying and communicating opportunities, and connecting students with relevant ecosystem actors.

To support these objectives, the programme integrated internal institutional initiatives, such as the Talent Marketplace and the READY programme, with external perspectives from organisations including Barclays Eagle Labs and The Big Issue. The training strengthened boundary-spanning capacity by helping staff translate knowledge between students, professional services, academic units, and external ecosystem partners.

4.2.2 From Research to Business (Finland)

The From Research to Business: Staff Training on Entrepreneurial Mindset and Business Finland Funding addressed the D1 competence area (Commercialisation of Research and Innovations) and was delivered as an in-person programme across the Lahti and Lappeenranta campuses. The training was designed to strengthen staff members' entrepreneurial mindset and their practical readiness to engage with research commercialisation pathways and national funding instruments. It brought together participants from Research, Development and Innovation (RDI), education, and support services, reflecting the cross-functional nature of commercialisation processes.

The programme combined keynote lectures, expert panels, real-life project cases, and interactive ideation workshops to provide both conceptual understanding and applied learning opportunities. The first session, held at the Lahti campus, focused on entrepreneurial mindset development and opportunity recognition. The second session, delivered at the Lappeenranta campus, concentrated on research-to-business pathways and Business Finland funding mechanisms.

The training content, with the exception of workshop activities, was recorded and made available to participants through the programme's MOOC platform, supporting continuity of learning and broader accessibility. The learning objectives emphasised both conceptual and practical competence development, enabling participants to understand commercialisation pathways, apply an entrepreneurial mindset within RDI activities, navigate and prepare for Business Finland funding instruments, and use ideation tools to generate and refine innovation ideas. In addition, the programme supported interdisciplinary collaboration and enhanced participants' ability to identify innovation opportunities within research projects and communicate research-based ideas effectively to relevant stakeholders. The activities supported absorptive capacity by

helping participants recognise, assimilate, and apply external knowledge on funding, commercialisation, and research-to-business pathways.

4.3 Outcomes of Staff Training Implementation

This section presents outcomes from the training interventions, focusing on changes in participant capabilities, applied practice, and learning experiences. The findings also show how the interventions supported knowledge sharing, absorptive capacity, and organisational learning, while revealing barriers to embedding new knowledge within institutional routines.

4.3.1 Outcomes of the Startup Sprint

The evaluation of the Startup Sprint indicates positive developments across participants' confidence, applied practice, and broader entrepreneurial competences, while also revealing constraints affecting implementation within institutional contexts. These gains suggest that participants developed not only individual competences but also greater capacity to interpret entrepreneurial knowledge in relation to their professional roles.

Participants reported increased confidence across all measured dimensions, with the most notable improvements related to strategic and reflective aspects of their roles. In particular, substantial gains were observed in developing strategies to support enterprise initiatives and in reflecting on employability and professional growth. More moderate improvements were identified in understanding entrepreneurial thinking and applying practical techniques for idea development, suggesting enhanced capability to support early-stage entrepreneurial activity within participants' roles.

Consistent improvements were also evident in applied entrepreneurial practice. Participants demonstrated stronger capacity to mobilise colleagues and resources, identify opportunities for innovation, and define value propositions. In contrast, the ability to communicate ideas clearly and persuasively showed more limited improvement, indicating a potential area for further development. Overall, these findings align with core D2 competences, particularly those related to opportunity recognition and early-stage venture support.

Analysis based on the EntreComp framework shows development across all competence areas, with the strongest gains in resource mobilisation, creativity, and motivation and perseverance. This pattern indicates that the training contributed not only to task-specific improvements but also to broader entrepreneurial competences, supporting the development of more opportunity-oriented and proactive behaviours. Despite these gains, participants identified several challenges in embedding entrepreneurship into their practice. These included difficulties in influencing stakeholders who do not perceive entrepreneurship as part of their role, limited time and competing priorities, challenges in engaging students who do not immediately recognise the relevance of entrepreneurship, and a lack of clarity regarding individual contributions to enterprise activity. The reported barriers point to limits in organisational learning: while individual knowledge and confidence increased, institutional routines, incentives, and role expectations did not always support application.

Participants reported a range of intended actions to apply their learning, including strengthening connections with external ecosystem partners, integrating entrepreneurial approaches into existing programmes, and enhancing collaboration across internal teams. In addition, there was evidence of a shift towards a more proactive and intrapreneurial orientation in their work. Participants' intended actions suggest an emerging community-of-practice dynamic, where enterprise support began to be understood as a shared responsibility rather than an isolated specialist function.

4.3.2 Outcomes of the from research to business

Participants entered the training with varying levels of prior experience in research commercialisation and entrepreneurship. While some were already engaged in related activities, others had more limited exposure and approached the training as an opportunity to better understand entrepreneurship, teamwork, and research-to-business pathways.

Participants highlighted that entrepreneurship requires courage, perseverance, risk-taking, and sustained commitment, and emphasized the importance of teamwork and collaboration in successful research and development and commercialisation processes. The training contributed to a clearer understanding of research-to-business pathways, the complexity of Business Finland funding instruments, and the role of RDI specialists within these processes. This indicates knowledge transfer from external experts and institutional cases into participants' understanding of commercialisation practice.

In terms of application, participants reported intentions to adopt a more innovative and opportunity-oriented mindset, further develop and refine ideas, and integrate business and financial perspectives into their work. Planned actions included exploring project ideas in more depth, seeking mentorship, reflecting on individual contributions to RDI activities, disseminating acquired knowledge, and reviewing Business Finland–funded cases, although some participants indicated no immediate follow-up actions. The mixed follow-up intentions suggest that absorptive capacity varied according to prior experience, role relevance, and access to support.

Collaboration emerged as a key outcome of the training, with participants valuing the opportunity to engage with colleagues and external partners. They highlighted the benefits of shared ambition, diverse perspectives, and exposure to entrepreneurial journeys, as well as the recognition of a strong but underutilized internal knowledge base within the organization. From a KM perspective, the training made hidden organisational knowledge more visible and created opportunities for cross-unit knowledge sharing.

Finally, participants suggested that future training could place greater emphasis on concrete next steps, mentoring, and follow-up support, as well as improved utilisation of internal expertise. At the same time, they emphasized the continued importance of practical case-based learning and peer interaction. These suggestions indicate that one-off training is insufficient for institutional learning unless supported by continuing communities of practice, mentoring, and mechanisms for embedding knowledge into everyday routines.

5. Discussion and Conclusion

The findings suggest that competence-based training, when grounded in a structured framework such as DACUM, can do more than support individual learning, it can also function as a mechanism for organising and mobilising knowledge within higher education institutions. Across both interventions, participants reported improvements in confidence and their ability to engage in entrepreneurial practices, particularly in opportunity identification, resource mobilisation, and early-stage support. These outcomes were most visible where training activities were closely aligned with concrete role tasks, indicating the importance of contextualising competences within everyday practice.

From a knowledge management perspective, the intervention can be understood as a process of knowledge elicitation, codification, transfer, and early-stage institutional learning, where new knowledge begins to influence roles, practices, and collaboration patterns. The needs assessment and competence mapping captured dispersed and often tacit knowledge about entrepreneurship support across partner institutions. The DACUM framework then translated this knowledge into a shared structure, making roles, tasks, and expectations more explicit. This positions DACUM as an organisational knowledge codification mechanism. Training activities acted as the primary vehicle for knowledge transfer, combining experiential learning formats with peer interaction and external input. The intervention therefore created a common language and boundary object through which entrepreneurship-related knowledge could be shared across roles, units, and institutional contexts.

At the same time, the results highlight limits in how far such processes can be sustained. While participants expressed intentions to apply what they had learned, this did not consistently translate into immediate or observable changes in practice. Reported barriers, including time constraints, unclear role boundaries, and difficulties in engaging stakeholders, point to challenges in embedding knowledge within organisational routines. This suggests that the main constraint is not only knowledge availability, but also absorptive capacity: the ability of institutions and staff to recognise, assimilate, apply, and institutionalise new entrepreneurial knowledge.

A similar pattern can be observed across both domains addressed in the study. In the Startup Sprint (D2), non-academic staff strengthened their role as intermediaries connecting students with internal and external resources, illustrating boundary-spanning roles that support knowledge flows across institutional and ecosystem boundaries. In the From Research to Business training (D1), participants developed a clearer understanding of commercialisation pathways and funding mechanisms, alongside a more opportunity-oriented mindset. However, in both cases, the absence of structured follow-up, such as mentoring, project pipelines, or dedicated time for application, limited the transition from individual learning to sustained organisational practice.

These findings point to the importance of moving beyond training as a standalone activity. While competence frameworks and training interventions can support knowledge articulation and transfer, their long-term impact depends on whether institutions provide conditions for continued use. This includes aligning roles, creating opportunities for collaboration, and supporting ongoing engagement with entrepreneurial activities.

Without such alignment, communities of practice may remain temporary and informal, and newly codified knowledge may remain at the level of individual capability rather than becoming embedded in institutional memory, routines, and decision-making.

The study makes a theoretical contribution to KM literature by showing how DACUM competence mapping can operate as a mechanism for organisational knowledge codification, transfer, and institutional learning in entrepreneurial universities. It demonstrates that competence mapping can be used not only for curriculum or training design, but also to structure, externalise, and share entrepreneurship-related expertise across institutions. The cross-institutional setting further contributes to KM debates by showing how shared competence frameworks can facilitate knowledge exchange across organisational boundaries, while also revealing that transfer requires local interpretation, absorptive capacity, and sustained communities of practice.

At the same time, the study has several limitations. The empirical analysis is based on a relatively small number of participants in the evaluated cases, and the findings rely primarily on self-reported data. In addition, the evaluation focuses on short-term outcomes, making it difficult to assess longer-term behavioural or institutional change. Future research could address these limitations by incorporating longitudinal designs, broader samples, and more objective indicators of impact, particularly measures of how codified entrepreneurial knowledge becomes embedded in organisational routines, roles, and institutional learning processes.

Acknowledgements

The authors would like to acknowledge the support of the European Institute of Innovation and Technology (EIT) Higher Education Initiative for funding the CODEUNITED project. We also thank the partner institutions and all participating staff members for their valuable contributions to the needs assessment, training activities, and evaluation processes.

Ethics Declaration: This study was conducted in accordance with standard ethical principles for research involving human participants. Participation in interviews, surveys, and reflection activities was voluntary, and all participants were informed about the use of the collected data. Informed consent was obtained prior to data collection. All data were anonymised to ensure participant confidentiality, and no personally identifiable information is reported. The study did not involve sensitive personal data or vulnerable groups. Data were used solely for research and evaluation purposes within the scope of the project.

AI Declaration: Artificial intelligence tools were used to support the development of this manuscript, including assistance with language refinement, structuring of sections, and editing for clarity. All substantive content, analysis, and interpretations are the responsibility of the authors.

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Intellectual Capital for Monitoring Technology Transfer Maturity in National Innovation Systems

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Abstract: This paper proposes a methodological framework for restructuring the innovation indicator system used to monitor Brazilian Scientific, Technological and Innovation Institutions (ICTs) through the lens of Intellectual Capital (IC). Traditional metrics of technology transfer, such as patent counts and licensing revenues, often suffer from an outcome bias, providing only a partial representation of innovation performance while overlooking the institutional capacities and organisational routines that enable knowledge generation and transfer. To address this limitation, the study reorganises 77 original metrics into the three core dimensions of Intellectual Capital: Human Capital, Structural Capital and Relational Capital. These dimensions underpin a causal analytical model linking intangible assets to innovation capacity, technology transfer processes and economic impact. Rather than relying on isolated outputs, the framework emphasises the role of systemic capabilities in shaping innovation performance. It further incorporates Absorptive Capacity (ACAP) as a contextual and mediating analytical dimension, enabling the assessment of institutional readiness to assimilate and exploit externally generated knowledge within the broader set of structural and relational conditions shaping transfer effectiveness. The methodology advances beyond descriptive measurement by establishing analytical relationships between indicators and by proposing a synthetic Technology Transfer Maturity Index (TTMI), designed to identify structural bottlenecks and institutional maturity profiles through cluster analysis. This approach enables policymakers to move from static reporting to a more structured interpretation of how knowledge is produced, mobilised and converted into value. The framework has been developed and submitted to a working group coordinated by the Brazilian Ministry of Science, Technology and Innovation (MCTI), which received it favourably as a basis for reconsidering the national data collection system for ICTs. By transforming fragmented metrics into structured analytical insights, the proposed approach provides a scalable model for national monitoring and evidence-based policy design. The study contributes to the Intellectual Capital and knowledge management literature by demonstrating how IC-based analytical structures can enhance the interpretation of innovation performance in complex national innovation systems.

Keywords: Intellectual capital, Absorptive capacity, Technology transfer, Innovation indicators, National innovation systems, Performative measurement

1. Introduction

The formulation of public policies for Science, Technology and Innovation (ST&I) requires monitoring systems that transcend passive data collection and move towards the production of strategic intelligence. Historically, the measurement of innovation has focussed on tangible results, such as patent filings or licensing revenues. However, contemporary literature demonstrates that such metrics reflect only a "final outcome bias", failing to capture the organisational dynamics that sustain technical progress.

The framework presented in this study was developed and submitted to a working group coordinated by the Brazilian Ministry of Science, Technology and Innovation (MCTI), which received it favourably as a basis for reconsidering the national data collection system for Scientific, Technological and Innovation Institutions (ICTs). Its full adoption remains subject to the internal coordination and approval processes inherent to public institutional reform. This work originates from a Professional Master's Workshop (PROFNIT/ITA), comprising 90 hours of voluntary activity undertaken as part of the programme's academic requirements.

2. Innovation as Organisational Capacity and Routine

Innovation is most usefully understood not as an isolated event or discrete product, but as a continuous learning process embedded in organisational routine. Traditional output-focused measurement ignores institutional behaviour and the adaptive capacities that sustain technical progress.

The robustness of a national innovation system depends on the synergistic interaction between its components: as Furman, Porter and Stern (2002) argue, the elements of innovative capacity are complementary, such that investment in one dimension amplifies returns across others. Monitoring systems must therefore focus on the routines and processes that condition the flow of new knowledge, treating the existing stock of institutional competence as the primary catalyst for future innovation.

3. Absorptive Capacity as a Mediating Dimension of Technology Transfer

Technology Transfer is an inherently relational process, presupposing at minimum a knowledge-generating institution and a receiving organisation capable of internalising and deploying what is transferred. Its effectiveness depends neither solely on the supply of knowledge nor on the availability of formal mechanisms, but on the interaction between institutional, structural and relational conditions across the innovation ecosystem. Within this framework, Absorptive Capacity (ACAP) occupies a specific and bounded analytical role: it characterises the readiness of the receiving organisation to recognise the value of externally generated knowledge, assimilate it into existing routines, and transform it into productive application (Cohen and Levinthal, 1990). ACAP thus operates as a contextual and mediating dimension of transfer effectiveness, characterising a property of the receiver rather than a feature of the transfer process per se. Academic literature and international reports emphasise that technological diffusion is not an automatic process; it requires sustained domestic investment in human capital and scientific infrastructure. Without such internal competence-building, institutions face the risk of technological "lock-out", becoming unable to absorb frontier advances even when they are available.

Following Zahra and George (2002), ACAP is subdivided into two critical dimensions:

- *Potential Absorptive Capacity (PACAP):* Involves the acquisition and assimilation of knowledge. Without these, the institution cannot identify opportunities in the external environment.
- *Realised Absorptive Capacity (RACAP):* Refers to the transformation and exploitation of knowledge to generate economic value.

When evaluating TT policies, it is therefore important to monitor whether incentives support the development of absorptive readiness within receiving institutions, alongside the structural and relational conditions that shape ecosystem-level transfer capacity. Policies designed without attention to these interdependent dimensions may generate knowledge exchanges that fail to translate into durable innovation capability, irrespective of the formal transfer mechanisms in place (Zahra and George, 2002).

4. Intellectual Capital as the Foundation for Measurement

Intellectual Capital (IC) emerges as the most appropriate analytical structure to operationalise the measurement of innovation from the lens of absorptive capacity. As Edvinsson and Sullivan (1996) established, IC represents the knowledge that can be converted into value and constitutes the main driver of productivity in knowledge-based economies. For the purpose of monitoring ICTs, IC is organised into three fundamental dimensions:

- *Human Capital:* Encompasses technical competence, qualification and the experience of teams, specifically in Technology Transfer Offices (TTOs). It is the factor that allows the recognition of knowledge spillovers and the execution of R&D activities.
- *Structural Capital:* Comprises institutional infrastructure, management systems, Intellectual Property (IP) regulations and governance that support innovation. Structural capital ensures that individual knowledge becomes a permanent organisational asset.
- *Relational Capital:* Measures the intensity and quality of interactions with the external ecosystem, including university-industry partnerships and innovation networks. This dimension is vital for the acquisition phase of ACAP, functioning as the entry channel for new technological flows.

The adoption of Intellectual Capital allows for the construction of a logical causal model: investment in Human, Structural and Relational Capital forms the basis of Innovation Capacity, which, when mobilised by efficient routines, generates results in Technology Transfer and, ultimately, the desired Economic Impact.

5. Methodology for Indicator Reduction: A Multi-stage Approach

The current system is not composed of indicators in the strict analytical sense, but rather of a large set of raw metrics and structural variables. The proposed framework transforms these measures into interpretable indicators and, subsequently, into strategic indices capable of supporting policy decision-making The transition from a descriptive repository of 77 metrics to a strategic intelligence system requires a robust multi-stage methodology. The existing volume of data often results in "structural redundancy", where multiple metrics capture variations of the same underlying phenomenon, such as institutional capacity or technical staff qualifications. To resolve this, a six-step process was designed to consolidate data into a coherent causal model based on Intellectual Capital (IC).

This methodological approach was developed and refined within a policy-oriented working group coordinated by the MCTI, ensuring alignment with institutional requirements and data collection constraints at the national level.

5.1 Step 1: Dimensional Classification and IC Alignment

The first stage involves reorganising the entire pool of 77 metrics into four structural dimensions. This classification aligns the existing data with the Intellectual Capital framework. Human Capital focuses on the technical capacity installed within the Technology Transfer Offices (TTOs), including staff qualification and experience. Structural Capital addresses the institutional innovation infrastructure, such as internal Intellectual Property (IP) regulations and laboratory availability. Relational Capital captures the intensity of interactions with the external ecosystem, including industry partnerships and participation in innovation networks. Finally, the Results dimension tracks outputs, such as patent filings and licensing revenues. This logical grouping ensures that every variable contributes to a specific stage of the innovation process (Gashe, Sime and Mada, 2024).

5.2 Step 2: Identification of Redundancies and Composite Creation

Many metrics currently collected measure the same core attribute. For instance, recording the total number of staff, the number of employees with exclusive dedication, and the count of PhD holders all point towards a single concept: the technical capacity of the TTO. In this step, these variables are consolidated into single composite indices. A "TTO Technical Capacity Index", for example, is constructed by weighting the total team size by their specific qualifications and level of dedication. This allows three or four individual variables to be represented by a single synthetic indicator, reducing the cognitive load for policymakers without losing the nuance of the original data.

5.3 Step 3: Separation of Segmentation and Performance Variables

A significant portion of the original list consists of structural or profile data, such as the legal nature of the institution, its administrative sphere (federal or state), and its geographic region. While these data are essential for filtering and benchmarking, they do not measure performance or maturity. This methodological step separates these "segmentation variables" from the performance indicators. By treating profile data as filters rather than active indicators, the system becomes leaner and more focused on institutional growth and efficiency.

The resulting indicators should be understood as a flexible analytical layer rather than a rigid enumeration: certain categories may be further disaggregated depending on the granularity required, preserving comparability at the strategic level while enabling deeper diagnostic precision when needed.

Table 1: Consolidation of 77 metrics into analytical indicators based on intellectual capital

IC Dimension	Original Metric Clusters (from 77 variables)	Examples of Raw Metrics	Consolidation Logic	Resulting Analytical Indicator (~35)
Human Capital	TTO staff size	Total staff; full-time staff	Aggregation and normalisation of team size	TTO Operational Capacity
Human Capital	Staff qualification	% with PhD; % trained in IP/TT	Weighted qualification index	TTO Qualification Index
Human Capital	Training and skills development	Training programmes; capacity-building actions	Consolidation into intensity measure	Training Intensity Index
Human Capital	Experience in TT activities	Years of experience; TT expertise	Composite experience score	TTO Experience Level

IC Dimension	**Original Metric Clusters (from 77 variables)**	**Examples of Raw Metrics**	**Consolidation Logic**	**Resulting Analytical Indicator (~35)**
IC Dimension	Original Metric Clusters (from 77 variables)	Examples of Raw Metrics	Consolidation Logic	Resulting Analytical Indicator (~35)
Structural Capital	Formalisation of innovation structures	Existence of TTO; year of creation	Maturity-based aggregation	Institutionalisation of Innovation
Structural Capital	IP governance and regulation	IP policy; internal regulations	Binary + maturity scaling	IP Governance Index
Structural Capital	Financial resources for innovation	Innovation budget; TTO funding	Resources adjusted per ICT	Innovation Investment Level
Structural Capital	Technological infrastructure	Laboratories; shared facilities	Infrastructure availability index	Technological Infrastructure Index
Structural Capital	Management systems	IP management systems; databases	Functional consolidation	Innovation Management Capacity
Relational Capital	Industry collaboration	Contracts with firms; joint R&D	Aggregation of firm interactions	University–Industry Interaction Intensity
Relational Capital	Scientific collaboration	Agreements with ICTs	Network-based consolidation	Scientific Cooperation Index
Relational Capital	Participation in innovation networks	Clusters; networks; ecosystems	Integration scoring	Network Integration Index
Relational Capital	External funding acquisition	Funded projects; grants	Resource mobilisation metric	External Funding Capacity
Relational Capital	Internationalisation	International partnerships	Global engagement index	Internationalisation Level
Relational Capital	Use of shared infrastructure	Shared labs; joint facilities	Utilisation ratio	Infrastructure Sharing Intensity
Technological Outputs	Patent production	Patent applications	Direct count normalised	Patent Production Rate
Technological Outputs	Software production	Software registrations	Direct count	Software Production Rate
Technological Outputs	Plant variety protection	Cultivar registrations	Direct count	Specialised IP Production

IC Dimension	Original Metric Clusters (from 77 variables)	Examples of Raw Metrics	Consolidation Logic	Resulting Analytical Indicator (~35)
Technology Transfer	Licensing activity	Licensing agreements	Aggregation of licensing outputs	Licensing Volume
Technology Transfer	TT contracts	Contracts signed	Direct count	Technology Transfer Volume
Technology Transfer	TT efficiency	Time to licensing	Efficiency ratio	Technology Transfer Efficiency
Technology Transfer	Conversion of IP into market	Licensed / total IP	Ratio construction	Technology Transfer Rate
IC Dimension	Original Metric Clusters (from 77 variables)	Examples of Raw Metrics	Consolidation Logic	Resulting Analytical Indicator (~35)
Economic Impact	Revenue generation	Royalties; service income	Aggregation of revenue streams	Innovation Revenue
Economic Impact	Productivity	Revenue per staff	Ratio	TTO Productivity
Economic Impact	Start-up creation	Number of spin-offs	Direct count	Start-up Generation Rate
System Dynamics	Time evolution of outputs	Historical series	Trend analysis	Innovation Growth Rate
System Dynamics	Combined institutional performance	Multiple IC dimensions	Weighted aggregation	Technology Transfer Maturity Index (TTMI)

5.4 Step 4: Hierarchical Tiering: Strategic vs. Operational

The restructured system is organised into two distinct levels (Table 2) to serve different stakeholders. Level 1 consists of 10 to 12 *Strategic Indicators* designed for national monitoring and public policy formulation. These include broad metrics such as the Innovation System Coverage, the University-Industry Interaction Intensity, and the Technology Transfer Rate. These metrics are selected for their comparability across diverse institutions. Level 2 consists of 20 to 25 *Operational Indicators*, such as the specific number of startups or the volume of R&D contracts, which provide the granular data necessary for internal institutional management and deep-dive audits.

Table 2: Hierarchical tiering of indicators: strategic vs. operational levels

Level	Indicator Type	Purpose	Typical Metrics	Analytical Role	Primary Users
Level 1	Strategic Indicators (10–12)	Support national monitoring and public policy formulation	Innovation System Coverage; University–Industry Interaction Intensity; Technology Transfer Rate; Innovation Revenue per ICT	Synthetic, comparable indicators that capture systemic performance across institutions	Government bodies, policymakers, national innovation agencies

Level	Indicator Type	Purpose	Typical Metrics	Analytical Role	Primary Users
		Enable benchmarking and cross-institutional comparison	Productivity of NITs; Institutionalisation of Innovation Index; Technology Infrastructure Index	Aggregated indicators derived from multiple operational variables	Decision-makers at national and regional levels
Level 2	Operational Indicators (20–25)	Support internal institutional management and performance tracking	Number of startups created; Number of TT contracts; Volume of R&D agreements; Number of patents	Granular, descriptive metrics that feed strategic indicators	ICT managers, NIT teams, institutional administrators
		Enable detailed analysis and auditing of innovation activities	Licensing agreements; Royalty income; Number of researchers involved; Participation in innovation networks	Diagnostic variables used for deep-dive analysis and causal interpretation	Analysts, auditors, programme evaluators

5.5 Step 5: Constructing Relational and Analytical Metrics

This stage moves beyond descriptive statistics to establish policy intelligence through correlations. By mapping the relationship between different indicators, the Ministry can address causal questions. For example, by correlating the "Institutionalisation Index" with "Innovation Revenue", the framework can determine if formalised internal regulations actually lead to better economic outcomes. Other critical relations include comparing technical capacity against technology transfer rates to determine ideal staffing levels, and evaluating whether participation in innovation networks significantly boosts licensing performance. These analytical relations allow for the identification of structural bottlenecks where knowledge fails to be converted into practical innovation.

5.6 Step 6: The Technology Transfer Maturity Index (TTMI) Synthesis

The final step is the construction of the Technology Transfer Maturity Index (TTMI), or *Índice de Maturidade em Transferência de Tecnologia* (IMTT). This is a synthetic "indicator of indicators" that provides a weighted average of performance across the four dimensions: Institutional Structure, Human Capital, Interaction with Companies, and Technological Results. Each dimension is scored on a scale of 0 to 100. The resulting index allows for the cluster analysis of institutions, enabling the government to identify maturity profiles and tailor public support programmes to the specific stage of development of each institution.

5.7 Strategic Indicators for National Monitoring

The final set of strategic indicators encompasses the entire innovation lifecycle. It begins with the Coverage of the system to evaluate representativeness, followed by indices for Technical Capacity and Institutionalisation to assess the readiness of the TTOs. Infrastructure and Interaction indices measure the physical and relational assets available for innovation. Performance is then captured through the Technology Transfer Rate (measuring the proportion of assets successfully moved to the market) and the Intensity of Knowledge Protection. Economic impact is monitored via Innovation Revenue and TTO Productivity (revenue per staff member). Finally, the TTMI provides the overall synthesis, while a Temporal Evolution Index tracks the growth dynamics of the national system over time. This streamlined set ensures that monitoring is focused on the capacity to produce results, rather than just the results themselves.

6. The technology Transfer Maturity Index (TTMI) Strategy

The Technology Transfer Maturity Index (TTMI) is conceived as the primary synthetic instrument of the proposed monitoring system, designed to provide a holistic overview of institutional performance. Its strategic role is to function as an ‘indicator of indicators’, integrating the four pillars of the conceptual model: Institutional Structure, Human Capital, Interaction with Companies and Technological Results. By consolidating these dimensions, the TTMI allows for the identification of *Institutional Maturity Profiles*, enabling the government to move beyond simple output rankings and towards a nuanced understanding of institutional stages of development.

The TTMI is currently being considered as a core component of the national monitoring dashboard under development by the MCTI.

This research focuses on the conceptual architecture and strategic logic required to organise these dimensions to reflect institutional maturity; the precise quantitative modelling of individual weights remains a subject for future empirical validation.

7. Analytical Relations: Leveraging Correlations for Policy Intelligence

The transition from a system of 77 fragmented metrics to a streamlined model of approximately 12 strategic metrics is predicated on the ability to move from descriptive statistics to predictive intelligence. The true power of the proposed framework lies not in the individual values of the indicators, but in the analytical relations and correlations established between them. By mapping these connections, the Ministry can move beyond "outcome bias" to understand the causal mechanisms that drive or hinder innovation within the national system.

7.1 Identifying Systemic Bottlenecks via the Absorptive Capacity Lens

A primary benefit of establishing relational metrics is the ability to diagnose structural bottlenecks where knowledge fails to be converted into practical innovation. Bottlenecks in national innovation systems are rarely attributable to a single institutional deficiency; rather, they tend to emerge from the interaction between multiple dimensions of Intellectual Capital operating simultaneously. Structural Capital conditions, including governance arrangements, regulatory frameworks, management systems and organisational routines, frequently constitute the foundational constraints that determine whether Human and Relational Capital can be effectively mobilised (Bontis, 1998). Poorly formalised IP governance, fragmented management systems or inadequate institutional infrastructure may constrain innovation capacity independently of the qualifications of staff or the breadth of external partnerships. Within this multidimensional picture, ACAP functions as a contextual analytical lens rather than a singular explanatory mechanism. It enables policymakers to assess the degree to which an institution's receiving capacity, understood as its ability to identify, assimilate and exploit external knowledge, constrains different phases of the innovation and transfer process (Zahra and George, 2002). An institution may exhibit strong Relational Capital through active industry partnerships yet demonstrate limited Realised Absorptive Capacity if the structural conditions required to transform those interactions into commercialised outputs remain underdeveloped. Conversely, well-developed Structural Capital without commensurate investment in Human Capital or relational networks may sustain procedural compliance without generating genuine knowledge flows. The diagnostic value of the framework lies precisely in mapping these configurations across institutions, enabling the identification of which IC dimensions require reinforcement at each stage of institutional maturity.

7.2 Concrete Examples of Policy Application

The following examples illustrate how specific correlations can be used to answer critical public policy questions and justify strategic investments:

- *Technical Capacity versus Transfer Efficiency:* By correlating the TTO Technical Capacity Index with the Technology Transfer Rate, the government can determine if increasing the number of dedicated professionals in a Technology Transfer Office (TTO) actually improves the proportion of assets successfully moved to the market. If a strong positive correlation is found, it provides empirical evidence to justify programmes aimed at expanding and professionalising TTO teams across the country. If the correlation is weak, it may suggest that the problem lies not in the quantity of staff, but in the institutional legal framework or the lack of laboratory infrastructure.
- *Institutionalisation versus Economic Impact:* Relating the Institutionalisation Index (the degree of formalisation of IP policies) to Innovation Revenue allows for an evaluation of whether bureaucratic and regulatory readiness translates into financial returns. This analysis helps determine if the simple existence of a formalised NIT is sufficient for success or if performance is more closely tied to specific management practices. A positive correlation here would support policies that mandate the adoption of standardised IP regulations as a condition for receiving federal research grants.
- *Infrastructure versus University-Industry Interaction:* Examining the relationship between the Technological Infrastructure Index and the Intensity of Interaction with Companies allows the Ministry to test the "anchor effect" of shared laboratories. If institutions with better-shared infrastructure show significantly higher levels of cooperation with the private sector, it justifies directing structural investments towards "open-access" laboratory models rather than isolated research centres.

- *Knowledge Protection versus Effective Transfer:* A crucial question for the national system is whether a high volume of patent filings (Intensity of Protection) actually leads to higher rates of licensing. If the correlation is negative or stagnant, it may indicate "defensive patenting" or "patent trolling" within public institutions, where resources are spent on protection without a clear commercialisation path. This insight would allow for a policy shift from incentivising the quantity of patents to prioritising the quality and marketability of the protected knowledge.

7.3 Strategic Benefits for National Monitoring

The use of relational intelligence offers three fundamental benefits for the management of the National Innovation System. First, it enables evidence-based resource allocation, ensuring that public funds are directed toward the specific capitals (Human, Structural, or Relational) that show the highest correlation with desired outcomes in a given region or sector. Second, it allows for differentiated policy design through cluster analysis. Instead of applying a "one-size-fits-all" policy, the Ministry can design specific incentives for institutions at different maturity levels, as identified by the Technology Transfer Maturity Index (TTMI). Finally, this approach provides predictive power, allowing policymakers to anticipate the impact of a new regulation or funding programme on the overall efficiency of the system before it is fully implemented. By focusing on these analytical relations, the monitoring system ceases to be a mere repository of past data and becomes a dynamic instrument for institutional and economic transformation.

7.4 Synthesis of Analytical Relationships for Policy Application

Analytical Relationship	Indicators Involved	Policy Question	Interpretation
Technical Capacity vs Transfer Efficiency	TTO Capacity Index × Technology Transfer Rate	Do more qualified teams increase effective transfer?	Identifies optimal staffing levels and capacity gaps
Institutionalisation vs Economic Impact	Institutionalisation Index × Innovation Revenue	Do formal IP policies improve economic outcomes?	Evaluates effectiveness of governance structures
Infrastructure vs Industry Interaction	Infrastructure Index × U–I Interaction Intensity	Does infrastructure foster collaboration with firms?	Supports investment in shared facilities
Network Integration vs Licensing	Network Index × Licensing Volume	Do innovation networks enhance commercialisation?	Reinforces cooperation policies
Knowledge Protection vs Effective Transfer	Patent Production Rate × Technology Transfer Rate	Do more patents lead to more transfer?	Detects inefficiencies such as defensive patenting
IC Dimensions and Absorptive Capacity	Structural Capital × Absorptive Capacity × TT Outcomes	Do governance structures and institutional routines enable knowledge absorption and transfer?	Locates structural and absorptive constraints across IC dimensions; supports targeted institutional intervention

8. Conclusion

The restructuring of the innovation monitoring system represents a fundamental shift in how the Brazilian state perceives and manages its scientific and technological assets. Raw data collection retains significant value within

the broader ecosystem: for the general public, transparent dashboards support accountability; for ICTs themselves, primary data provides a benchmark for institutional self-assessment.

However, for the strategic guidance of the Ministry of Science, Technology and Innovation, raw data alone is insufficient and often counterproductive. As observed in the previous system of 77 fragmented metrics, a high volume of data without analytical structuring leads to "outcome bias" and "structural redundancy", where everything is collected but nothing is interpreted. To effectively guide national policy and address complex socioeconomic challenges, a more qualified and sophisticated analytical framework is required, one that moves beyond descriptive reporting and towards the production of causal intelligence.

The strategic transition to a set of approximately 12 strategic indicators, focused on the dimensions of Intellectual Capital, provides this necessary sophistication. By monitoring institutional maturity through Human, Structural and Relational Capital, national monitoring ceases to be a mere repository of historical data and evolves into a predictive instrument. This approach allows for the precise identification of structural bottlenecks, namely the specific points in the institutional journey where knowledge fails to be converted into practical innovation.

Ultimately, this framework provides the empirical evidence needed to guide public investment with surgical precision. By attending to absorptive readiness alongside the governance structures and relational networks that condition knowledge flows, the Ministry can pursue a more systemic and institutionally grounded approach to technology transfer effectiveness. This ensures that the National Innovation System does not merely generate scientific papers and patents, but effectively transforms knowledge into sustainable economic and societal value (Gashe, Sime and Mada, 2024; Corrente et al, 2023).

The adoption of this framework within the Brazilian national innovation monitoring system represents a transition from descriptive reporting to strategic intelligence, providing a foundation for future empirical validation and longitudinal analysis.

Ethics Declaration: The authors declare that this theoretical study did not require ethical clearance as it is based on the analysis of existing literature and institutional indicators.

AI Declaration: An AI tool (Large Language Model) was used in the development of this paper to assist in the translation of technical concepts from Portuguese to British English and to ensure compliance with the specific formatting guidelines of the Style Model Paper. The authors reviewed and edited all generated content to ensure technical accuracy and theoretical consistency with the cited sources.

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From Tacit Knowledge to Structured Documents: A Framework for Knowledge Elicitation

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Abstract: Recent advances in Large Language Model (LLM) "agent" systems have moved language models beyond single-turn generation toward goal-directed workflows that can plan, ask clarifying questions, and iteratively refine outputs. In parallel, retrieval-augmented generation (RAG) has become a practical way to ground these agents in enterprise knowledge—enabling models to leverage internal documentation and policies without expensive and recurring retraining. However, RAG is only as strong as the underlying corpus: when key information is missing, outdated, or fragmented, retrieval cannot fill the gaps. In many organizations, assembling high-quality, up-to-date documents remains a persistent bottleneck, limiting both the reliability of downstream applications and the speed at which knowledge can be operationalized. To address this, we introduce the Assistant-Scribe-Knowledge Checker (ASK) framework for generating structured specification documents through guided interviews. ASK decomposes the end-to-end workflow into three specialized LLM agents: an Assistant that asks questions to the user and steers the interview through adaptive follow-ups; a Scribe that continuously summarizes what has been said and records it into a schema-constrained specification document with explicit content requirements; and a Knowledge Checker that evaluates the evolving document against those specifications, detects gaps or weakly supported entries, and advises the Assistant on the next best questions to ask to reach the desired completeness and quality. This separation supports seamless document creation while improving quality control over content, structure, and coverage. By distributing responsibilities across three lightweight, role-specific agents, ASK reduces reliance on a single large model and enables modular scaling across teams and domains. We evaluated the ASK framework in a consulting-firm setting where consultants are required to produce project "return-of-experience" documents (successes, failures, challenges, and solutions) to capture reusable knowledge. Compared to documents authored manually, ASK-guided interviews consistently produced more complete, better-structured, and higher-quality specifications with less variability across authors. Beyond measurable quality gains, consultants also reported a clear preference for the interview-based workflow, citing lower effort and a more natural way to articulate tacit project knowledge.

Keywords: Knowledge management, Agentic AI, Large language models, Generative AI, Knowledge elicitation

1. Introduction

Recent advancements in the capabilities of Large Language Models (LLMs) have renewed interest in AI-driven knowledge management. As these models demonstrate increased proficiency in interpreting unstructured information, synthesizing dispersed evidence, and generating natural language responses, they provide a robust foundation for systems that help organizations manage and mobilize internal knowledge. This is particularly critical in modern companies, where the scale and speed of business operations frequently surpass the capacity of unaided human effort (Microsoft WorkLab 2025).

Employees are required to navigate increasing volumes of information across multiple platforms while maintaining productivity and decision quality, making agentic AI a compelling solution for augmenting organizational processes. Concurrently, the demand for knowledge management technologies is rising (Grand View Research 2025; Singla et al. 2025), reflecting a widespread recognition that knowledge accessibility constitutes a strategic organizational capability. However, organizational knowledge often remains hard to access because it is dispersed, siloed, or never explicitly documented in the first place (Atlassian 2025; Malgard et al. 2024). Much of the most valuable knowledge in a company exists tacitly in the experience of employees, rather than in structured repositories.

Consequently, effective AI-driven knowledge management requires not only better retrieval, but also better elicitation of undocumented expertise. A knowledge elicitation agent addresses this gap by helping transform tacit, fragmented knowledge into explicit and operational knowledge resources.

2. State of the Art

Capturing the knowledge held by employees - particularly tacit knowledge, which Polanyi (1966) defined as knowledge that individuals possess but cannot easily articulate - has long been recognized as a critical challenge for organizations. Nonaka and Takeuchi (1995) formalized this challenge through their SECI model, describing how tacit knowledge must be externalized into explicit form before it can be shared and reused.

Traditional elicitation methods, such as structured interviews, think-aloud protocols, and observation sessions, remain resource-intensive and difficult to scale. A systematic review by Rosario and Amaral (2021) identified social, technical, and organizational barriers that hinder elicitation efforts, while Kerrigan et al. (2021) found that most processes remain ad hoc, poorly documented, and lack methodological rigor. These findings highlight the need for more systematic and scalable approaches to capture knowledge.

Conversational agents have emerged as a promising avenue for addressing these scalability issues. In the space domain, Mihaylov et al. (2022) developed SCARLET, a conversational agent designed to elicit expert-level tacit knowledge from mission personnel for structured retrieval. SCARLET relied on rule-based dialogue management and a dedicated question generation module, demonstrating the potential of automated knowledge capture but also exposing the limitations of non-generative architectures in handling complex, open-ended conversations. In the manufacturing domain, Freire et al. (2023) introduced CLAICA, a continuously learning cognitive assistant that captures knowledge from experienced production-line workers through conversational interaction, formalizes it, and shares it with novices. A user study with 83 participants yielded design guidelines regarding the effects of prior training, context expertise, and interaction modality on user experience.

These systems demonstrated that conversational interfaces can effectively support knowledge exchange, but they were built on pre-LLM natural language understanding pipelines, which limited their ability to handle diverse topics and generate contextually rich follow-up questions.

The advent of LLMs has fundamentally shifted the landscape. Studies suggest that LLMs can effectively support tacit knowledge elicitation from operators through natural language interaction, yet challenges around user acceptance and output quality persist (Bubeck et al. 2023; Chen et al. 2025; Dwivedi et al. 2023; Lee, Jung, and Baek 2024). In Kuks et al. (2025), a ChatGPT-5-based chatbot conducted semi-structured expert interviews and produced structured summaries for a knowledge database. Experts rated the interviews positively, but the summaries showed gaps in completeness and occasional hallucinations, highlighting the gap between conversational quality and reliable output. Korn et al. (2025) introduced LLMREI, a GPT-4o-powered chatbot for requirements elicitation interviews using two prompting strategies: minimal zero-shot and iteratively refined least-to-most prompts. Across 33 simulated interviews, the refined prompt matched trained human interviewers in error rates and captured approximately 70% of intended requirements, though limitations included missing non-verbal cues, overly broad questioning, and challenges with long-term coherence. Similarly, Görer and Aydemir (2023) explored LLM-generated interview scripts, finding that task decomposition improved coherence but complex conversation graphs remained challenging.

While these studies demonstrate the potential of LLM-driven automated interviews, they focus primarily on software requirements engineering and produce outputs as requirement lists or raw transcripts. None of them address the broader challenge of corporate knowledge elicitation nor the generation of structured documents conforming to predefined specifications. Our work bridges this gap by proposing a framework in which an LLM autonomously interviews employees according to a document specification, progressively building a structured document as the conversation unfolds. To our knowledge, this combination of specification-driven document generation and automated conversational elicitation is a novel contribution at the intersection of knowledge management, conversational AI, and LLM-based document automation.

3. Material and Methods

3.1 System Requirements

We designed this framework around a set of core objectives and constraints. First, we aimed to develop a system that can run on reasonably sized machines, enabling companies to deploy it locally with limited infrastructure investment while maintaining full control over their internal data and avoiding reliance on remote LLMs. Second, we sought to ensure compatibility with small-to-medium-sized LLMs in order to improve scalability and accessibility. Third, we wanted the framework to remain agnostic to document structures and context, so that it could be adapted to a wide range of use cases. Finally, we aimed to provide a system capable of seamless interaction throughout the knowledge acquisition process.

The design of the framework was inspired by interview-based knowledge gathering practices commonly used in companies, where an interviewer elicits information from an employee, takes notes, and continuously adapts subsequent questions according to the information collected during the exchange.

3.2 Architecture

We introduce ASK, a novel architecture for document elicitation shown in Figure 1. This architecture is based on three specialized stateful LLM agents: the Assistant, the Scribe and the Knowledge Checker. These agents interact by modifying a shared global state, which allows the document to be progressively constructed as the user interview is conducted. The document drafting process is guided by drafting instructions, that define the expected content and specify requirements for each section and subsection.

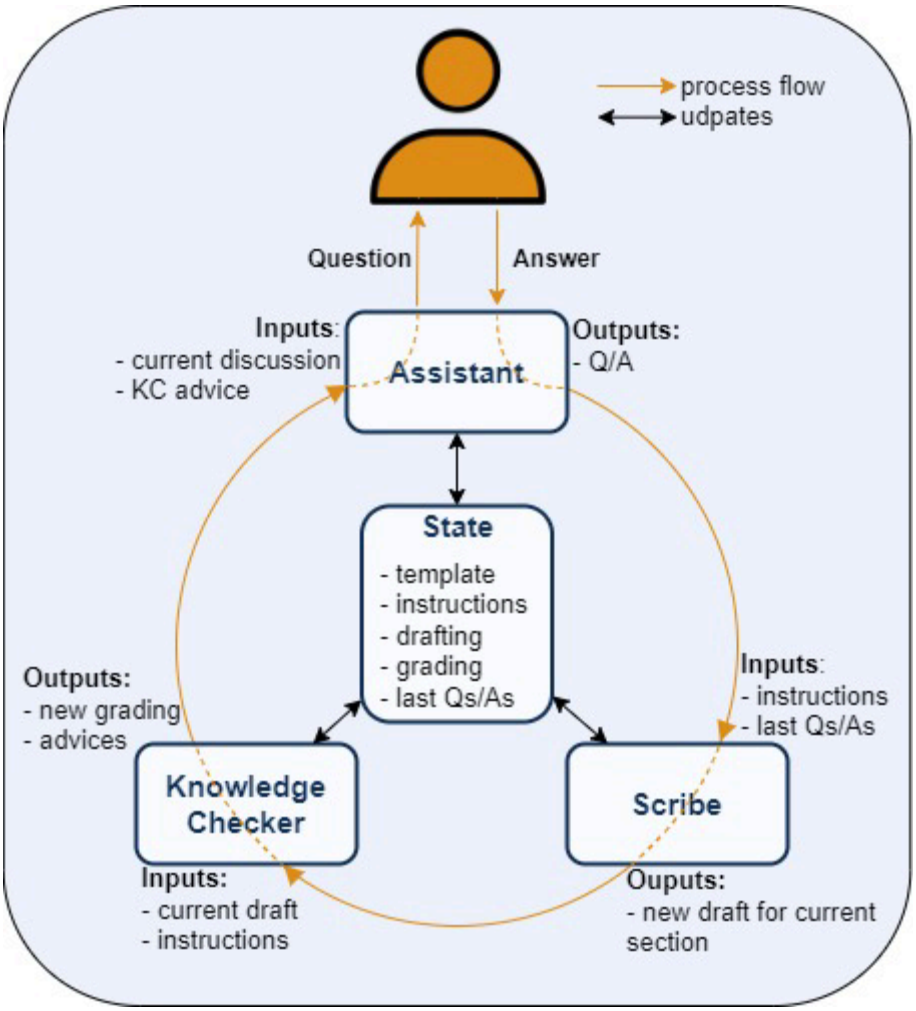


Figure 1: ASK framework for knowledge elicitation

3.2.1 Assistant

The Assistant is the agent performing the interview. It is the only agent the user interacts with. Its role is to pose questions to the user in accordance with the guidance provided by the Knowledge Checker. Its inputs are the current discussion it's having with the user, as well as the advice given by the Knowledge Checker. Once the user replies with an answer, the Scribe starts writing.

3.2.2 Scribe

The Scribe is the agent responsible for drafting the document. It takes as input the latest question-answer exchange between the Assistant and the user, along with the drafting instructions for the current section. The Scribe then produces an updated version of the section draft, incorporating the new information obtained from the exchange. By limiting its focus to the current section and its associated requirements, the Scribe reduces the likelihood of hallucinations or unnecessary modifications to unrelated sections.

3.2.3 Knowledge checker

The Knowledge Checker (KC) is designed to emulate the role of a human interviewer by guiding the interview to elicit information that satisfies the document requirements. It considers the context previously provided by

the user, ensuring that questions remain relevant and dynamic. The KC takes as input the current section draft and its associated requirements. For each requirement, it assigns a score from 0 to 5 according to the following scale: 0 - not met at all, 1 - not met, 2 - almost met, 3 - barely met, 4 - met, and 5 - met beyond expectations. This score is then used to select a requirement and its associated subsection, and make the KC generate an advice for the Assistant to stir the discussion towards fulfilling the selected requirement.

3.2.4 Drafting instructions

The drafting instructions have the structure described in Figure 2.

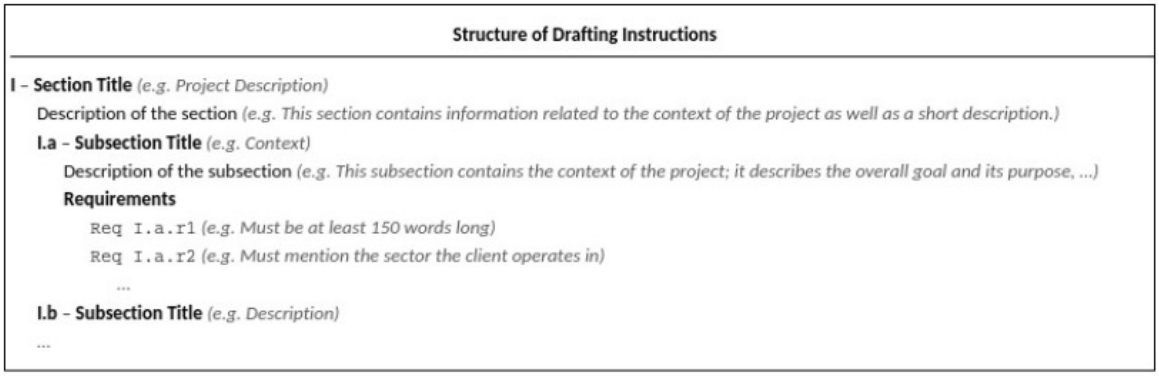


Figure 2: Drafting instructions structure

The Scribe is provided with the complete drafting instructions for the current section, including section and subsection identifiers used to structure the output and ensure that updates are applied to the correct subsection. Requirement identifiers are not provided to the Scribe, as they are not necessary for drafting and may be misinterpreted as subsection identifiers.

In contrast, the KC has access to requirement identifiers, which are used to associate each requirement with its corresponding evaluation score. Additionally, a word count is dynamically computed for each subsection to assist the agents in satisfying length-related requirements.

For each section of the document, the process goes iteratively through the following steps:

- The Assistant asks the user a question and receives a response.
- The Scribe then follows the available drafting instructions to update the draft of the current section using the information obtained from the latest question-answer exchange.
- The KC evaluates the newly drafted version of the current section to assess its content quality. It assigns a score ranging from 0 (requirement not met) to 5 (requirement met beyond expectations) for each requirement associated with the section under consideration.
- If all requirements receive a score of 4 or 5, the section is considered validated, and the drafting process proceeds to the next section (or terminates if the last section has been completed). Otherwise, a requirement with a score of 3 or lower is selected, and the KC generates guidance for the Assistant to steer the next question toward addressing the unmet requirement.

3.2.5 LLM model

During development and experimentations, the model used was Gemma 3 27B. This model was chosen because of its lightweight and relatively good performance on benchmark related to summarization at the time. It is representative of the type of model a company could run with relatively low investment as it can run, unquantized, on a single high-end GPU.

3.3 Mission Reporting Document

To assess the ASK framework, we conducted a pilot study involving a subset of employees within the company. As part of data collection for the knowledge management system, each employee must complete a Mission Reporting Document (MRD). This document requires administrative information about the employee, details of their mission, and information about the current client. The remainder of the document, however, is left in a relatively free format. Its primary purpose is to collect information on the following aspects:

- Context of the mission

- Objectives (success criteria, who will benefit from the work done)
- Role of the employee, their tasks, their contribution, their deliverables
- Technological context of the mission (technologies used, algorithms, technological components, …)
- The challenges, obstacles or difficulties encountered during the mission or linked to the mission.
- The mission evolutions (if the scope/planning of the mission changed, how and why)
- The results of the mission (ideally with metrics)
- The next steps of the mission

The document is divided into 4 sections: Administrative information (name, project name, job), Context and Objectives, Consultant role and tasks, Results and perspectives. For each section of the document, employees are provided with example questions intended to guide the writing process. Yet, as a consulting company, our employees operate across a wide range of clients, contexts, technologies, methodologies, and skill sets, which introduces significant variability in document content. As a result, assessing the quality of these documents is a complex task. Currently, this evaluation is performed by a senior employee with extensive functional expertise, who reviews the MRDs and provides feedback via email or schedules meetings when critical or essential information is missing. Employees are required to complete an MRD every three months. After one year of data collection, only 25% of the expected 1,200 documents had been submitted, and among these, 33% required additional feedback.

3.4 Pilot Study

We evaluated the use of the ASK architecture for MRD drafting by developing an application with which employees could interact. The user interface (UI) is illustrated in Figure 3. The app has been built in Python with the Streamlit library as its ease of implementation makes it perfect for proof-of-concept development.

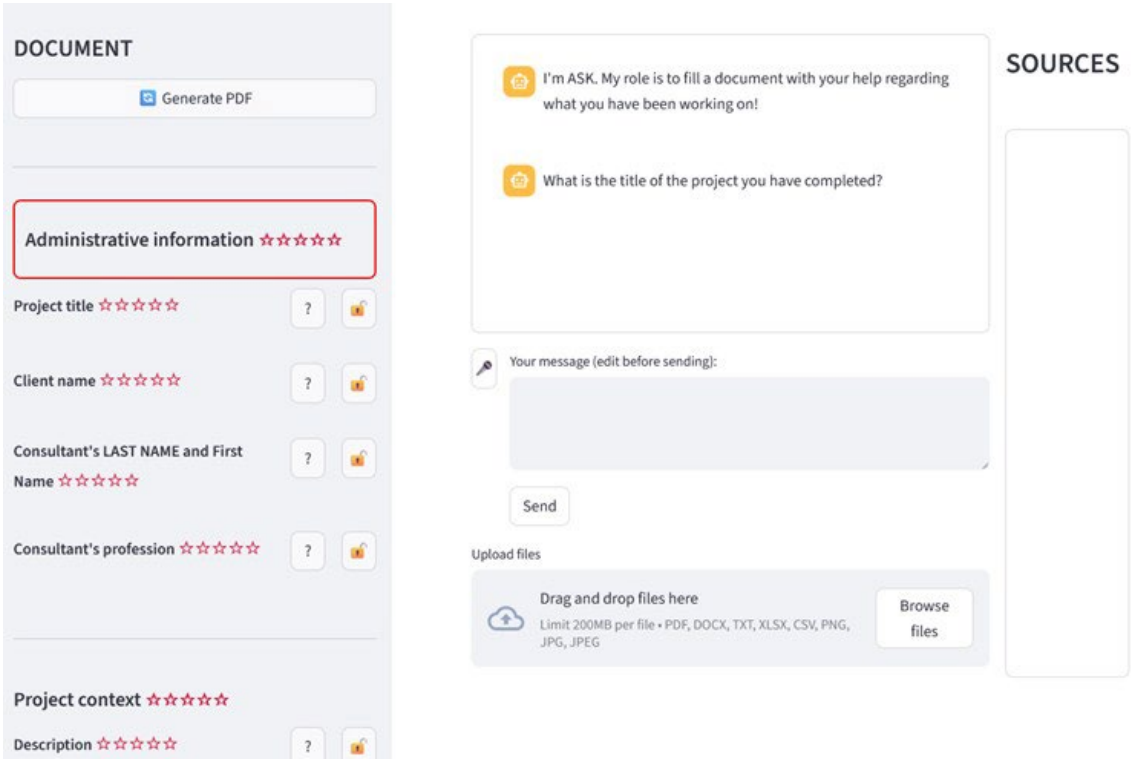


Figure 3: Streamlit app built to interact with ASK

The UI enables interaction with the ASK agents and provides several functionalities. Users can input responses either by typing or by using a local, real-time speech-to-text feature, allowing them to dictate their answers. The transcription, generated using the *faster-whisper* library with a locally deployed large Whisper model, can be edited before submission. The interface also allows users to view the current draft of all document sections, upload files for automatic content extraction and completion, and submit images to be included in the final document.

To mitigate common limitations of LLMs, additional features were introduced: a lock button enables users to "lock" a subsection, meaning mark it as final, preventing further modifications by the agent; and a "?" icon allows users to inspect subsection requirements along with their current evaluation scores.

Users were instructed to interact with the ASK agents until the system indicated that the drafting process was complete. Prior to this interaction, they were provided with a brief overview of the interface and its functionalities.

After the completion of each section, a validation page is presented. On this page, users are asked to review the generated content and make corrections if necessary. They are also asked to rate from 1 to 10 their overall satisfaction with the section and provide open-ended feedback. This feedback is used to identify friction points in the human-AI interaction process.

4. Results

A total of 12 participants were involved in the study, covering a range of job roles (five developers, one QA engineer, four industrial engineers, and two project managers). The experimentation was conducted using the Gemma 3 27B model, deployed on a system equipped with two NVIDIA GeForce RTX 4090 GPUs. As the first section of the document consists solely of administrative information (name of the consultant, client, role), it was excluded from the statistical analysis, as it does not reflect active interaction with the ASK agents.

Sessions lasted on average 94.3 minutes, representing a substantial reduction from the 4-5 hours previously required for manual completion of the MRD by consultants.

Table 1: Distribution of time spent in each ASK state during experimentations

State	Avg total time per session (min)	Avg time per occurrence (min)
Input phase	71.1	5.8
of which audio recording	9.1	1.0
Knowledge Checker	8.9	0.5
Scribe	3.3	0.3
Assistant	1.1	0.1
Feedback Review	9.2	2.3
Final Feedback	2.5	2.5

Table 1 shows the distribution of time spent in each state of the ASK architecture. As expected, the input phase represents most of the time spent on the app even with the availability of audio transcription. On average, users waited 54.4 seconds between input phases while the agents completed their processing: 16.2 seconds for the Scribe, 32.7 seconds for the KC and 5.5 seconds for the Assistant. On average, 12.3 user-agents exchanges were required to complete the MRD: the agent asked an average of 29.6 questions, as it usually posed two or three questions within the same message.

Table 2 shows the average time spent for each of the MRD sections with their corresponding satisfaction rating from the user. A clear correlation was observed between the time spent on a section and the corresponding user satisfaction rating. Section 3 required the most time to complete, despite also being the most frequently locked section, with seven out of twelve participants fully locking it to force the ASK agent to proceed to the next section.

Table 2: Distribution of time spent in each MRD section during experimentations

Section	Time spent of total (%)	Satisfaction Rating (/10)
2 - Context & Objectives	35.8	7.1
3 - Task performed	45.3	5.4
4 - Results and perspectives	18.9	7.9

Several key insights emerged from the open-ended feedback collected during the study:

- Users were generally satisfied with the quality of the agent's writing but noted that proofreading remains necessary as the agent occasionally produced hallucinated content.

- Users found the questions posed by the agent to be highly relevant, although sometimes it became repetitive by asking similar questions.
- Processing times were perceived as slightly long, indicating potential for optimization.

The quality of MRDs produced by ASK was evaluated through systematic comparison with manually assessed non-ASK MRDs. A corpus of 191 documents was labelled across three quality tiers — low, medium, and high — by a senior domain expert responsible for data collection, based on criteria of content quality and completeness. A set of quantitative metrics was subsequently extracted from both the manually classified documents and the ASK-generated documents. These metrics comprised word count and six content quality dimensions assessed by an LLM-based judge (Gemma 3 27B): Grammar, Structure, Vocabulary, Clarity, Completeness, and an overall Score, each rated on a ten-point scale.

As illustrated in Figure 4, a clear positive correlation is observed between the quality labels assigned by the domain expert and the scores produced by the LLM judge. Specifically, low-quality MRDs received a mean overall grade of 5.33, medium-quality MRDs a mean of 5.94, and high-quality MRDs a mean of 6.47. This monotonic relationship holds consistently across all individual metrics, including word count, where low-quality documents contain on average three times fewer words than their high-quality counterparts.

The 12 MRDs generated by ASK achieved a mean LLM grade of 6.84, with a mean standard deviation of 0.67. ASK-generated documents thus outperform the average high-quality document in the reference corpus and exhibit consistently higher scores than medium-quality documents across all metrics. Notably, this superior performance is achieved with a lower average word count compared to high-quality reference documents, suggesting that ASK produces more concise yet higher-quality outputs.

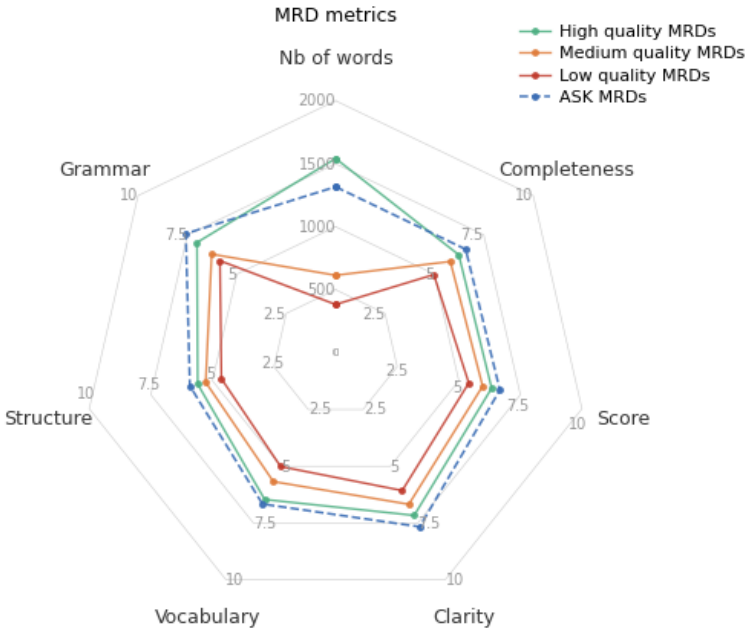


Figure 4: MRDs evaluation metrics results

5. Conclusion and Perspectives

The results of this study suggest that the ASK framework is a promising approach for automating knowledge elicitation. Using the ASK framework, the quality of MRDs improved significantly, surpassing manually written high-quality MRDs on all metrics while having a lower average word count, suggesting better conciseness. The time required to complete them was also substantially reduced compared to manually written MRDs.

Yet several improvements could be made to address the limitations identified during the experimentation. First, providing the Scribe and KC with access to a dynamic memory containing key information gathered throughout the interview—rather than restricting them to the current section and instructions—could improve the relevance and coherence of the KC's guidance. Currently, the KC evaluates requirements sequentially, focusing on the first requirement with a score below four. While this approach preserves the logical flow of questions according to subsection order, it can result in some requirements remaining unmet, causing the

agent to repeatedly ask similar questions. To mitigate this, the system could track previously asked questions and introduce randomized selection of target requirements, reducing redundancy and increasing coverage. Another approach could be to allow the agent to dynamically adjust requirements based on user input. For example, the system could lower the threshold for requirements that the user struggles to fulfill or add new requirements when noteworthy information emerges during the interview. Such adaptability would enhance the agent's responsiveness, better capture relevant knowledge, and further streamline the knowledge elicitation process.

Overall, these refinements could make ASK a more robust and flexible framework, capable of handling the variability of profiles inherent in consulting companies while maintaining high-quality document generation.

Ethics Declaration: The collection of MRDs was an established practice within the organization prior to this study; ASK constitutes a novel means of producing such documents within this existing workflow. All large language models and associated frameworks employed throughout the study were deployed on company-owned servers, ensuring that no data was transmitted to or processed by external systems. Participation in the study was voluntary, and all participants provided informed consent prior to submitting open-ended feedback. In accordance with applicable guidelines governing minimal-risk research, the study was exempt from formal ethical review.

AI Declaration: AI-based tools were used in the preparation of this manuscript to assist with language refinement. Specifically, these tools were used to reformulate and proofread selected sections to improve clarity, grammar, and overall readability. The authors reviewed and validated all outputs to ensure accuracy and integrity of the content.

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Tacit Knowledge Sovereignty: Are Some Small Family Businesses Reluctant to Relinquish Their Smallness?

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Abstract: It is a conventional understanding that all businesses desire to grow and expand in terms of revenue, bottom-line profit margins, and employee count. In an apt environment, growth is natural, and all small businesses – including family businesses - desire to scale up into medium and eventually large firms. Nevertheless, despite supportive macroeconomic factors, some family businesses deliberately choose to remain small. This research aims to identify the reasons behind this counterintuitive but conscious decision of some small family businesses to remain small. Specifically, this paper challenges the conventional development framework of small family businesses and questions the assumption that all small family business owners desire their firms to grow. The purpose of this paper is to explore the reasons for maintaining such intentional resistance to expand and also to generate research propositions that support the implausible argument that at least some small family business owners deliberately remain small for varied reasons. A qualitative grounded theory method was used with small family business owners who were willing to participate in the study. Purposive sampling was used to identify small family business owners, and unstructured, in-depth interviews with 12 such participants were conducted, recorded, and transcribed. Open and axial coding identified two major and three minor themes. A major inference was an unwillingness to share tacit knowledge outside their family. The participants revealed that, as they did not want their embodied family knowledge to lose its boundaries and to maintain tacit knowledge sovereignty, they opted to stay small while remaining content with the growth of their business. Another major reason was to ensure the members' well-being, making succession planning easier. In addition, three minor themes emerged to explain why they are reluctant to relinquish their smallness: core skill focus, relinquishing authority, and compliance overhead. The identified themes were validated through member checking, thereby enhancing the credibility of the findings. Research propositions are developed from these themes and could fuel further research.

Keywords: Family business, Small business, Tacit knowledge, Grounded theory, Tacit knowledge sovereignty

1. Introduction

Family Businesses are enterprises in which two or more family members hold management positions, have sufficient voting rights, and have a succession process (Cano-Rubio et al., 2017). Conventional wisdom suggests that organisational growth is a natural phenomenon (Greiner, 1998), and therefore, family-run small businesses (FSBs) should mature into medium-sized enterprises and eventually become large. Firm's growth may be identified as increased financial turnover, increased employee strength, or improved market share (Figueroa Herrera and Murcia, 2025) or all of these. However, many FSBs maintain the status quo, despite being small for a long time by any given measure of growth. Researchers have offered varied explanations for this stuntedness, including the unavailability of financial support, a lack of infrastructure, and a shortage of skilled labour (Adhikari, 2017). These external factors assume that the FSBs desire to grow and scale up. It is only rational to presume that although they want to, FSBs could not scale up due to various reasons [*want to grow, but can't grow*] (Tsuruta, 2018). We challenge this presumption and explore a meaningful heterodoxy (Pidduck and Tucker, 2022) that, although they could, at least some FSBs do not want to grow and scale up [*can grow, but don't want to*]. There can also be some FSBs that want to grow and can grow, but are putting it off until it becomes absolutely necessary for them to do so [*can grow, but not so soon*]. We aim to generate a taxonomy of reasons and propositions and establish a research agenda that revolves around the fundamental question of whether the smallness of FSBs is by purpose (Khan, 2019). We specifically seek answers to understand the reasons for this meaningful heterodoxy.

2. Growth of FSBs as a Choice Rather Than a Natural Progression

There are more than 63 million micro enterprises and 0.33 million small enterprises in India (MSME, 2026), and more than 50% of these are family-owned (SPIJMR, 2023). Most of these FSBs are more than a few years old and, by conventional standards, have well surpassed the typical growth period (Hanks et al, 1994). If the owner-manager is satisfied (Pechlaner et al, 2004; Rachevski and Shami, 2025) with the FSB's current state, s/he could decide not to grow any further. The owner-managers of such FSBs do not consider their smallness a liability, nor

are frustrated by it; instead, they may even derive pleasure and satisfaction from questioning the status quo. By doing so, they apparently build a cult (Bainbridge and Stark, 1979), simply by defying societal expectations.

It is indeed important to have a purpose for an organisation (Jones-Khosla and Gomes, 2023) to justify its existence. It is also beneficial to have a defined or tacit boundary within which the firm can formulate ad hoc tactics to serve its purpose. Resource management in FSBs – financial, human, or infrastructure - is often practiced in an impromptu fashion (McPherson, 2008). Advocates of formalisation of processes in FSBs assume that a miniature of similar processes in large organisations would suit FSBs (Nolan and Garavan 2016). We do not argue against formalisation. A complete formalisation of management processes in FSBs is impossible, non-pragmatic, and futile. It may save time by developing templates or processes for repetitive tasks (such as payroll, tax returns), but the cost of designing and implementing them should justify their benefits (Singh and Vohra, 2009). Such formal and informal practices should coexist (Heilmann et al., 2020), and the FSB should have the flexibility and ability to sense the situation, assess, and select an appropriate process. Relinquishing the informality in management processes thereby avoiding formalisation may be a conscious decision by the owner-manager (Nguyen and Bryant, 2004).

Formalisation may introduce standardisation of procedures and eliminate subjectivity. This is precisely what some FSBs are trying to avoid. They would want to preserve their competency by building an intangible moat that prevents knowledge leakage. These FSBs fully understand the opportunity cost and voluntarily choose to remain small. No studies have been found that explore this paradoxical phenomenon.

3. Method

The precursor to this study was data collected from owner-managers of FSBs to analyse their HRM practices, conducted as part of a classroom assignment for MBA students. The students contacted and interviewed 71 owner-managers of Indian Family-owned MSMEs to gain an understanding of the formalisation of the HRM practices in their respective FSBs. While evaluating the transcripts based on these interviews, we observed that a few owner-managers indicated they had intentionally limited the growth of their FSBs. This counterintuitive information led to the design of the research that resulted in this paper.

We conducted interviews with 39 additional owner-managers of FSBs. Of the total 110 owner-managers, 92 were contemplating growth, and 18 acknowledged that they chose to stay small or preferred to grow very slowly. Own-account enterprises (small firms that do not employ any staff), as well as unorganized and agricultural businesses, were excluded. We also excluded four FSBs that were less than five years old, following the rationale of Hanks et al (1994): the average age of a start-up is 4.29 years, with 6.4 employees, before it expands. Only owner-managers who manage an enterprise with at least six employees were interviewed (inclusion criteria). Two owner-managers declined to participate. Finally, we conducted unstructured, in-depth interviews (Fontana and Frey, 2005) with 12 owner-managers. All the owner-managers we interviewed were founders of their respective firms. Qualitative studies using depth interviews typically employ 12-60 participants (Saunders and Townsend, 2016). Given the unique nature of our research question, the information gathered from 12 participants is sufficient to generate research propositions. We obtained their consent prior to each interview and visited them several times to establish rapport. We ensured that the necessary ethical considerations, such as information confidentiality and anonymity, were in place.

The objective of our interview was to identify the reason(s) for their choice to stay small. The mean interview duration was about 84 minutes. Although not purposeful, all the owner-managers in this study were males. Five of them were under 35, and seven were between 35 and 50. Six had completed their engineering degrees, two were science graduates, one had completed high school, and the other participants chose not to disclose. Interview questions were loosely framed and structured to identify their reluctance to grow, the reasons for their choice to remain small, and their perceived future position in the FSB. Some of the questions we asked were: “Why are you maintaining the growth level in a small and more or less uniform manner while many of your contemporaries have scaled fast?” “Why are you not planning to add more employees?” “How do you feel about the growth you have had so far, and do you think you could have grown better and faster?” and “What stops you from scaling up?” We prepared detailed transcripts after each interview. The responses were translated into English.

3.1 Qualitative Grounded Theory Approach

We used qualitative Glaserian grounded theory (GGT) (Glaser, 1998; 2009) to analyse the transcripts and derive themes. The GGT method was adopted over other known qualitative methods, specifically grounded theory

methods, as we aim to generate propositions rather than validate existing theories. To conceptualise the raw information into an emergent theory, we employed theoretical sensitivity (Simmons, 2025).

4. Results and Discussion

Following the guidelines recommended by Glaser (2009), we analysed the transcripts to delineate meaning units and five basic emergent themes that influence the owner-managers of family business to remain small were generated: tacit knowledge sovereignty, member benevolence, core skill focus, authority relinquishment, and compliance overhead (Figure 1)

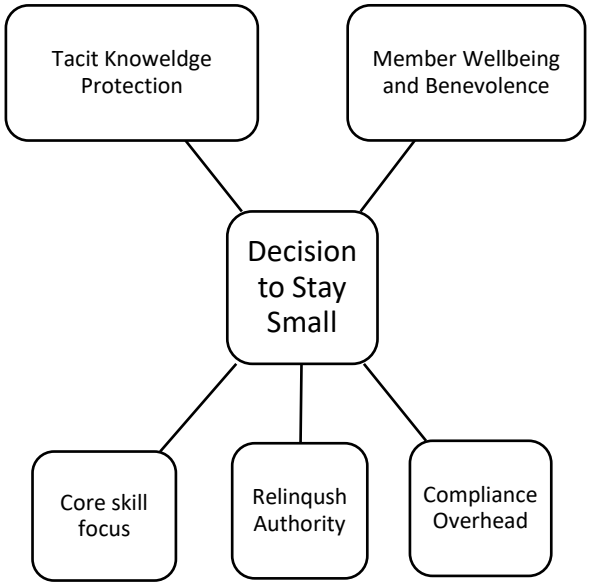


Figure 1: Reasons why some small family businesses stay small

4.1 FSB and Tacit-knowledge Protection

All the owner-managers in our study repeatedly indicated that if their business grows beyond a certain point, they will be forced to enforce systems and procedures. They divulged that their business is guided by conventional philosophies and that they did not want them diluted by introducing a revolutionary thought process, which they feared might weaken their supremacy and dominance (Duh, 2014). They confessed that they have been maintaining a tradition in place for decades and did not want any standardisation process, so as not to make the business feel impersonal. Although this may bring in more revenue and growth, they may be forced to share their specific knowledge, such as culinary intuition by way of secret ingredient for food and beverage manufacturers, mastering craftsmanship by way of continued training since their childhood, or design sensitivity that they honed by way of multiple instances of trial and error. There are cultural and political reasons for this behaviour as well (Mansouri and Moufdi, 2026).

Such tacit knowledge deeply embedded in their family tradition, they say, is their strategic asset and competitive advantage (Luong et al, 2024). When such knowledge is made explicit, it may become easy for competitors to copy and customize. Tacit knowledge is often an intellectual property that owners choose not to disclose for fear of losing not only revenue but also their heritage. By maintaining sovereignty over their tacit knowledge, family businesses preserve their socio-emotional wealth and ensure continuity through a proper succession plan.

Proposition 1: Some FSBs choose to remain small so as to maintain their tacit knowledge sovereignty and protect their competitive advantage.

4.2 Informal Work Relations at FSB and Member Benevolence

Some owner-managers are genuinely happy with the size they are currently at. They said they are operating at full capacity and do not want to add more employees unless it is absolutely necessary. In this way, they can pay more and better attention to the needs of existing employees. They (inadvertently) follow Theory Y (McGregor,

1960) and presume that existing employees can perform better when well cared for. In particular, most of them are strong proponents of stewardship theory regarding member benevolence (Waldkirch and Nordqvist, 2016). They are convinced that increasing the number of employees does not necessarily translate into better collective performance.

Members of FSBs are not typically recruited through a formal process. The owner-manager develops a sense of kinship and accepts the member as part of the business. With such closely knit groups, the owner-managers can better communicate the business objective and get acceptance of the vision. This shared vision helps all members to stay on the same page and is reflected in all other activities in the firm. Such affinity of the owner-manager towards their employees creates and thickens the bond.

Proposition 2: Some FSBs willingly remain small to ensure member benevolence.

4.3 FSB and Core Skills Concentration

All the owner-managers in our study were experts in their fields and built their businesses to operationalise their ideas. They are well-versed in their core skills (often technical), but are not very competent at managing the business (Chatterji et al, 2019). Lack of management sophistication, combined with their years of experience running their business on a small scale, has left them fixated in a comfort zone from which they are reluctant to deviate.

The owner-managers of FSBs, by virtue of their position, are expected to manage other family members, their employees, sales, and finance (Ahmadi et al, 2021), albeit on a smaller scale. Some decide to keep such non-core activities to a minimum so they can focus on their core. By focusing on what they are good at, they can carve out a personal niche. There could be an intrinsic motivation (Tripathi et al, 2025) and desire among these owner-managers to be known for their technical skills rather than as 'successful' businesspersons.

Proposition 3: Some FSBs choose to remain small so as to focus on and to build on their core skills.

4.4 FSB and Owner-manager Authority

A few owner-managers reported deriving pleasure from retaining decision-making power in their firms. They would demand and expect all information concerning their firm to pass through them and to be at the forefront of matters that concern the firm. Some were apprehensive that, with higher growth, they might be relegated to a "corner office" and bypassed in major decisions. This fear of relinquishing their overall authority makes them reluctant to add more employees, except for replacements.

Ostensibly, there exists some degree of fuzzy trust among members and owner-managers. In an extreme scenario, they anticipate a boardroom coup (Croucher et al, 2007). This air of mistrust might also be reflected in poor production or service that indirectly contributes to their smallness. It is quite possible that they have developed an attitude of continuing to operate in a highly centralised way and not growing beyond what is required. Most owner-managers do not want to give up their style, personality, and the firm's culture that they have nurtured so far.

Proposition 4: Some Owner-Managers of FSBs deliberately remain small so that they retain their authority and autonomy.

4.5 FSB and Compliance Overhead

Some owner-managers presume that the larger the number of employees, the more complicated the process - not just the internal processes, but also the administrative responsibilities associated with legal compliance. The applicability of labour regulations increases in proportion to the number of employees in an organisation (Gupta, 2019; Mehrotra, 2019). While outsourcing the statutory compliance process saves time and effort, they fear that confidentiality may be compromised and that they may become susceptible to undue advantage from a third party (Jovanovic, 2018). Although the procedural entanglement associated with legal compliance is not a pull-back factor per se, it can delay the decision to grow beyond a threshold for a considerable period.

Proposition 5: Some FSBs choose to remain small so as not to be too focused on statutory compliance and to avoid procedural entanglement.

The representative statement from the owner-managers of FSB, the axial coding using GGT, and the emergent themes are detailed in Table 1.

Table 1: Emergent themes identified from GGT

Emergent Themes	Axial Codes	Representative Statement
Tacit knowledge sovereignty	Sustaining family legacy	*" We have been in this* [jewellery] *business for about a century. There are methods by which we do business. Gold and precious metals are considered divine, and we have been prosperous due to this. If we let someone else run the business, we lose our heritage."*
	Preventing knowledge leakage	*"We are a close-knit family. There are customs and procedures that will only be shared with one member in the next generation. This way we maintain our tradition and avoid a third person getting to know what we do and how we do."*
	Retaining Power and Control	*"What comes to your mind when you say a formal organisation? Yes, maybe we can make more money. But we will then be answering someone else's questions and attending a business meeting where we stand there giving ridiculous sales figures. We don't want that to happen. Here* [in that FBS], *what I say is the rule, and I can easily sense the changes and ask my family to act accordingly. Quick decisions can be taken. I want to maintain that."*
	Avoiding cultural dilution	"*I do not really believe in the concept of standardization; I believe in intellectual valuation. I want to learn about technology and processes, and manage a small team. This way, I can protect my culture. Having our knowledge within the family, we would increase our collective intelligence, and, of course, this will be reflected in our offerings. This can only happen if we can maintain a strong and stable culture, where all members are dedicated, particularly in maintaining our talents and knowledge*".
Member Benevolence	Member well-being	*"As the most experienced member in the family running this business, I feel it's my responsibility to make my family members comfortable running this business. If I hire a professional help, then they may start directing, without really understanding the family sentiment. I will not let that happen, and family members are my priority."*
	Succession of business	*"See, this is a family business. What does that mean? It means that when I step down, someone else in my family should run the business. For this, we have our own bylaws and codes that govern our selection of a successor. We don't let anyone else interfere in our business, and it that restricts our growth, so be it."*
	Family bond and altruism	*"Simply put, business is a way of maintaining the close ties with all out family members. I can also say that it is because of this business, our family members are closely attached with each other. So it is our responsibility to take care of each other. When we grow, we may branch out, and eventually this close ties will fall out of place. That will be sad."*
Core skill mismatch	Not interested in people management	*"For the last 12 years I have been doing this, and I am very happy with what I do. Occasionally there are some issues in the company that requires me to mediate a negotiation. However, I don't want any more issues and from my experience, more employees mean more issues. I can't manage that. I'm just happy with my current size."*
	Focus on learning and improving skills	*"I joined my family business 10 years back, before which I was with an MNC. I can finally do what I am interested. I don't want to loose this freedom, and am happy with what I can do and learn from this position "*
Relinquishing autonomy	Decision Making	*"I am the CEO, which means all executions should be overseen by me and based on my decision. If someone else is deciding for me, what then is the point of me being the CEO? "*

Emergent Themes	Axial Codes	Representative Statement
	Leadership	*"I have invested my effort in this* [firm]*; Nobody else can fathom the dream I have for this organisation and I should have the ultimate authority to make any decisions inside my organisation. I do not want to outsource my decision making authority."*
Compliance Overhead	Avoiding bureaucratic encounters Procedural entanglement	"*Too many people, would mean to many issues. I follow rightsizing. This way I don't have to pay more for various acts and laws, which are too complicated for me to understand.*"

5. Theoretical Implications

We employed an abductive reasoning approach to offer a paradoxical set of propositions: not all FSBs want to scale up and grow. Smaller firms are easier to manage and control (Schumacher, 2011) and would also effectively deflect regulatory barriers (Padmakumar, 2022). While several factors affect the growth of small firms (Garcia-Martinez et al, 2023), the owner-manager's attitude is scarcely discussed. We contribute to the existing literature by showing that owner-managers' attitudes also determine the firm's smallness. This attitude is driven by internal or external attributions, as proposed by attribution theory (Kelley and Michela, 1980; Stiensmeier-Pelster and Heckhausen, 2025). The findings underscore that FSB growth is attributable to the internal attributes of owner-managers, regardless of conducive external factors. Furthermore, the owner-manager's confidence in maintaining the firm's smallness would also stem from a high internal locus of control (Pandey and Tewari, 1979; Nazir and Das, 2025). As opposed to agency theory (Eisenhardt, 1989), the owner-managers of the FSBs evidently adhere to stewardship theory, which characterises them as trustworthy individuals who maintain a conflict-free work environment and maximise organisational health and sustainability. These characteristics ensure that their tacit knowledge remains within their FSBs and is not promulgated, thereby reducing the risk of threats to their survival. They maintain their enigmatic existence, partially protected by their sovereignty over tacit knowledge.

6. Agenda for Future Research

As a preliminary exploratory study, we identified several notable characteristics among the cognitive patterns of some FSB owner-managers and proposed additional questions for further consideration. We relaxed the conventional presuppositions - growth as a natural phenomenon, FSBs with informal procedures are harder to manage, and all owner-managers of FSBs want to grow. The owner-manager of FSBs need not be an expert in all functional areas of business management to commence operations (Read and Sarasvathy, 2005); rather, their growth is facilitated by entrepreneurial thinking focused on building a strong enterprise (Read et al, 2016). Some owner-managers develop a status quo bias (Cossette, 2014) and regulate the number of employees. It is interesting to note that Gibrat's Law of Proportionate Effect (the growth rate of a firm is independent of its size) applies to these FSBs, and owner-managers do not juxtapose growth and the number of employees (Nassar et al, 2014). It would therefore be interesting to explore the cognitive patterns of owner-managers who choose to remain small along the dimensions we identified. A deductive method to confirm these possibilities could enable policymakers and researchers to design a more effective plan for scaling up.

7. Conclusion

In this paper, we explored possible reasons why some small family businesses choose to remain small, despite a conducive environment for growth. Using grounded theory, we identified five reasons that explained their apprehension about 'mature' moving into the next phase: tacit knowledge sovereignty, member benevolence, core skill focus, relinquishing autonomy, and compliance overhead. We developed propositions and research agendas based on these themes. There are limitations regarding the number of participants, which, although it satisfies the methodological requirements, is too small and homogeneous to support generalization with certainty. The propositions need to be corroborated with a larger sample of owner-managers through an empirical study.

Ethics declaration: Ethical protocols were followed for interviews, and no specific ethics clearance was required for the study.

AI declaration: The authors used AI only for grammar checks, not for creating this paper.

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A Model Integrating Organizational Culture into Knowledge Sharing and Employee Development

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Abstract: While knowledge sharing and employee development are recognized as important drivers of performance of an organization, existing research often examines organizational culture, structure, and knowledge processes separately. Currently there is an emerging need for integrated frameworks explaining how these organizational dimensions create conditions for effective knowledge sharing and continuous learning. This paper aims to create an integrated conceptual model linking organizational culture, management practices, organizational structure, knowledge sharing, and employee development. Drawing from literature oriented towards knowledge management (KM) and human resource management (HRM), the study proposes a framework that explains how characteristics of an organization, including trust, collaboration, communication openness, and learning, together with leadership approaches and structural arrangements shape knowledge related behaviors and learning opportunities for employees. The proposed model is primarily built to emphasize the interconnected nature of cultural and structural factors in enabling and improving knowledge flows within an organization. To evaluate the relevance and applicability of the proposed model, it is examined through empirical research conducted in selected organizations. This phase aims to explore the relationships between the key characteristics and to provide an initial evaluation of the model's utility in practice. The study offers an integrated perspective that bridges organizational culture, structure, and management with knowledge sharing and employee development, addressing a gap in current KM and HRM research. By demonstrating how these factors interact, the model supports the streamlining of knowledge management processes. It is useful for managers and HR professionals who are trying to create or improve organizational environments that are more supportive of knowledge sharing and continuous employee learning. A comprehensive view of the factors that shape a knowledge-oriented work environment is a starting point for academic discussion and for further verification of the identified influences in business practice.

Keywords: Organizational culture, Knowledge sharing, Employee development, Knowledge management, Human resource management

1. Introduction

Knowledge is recognized as a strategic organizational resource that contributes to competitiveness, innovation, and long-term performance (Alavi and Leidner, 2001). However, its value depends not only on the fact that it exists, but also on the extent to which it is shared and applied in practice. For this reason, knowledge sharing is viewed as a central process of knowledge management, connecting individual expertise with organizational outcomes (Raziq et al., 2024).

But knowledge sharing does not occur in isolation. The organization as a whole shapes it. It influences its employees through certain dimensions and that leads to their willingness and ability to exchange information (Ng, 2022). These conditions are relevant to developing the employees, as knowledge exchange may support parts of their professional life such as professional growth, competence, skill acquisition and other (Kozhakhmet et al., 2020; Kwon et al., 2024).

Although these dimensions have been previously examined, they are often addressed separately. The goal of this paper is to propose an integrated conceptual model linking the organizational dimensions with knowledge sharing and employee development, and to subject this model to an initial empirical examination through qualitative research.

2. Literature Review

2.1 Knowledge Management and Knowledge Sharing

Knowledge management (KM) is commonly understood as a set of organizational processes related to the creation, storage, transfer, and application of knowledge. Within this framework, knowledge sharing represents one of the most important mechanisms through which knowledge can be used across the whole organization (Alavi and Leidner, 2001; Raziq et al., 2024). Literature differentiates between a knowledge-sharing tendency and knowledge-sharing behaviour. Knowledge-sharing tendency is described as individual willingness to share, and behaviour refers to the actual act of exchanging knowledge. Both factors are

important because positive attitude alone does not guarantee that knowledge will be transferred in practice (Raziq et al., 2024).

Research also shows that the nature of knowledge affects how it can be shared. Tacit knowledge, that is rooted in individual experience and skills, is more effectively transferred through direct interaction, informal communication, and collaborative work. Explicit knowledge on the other hand is transferred through formal documentation or information systems. Organizations accordingly rely on formal mechanisms, such as training, and informal channels, including discussion groups and personal networks, to support knowledge flows (Alavi and Leidner, 2001).

A range of organizational enablers has been identified, including information systems, trust-building activities, teamwork and support from leadership. Transformational and supportive leadership approaches are particularly associated with stronger knowledge sharing because they foster trust within their respective organizations (Mokhchy, 2025). At the same time, barriers such as low trust, weak interpersonal ties or rigid hierarchy may limit voluntary knowledge exchange (Gajda, 2019; Al-Tarawhneh and Al-Adaileh, 2021). Existing studies further show that effective knowledge sharing contributes to employee performance, which includes innovation and organizational competitiveness, highlighting its role in both KM and employee development (Azeem, 2021).

2.2 Organizational Culture in Knowledge Management

Organizational culture refers to the system of shared values, norms and assumptions that guide behaviour within organizations and shape how employees interact with and perform their work (Daft, 2005). In the context of knowledge management, culture is identified as one of the key factors influencing whether employees are willing to exchange knowledge, collaborate, and engage in learning activities. Organizational culture creates conditions that can either support or hinder knowledge processes by shaping relationships, communication or attitudes toward cooperation (Alavi and Leidner, 2001).

Several theoretical frameworks have been developed to conceptualize organizational culture in research. One of the most applied approaches is the Competing Values Framework developed by Cameron and Quinn (1983), which includes four orientations: clan, adhocracy, hierarchy, and market cultures. Clan cultures show collaboration and trust, adhocracy focuses on innovation and flexibility, hierarchy prioritizes stability and formal procedures, and market emphasizes competitiveness and performance. Another influential perspective is provided by Schein (2010), in which he identifies three components: visible artifacts (visible, audible, observable elements), espoused values (beliefs and norms of an organization), and underlying assumptions (unconscious and deeply rooted).

Empirical research suggests that cultural characteristics significantly influence knowledge sharing behaviour. Cultures that are collaborative and trust-oriented tend to encourage their employees to share knowledge and support learning, while cultures that are primarily hierarchical may limit knowledge exchange (Ng, 2022). Other cultural elements such as respect for colleagues and job stability have also been shown to help knowledge sharing practices. These findings indicate that organizational culture represents an important mechanism through which knowledge can be shared within organizations (Rahman et al., 2022).

2.3 Management Practices and Organizational Structure

Management practices and organizational structure represent important conditions shaping how knowledge is shared and applied in practice. The term management practices is used to refer to activities like leadership, strategic planning, HRM, performance appraisal, training, and knowledge management processes themselves (Daft, 2005).

Organizational structure is also identified as a relevant factor influencing knowledge flows within an organization. Most commonly separated into two categories. Mechanistic structures, characterized by centralized hierarchy, and organic structures, focusing on flexibility through open communication and decentralization (Al Koliby et al., 2025). Evidence suggests that organic structures increase knowledge sharing, while rigid hierarchical arrangements may create barriers to communication and reduce passing of knowledge. These structural effects rarely operate in isolation. Structural impact is often moderated by leadership, culture, and management practices, suggesting that knowledge processes are shaped by the interaction of multiple dimensions rather than a single factor (Al Koliby et al., 2025).

2.4 Employee Development

Employee development is closely connected with learning processes and with conditions that help employees acquire and apply knowledge in the workplace. Development is not only shaped by formal training activities, but also knowledge sharing and collaborative work in a learning-oriented environment. Learning orientation, trust and primarily commitment are identified as mechanisms through which cultural and knowledge-sharing conditions are translated into outcomes (Rahman et al., 2022).

Research indicates that training and development activities can strengthen employees' tendency to share knowledge and can reinforce relationships in team-oriented work environments. This suggests that employee development and knowledge sharing are processes that support each other rather than work separately (Ng, 2022). Commitment and trust also play an important role as mediators of relationships between organizational culture and knowledge sharing. Employees are more willing to exchange their knowledge when they feel attached to the organization and perceive interpersonal relationships in it as supportive and trustworthy (Ng, 2022).

Human resource management (HRM) practices further contribute to this relationship. Innovation and learning are positively influenced by performance evaluation, career development and training support, although some studies report that these effects are indirect rather than immediate (Lee et al., 2023). Evidence also suggests that sharing of knowledge contributes to professional competence and career progression (Ng, 2022; He, 2025). In addition, generational differences may shape employees' motivations for knowledge sharing, indicating that initiatives for development may need to be adapted to the expectations of different employee groups (Gajda, 2019). Overall, literature supports the view that knowledge sharing is an important pathway through which employee development can be increased.

2.5 Model Inspiration

The proposed model builds on several established knowledge management frameworks that explain knowledge as an organizational resource shaped by both social and structural conditions. Nonaka and Takeuchi's (1995) SECI model emphasizes the conversion of tacit and explicit knowledge through socialization, externalization, combination, and internalization, highlighting the importance of interaction and shared experience in knowledge creation. Dalkir's (2011) integrated knowledge management cycle extends this perspective by structuring knowledge processes into creation, sharing, and application, showing that knowledge must not only be created, but also transferred and used in practice. Similarly, Wiig's (1993) model stresses the progression from building and holding knowledge to pooling and finally applying it, while Bukowitz and Williams' (1999) KM life cycle focuses on the strategic management of knowledge through processes like acquiring, using, learning, contributing, and sustaining knowledge resources.

Further inspiration comes from McElroy's (2003) knowledge life cycle and Choo's (2006) knowing organization model, both of which broaden KM beyond simple transfer. McElroy highlights knowledge production and integration as part of an ongoing organizational learning process, whereas Choo connects sensemaking, knowledge creation and decision making to organizational action. Meyer and Zack (1996) also contribute a process-oriented view by presenting knowledge as a resource that must be acquired, refined, stored, distributed, and presented for use. Together, these models suggest that knowledge management should be understood as an integrated organizational process influenced by context and directed toward practical outcomes. On this basis, the proposed model links organizational culture, structure, and management practices with knowledge sharing and employee development.

3. Methodology

3.1 Research aim and Research Questions

The aim of this study is to develop an integrated conceptual model linking organizational culture, structure, management practices, knowledge sharing, and employee development

- RQ1: Which organizational conditions are perceived as most important for knowledge sharing?
- RQ2: Which management practices support or hinder knowledge sharing and employee development?
- RQ3: How is employee development related to knowledge sharing in the examined organizations?
- RQ4: To what extent does the proposed model reflect organizational reality, and which relationships appear strongest or weakest in practice?

The study uses a qualitative research methodology aimed at providing an initial empirical examination of the proposed conceptual model. The methodological approach combines literature-based development of the model with a pilot empirical study. The qualitative approach allows a deeper understanding of how the individual constructs are perceived in practice and how they interact within a real organizational context.

3.2 Research Design

The study proceeded in two phases. First, a conceptual model was developed on the basis of reviewed literature. Second, the relevance and applicability of this model were assessed through interviews conducted with managers. Through the interviews, connections between the main parts of the model were reviewed and decision about their linkage was made.

3.3 Data Collection

The empirical part of the study is based on semi-structured interviews conducted with four managers from two selected organizations. Company A is a multinational agrochemical company whose activities are strongly connected with sales representatives. Company B is a holding company bringing together multiple firms operating in building, civil engineering and infrastructure projects. Respondents with direct managerial experience and insight into their organizations were chosen for the interviews. The sample included one middle-level and one upper-level manager from Company A and two upper-level managers from Company B.

The interview guide was developed directly from the proposed conceptual model. Questions were structured around the models' main constructs (culture, structure, management, knowledge sharing, and employee development). Exploration of whether the relationships suggested by the literature are also reflected in managerial perceptions is made possible by this practice.

3.4 Data Analysis

The collected data was analyzed using thematic analysis. Interview responses were reviewed and coded according to recurring themes related to the main relationships and constructs of the proposed model. Attention was given to whether managers perceived the organizational layer of the model as factors influencing knowledge sharing, and whether knowledge sharing was viewed as contributing to employee development.

The purpose of the analysis is not to validate the model statistically, but to provide an initial qualitative assessment of its relevance and applicability in practice. The empirical findings were used to identify areas of support, possible refinement, and selected contextual differences across the settings of selected organizations.

4. Proposed Conceptual Model

4.1 Reasoning for the Model

Based on the reviewed literature, the present study proposes an integrated conceptual model linking aforementioned dimensions. The rationale for the model stems from the observation that existing research has frequently examined these constructs separately, while fewer studies have addressed them within a single analytical framework. The literature reviewed in this paper suggests that knowledge sharing is shaped by a combination of cultural, managerial, and also structural conditions and that it also plays an important role in supporting employee development. The proposed model treats knowledge sharing as the central process through which key organizational conditions are translated into developmental outcomes for employees.

The model is designed as a conceptual framework for the pilot empirical phase of the study. Its purpose is not to claim universal validity, but to provide a theoretically grounded structure for examining how the selected organizational dimensions interact in practice.

4.2 Constructs and Dimensions of the Model

4.2.1 Organizational culture

Based on the reviewed literature, organizational culture is represented in the proposed model through *trust, communication openness, collaboration, and learning orientation*. These dimensions were selected as they are the most recurring relevant cultural conditions shaping knowledge-related behaviour. Trust reduces the perceived risk of sharing and supports psychological safety, making employees more willing to exchange both tacit and explicit knowledge (Rohim and Budhiasa, 2019). Communication openness facilitates the flow of information across vertical and horizontal relationships and lowers barriers associated with status differences

or fear of negative evaluation. Collaboration helps knowledge exchange in everyday work, sharing a routine practice rather than occasional activity (De Long and Fahey, 2000). Learning orientation reflects the extent to which the organization values continuous improvement and the acquisition of new knowledge, linking culture not only to knowledge sharing but also to employee development directly to some degree (Alavi and Leidner, 2001). Together, these dimensions capture the aspects of culture that are most directly connected to knowledge processes.

4.2.2 Management practices

In the proposed model, management practices are represented through *leadership support, training and development support, and rewards and recognition.* These elements were chosen because the literature consistently identifies them as key managerial actions for promoting knowledge-related behaviour. Leadership support is important for signaling that knowledge sharing is strategically valued and provides employees with the resources and encouragement needed to exchange their knowledge (Khan and Mishra, 2023). Training and development strengthen employees' capacity to acquire, articulate, and apply knowledge, while promoting a learning-oriented environment in which sharing becomes more meaningful and useful (Kozhakhmet et al., 2020). Rewards and recognition provide an additional mechanism for motivating employees by reinforcing the value of contributing knowledge, although its effectiveness depends on perceived fairness and broader cultural context (Rohim and Budhiasa, 2019). Taken together, these practices capture the ways in which management translates its values into concrete behavioural expectations for knowledge sharing and employee development.

4.2.3 Organizational structure

Organizational structure is represented in the model through *decentralization, flexibility and reduced hierarchy.* These dimensions were included because it is repeatedly shown that structural arrangements influence how easily knowledge can move within organizations. Decentralization gives employees greater autonomy and places decision-making closer to the point where knowledge is created and applied, which can accelerate knowledge use and employee learning. Flexibility, often connected to organic structures within organizations, enables informal communication of employees, which supports the exchange of ideas despite organizational boundaries. Reduced hierarchy lowers barriers caused by bureaucracy, leading to shorter communication pathways (Al Koliby et al., 2025). These dimensions capture the degree of which the structure of an organization enables knowledge flows and creates favourable conditions for employee learning and development.

4.2.4 Knowledge sharing

Sharing of knowledge is conceptualized in the model through *willingness to share, knowledge sharing behaviour, and formal and informal exchange.* Willingness to share refers to an employee's intention to make knowledge available to others and is shaped by factors such as trust and support (De Long and Fahey, 2000). Knowledge sharing behaviour refers to the actual enactment of sharing (Kozhakhmet et al., 2020). Formal and informal exchange are included because organizations rely on both structured mechanisms (training sessions, scheduled meetings, etc.), and informal mechanisms (peer interaction, mentoring, spontaneous problem-solving conversations (De Long and Fahey, 2000; Alavi and Leidner, 2001). Distinguishing these dimensions is important because positive attitudes do not automatically translate into behaviour, and actual sharing may take different forms depending on organizational conditions.

4.2.5 Employee development

Employee development is represented through *skill development, professional growth, and growth of* competence. These dimensions were selected because knowledge sharing contributes not only to immediate learning, but also to broader development outcomes. Skill development reflects the acquisition and improvement of competencies through formal training and through interaction with colleagues, it helps the application of shared knowledge in work tasks (Ben Zammel and Najar, 2022). Professional growth captures longer term development processes like career progression or continuous learning within the organization (Kwon et al., 2024). Competence growth is included as a development related outcome, because shared knowledge often provides the basis for new ideas, improved work practices, or one's capacity to contribute creatively to organizational goals (Ben Zammel and Najar, 2022). Employee development dimensions reflect the view that it is not limited to formal training but shaped by the organization's knowledge environment and the extent to which employees participate in exchange as well.

4.2.6 Relationships within the model

The proposed model assumes that organizational culture, management practices, and organizational structure shape the conditions under which knowledge sharing occurs. Culture provides the foundation for knowledge exchange, management practices translate priorities into concrete support mechanisms, and structure influences communication pathways and access to knowledge within the organization.

This framework displays knowledge sharing as a central process that links conditions within the organization with employee development. The model proposes that supportive organizational conditions increase knowledge sharing, which in turn contributes to development of its employees. The model also acknowledges secondary relationships and feedback logic, which lead to outcomes that may influence future support for knowledge processes.

5. Findings

The conducted interviews with managers from two different organizations indicate that knowledge sharing is strongly shaped by organizational conditions, particularly its culture and support from management. Company A is a multinational agrochemical company that mostly employs sales representatives. Company B is a holding company that brings together multiple firms across different areas of building, civil engineering and infrastructure projects. In relation to RQ1, the interviews suggest that organizational culture and management support are perceived as the most important conditions influencing knowledge sharing.

The first organization used primarily formal channels for information exchange, including e-mail, WhatsApp, phone communication, Microsoft Teams, and shared company spreadsheets. However, during the questioning a different problem was emphasized. The main problem for this organization was not the absence of information and its sharing, but employees' unwillingness to share or effectively use the knowledge available to them. The interview pointed to inconsistency among employees, low responsiveness, and behaviour related to ego which served as barriers, while structure and management were described as weak and outdated. In this case, knowledge sharing was limited less by a lack of formal mechanisms and more by dysfunctional organizational conditions.

In contrast, the second organization reflected a more supportive environment for sharing knowledge. The organization was described as open and growth-oriented, with mentoring, regular discussions, annual evaluations, feedback, and talent development contributing to the exchange of knowledge. Management support appeared particularly important, as respondents repeatedly emphasized the role of mentors and managerial communication in encouraging employees to learn and share. Time constraints were mentioned as a barrier, but the overall picture was that knowledge sharing was embedded in the organization more effectively than in the first company.

The interviews also suggest that sharing contributes to employee development, although the strength of this relationship differs across organizations. Company A had limited development beyond mandatory training, and the respondent stressed that experience was the most important source of growth. Sharing was still viewed as relevant, especially for building professional expertise, but the organization did not appear to provide strong developmental support beyond basic requirements.

Company B linked knowledge sharing more clearly with employee development. Regarding RQ2 and 3 respondents described mentoring, informal discussions, and feedback processes as important mechanisms through which employees develop skills and grow professionally. Informal exchange was emphasized through conversations during coffee breaks and everyday interactions. This suggests that employee development is strengthened when knowledge sharing is supported not only formally, but also through routine interpersonal exchange.

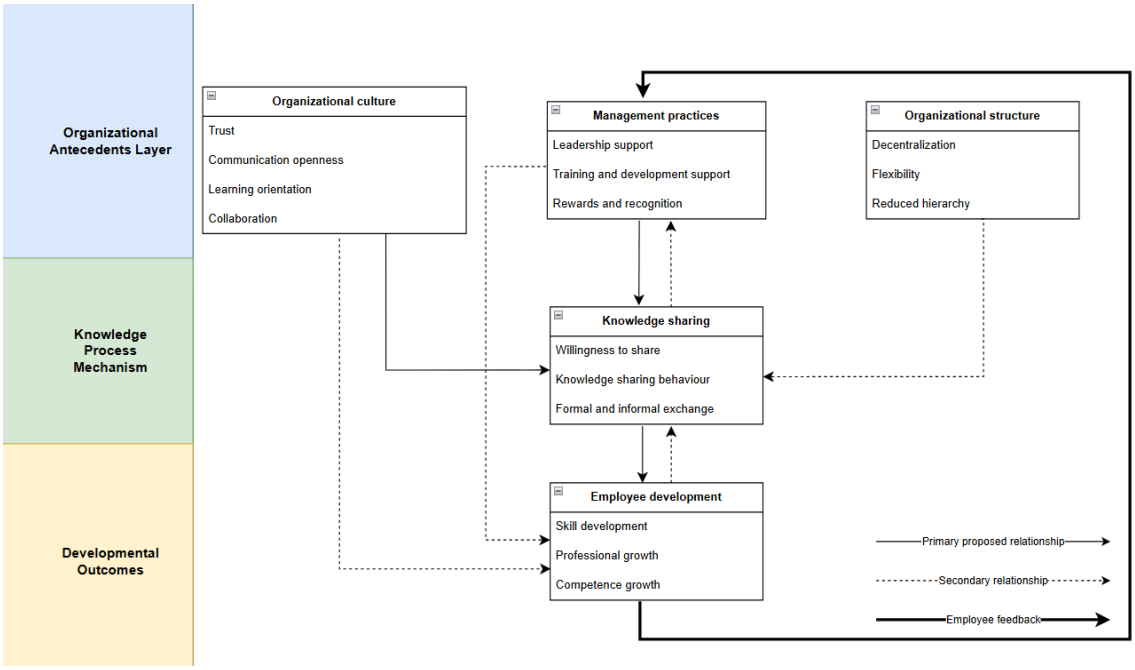


Figure 1: The proposed conceptual model

5.1 Assessment of the Proposed Model

Overall, the findings provide initial support for the proposed conceptual model. In both organizational contexts, respondents considered the relationships included in the model meaningful. At the same time. The interviews showed that the model is reflected in practice to different degrees. For company A, the model described a set of conditions that conceptually made sense but were not functioning effectively in their reality. In company B, the model was perceived as much closer to actual practice, primarily in the links between culture, management, knowledge sharing, and employee development.

The findings suggest that the model is useful not only for describing supportive organizational environments, but also for identifying missing or weakly developed conditions in less effective settings. Through the interviews, organizational culture appeared to be the most influential factor, while structure played secondary but still relevant role. The pilot empirical phase thus supports the relevance of the model, while also indicating that the strength of individual relationships is context dependent.

6. Discussion

The pilot findings suggest that the proposed model captures meaningful relationships between organizational conditions, knowledge sharing, and employee development. In both examined contexts, organizational culture and management support appeared more influential than structure, although structure still affected the ease of knowledge exchange. The comparison of the two organizations indicates how the model can help describe their respective environments. In the first case, the model reflected conditions that were weakly implemented in practice, while in the second case it was more closely aligned with everyday organizational functioning. This suggests that the model may be useful not only as a framework, but also as a tool for identifying missing conditions for knowledge sharing.

7. Conclusion and Limitations

This paper proposed an integrated conceptual model linking organizational dimensions with knowledge processes leading to employee development. Drawing on knowledge management and human resource management literature, the model was designed to explain how organizational conditions shape knowledge-sharing processes and how these processes contribute to development of employees. The pilot empirical phase provided initial qualitative support for the relevance of the model in practice. The findings suggest that culture and support from management are particularly important in shaping knowledge sharing. The comparison of the examined organizations showed that the strength of these relationships depends on the context.

The paper has several limitations. First, it represents a pilot qualitative inquiry based on a small sample of managers from two organizations, which limits the generalizability of the findings. It is important to note that the empirical study is limited by presenting managerial perspective only. The study does not statistically test the proposed relationships and therefore cannot confirm their causal strength. The findings should be understood as an initial assessment of the model rather than its full validation. Future research could extend the sample, include multiple organizational levels, and add quantitative survey-based testing in order to examine the model more comprehensively.

Acknowledgements

This paper was prepared with the support of the project Systemic and Institutional Approaches to the Development of Innovation Ecosystems SGS_2026_013. The authors gratefully acknowledge this support.

Ethics Declaration: Ethical clearance was not required for this research.

AI Declaration: Generative artificial intelligence was used solely for language editing and formatting support. All content was critically reviewed to ensure academic integrity.

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An Optimisation Approach for Prioritising Actions to Mitigate Collaborative Knowledge Management Barriers

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Abstract: Collaborative Knowledge Management (CKM) initiatives often struggle in practice because organisations face everyday managerial challenges such as limited coordination, misaligned objectives, uneven skills, and unclear documentation practices. Although many studies identify these barriers, managers still lack simple tools that help them decide which improvement actions should be implemented first when time, budget, and organisational capacity are limited. This paper proposes an optimisation-based approach designed to support these decisions. The model helps organisations select the combination of actions that is expected to reduce management-related knowledge barriers the most, while considering real-world constraints such as budget limitations, implementation capacity, feasibility conditions, and logical relationships between actions, including prerequisites and mutually incompatible initiatives. Besides suggesting which actions to implement, the approach also shows how much each barrier is likely to decrease, helping managers clearly understand the expected benefits and making the results easier to explain and discuss in decision-making processes. Finally, a real application illustrates how the proposed approach supports managerial decision-making by identifying practical actions, such as training initiatives, coordination mechanisms, and clear documentation practices, that can simultaneously reduce several management barriers and prepare the organisation for more advanced collaborative knowledge initiatives in later implementation phases. Future research may extend the proposed approach by incorporating uncertainty in the estimation of action effectiveness, multi-period planning considerations, and dynamic learning mechanisms that update decision recommendations as new implementation data becomes available.

Keywords: Collaborative knowledge management, Optimisation, Knowledge barriers, Managerial decision-making, Prioritisation

1. Introduction

In today's global and connected business environment, organisations increasingly collaborate with external partners such as suppliers, customers and sometimes even competitors. In these collaborative networks, knowledge is one of the most valuable resources for innovation, problem solving and improving organisational performance. The ability to share and combine knowledge across organisational boundaries is therefore considered an important capability for modern enterprises and supply chains (Grant, 1996; Cheng et al., 2024). Organisations that are able to manage knowledge effectively are usually better prepared to adapt to changes and remain competitive.

Collaborative knowledge management (CKM) plays an important role in supporting these interactions. Through CKM processes, organisations can share experiences, expertise and information in order to generate new ideas, improve decision-making and respond more effectively to changing market conditions (Li, Ye and Sheu, 2014; Zighan et al., 2024). When knowledge flows easily between organisations, companies can learn from each other and avoid repeating the same mistakes.

However, in practice many CKM initiatives do not achieve the expected results. One of the main reasons is the presence of barriers that make knowledge sharing and collaboration difficult among individuals, organisations and networks (Chua and Banerjee, 2023; Koivisto and Taipalus, 2025). These barriers can appear at different levels. For example, employees may lack motivation to share their knowledge, organisations may have different objectives, or technological systems may not be compatible.

Although previous studies have identified many of these barriers, managers still face difficulties when deciding how to address them in practice. In almost all organisations, resources are limited. Companies often have limited budgets, limited time and limited capacity to implement many initiatives at the same time. For this

reason, managers must decide which actions should be implemented first in order to reduce the most important barriers while using the available resources efficiently (Marra, Ho and Edwards, 2012; Danko and Crhová, 2025).

Although that are many research studies focused on CKM, there is still a lack of practical and easy-to-use tools that help managers decide which improvement actions should be implemented to minimise the impact of the barriers and improve the CKM process. In addition, there is also a need for tools that take into account the daily operation of companies, such as budget limitations and organisational constraints.

To address this problem, this paper proposes a mixed-integer linear programming (MILP) model that helps organisations select the most appropriate actions to reduce CKM barriers. The model considers: (i) the effectiveness of different actions to mitigate specific barriers; (ii) the implementation costs of the actions; (iii) the budget that the organisation is willing to invest; and (iv) the organisation's capacity to implement change. In addition, the model also considers the relationships between actions, since there are situations where one action needs another action to be implemented first, and there are also cases where two actions cannot be implemented at the same time.

The rest of the paper is organised as follows. Section 2 describes the antecedents of the research focusing on the framework used to analyse CKM barriers. Section 3 presents the optimisation model and the case study used to validate the approach. Section 4 presents and discusses the results obtained. Finally, Section 5 summarises the main conclusions of the study and suggests possible directions for future research.

2. Antecedents

CKM has been investigated in recent years in order to improve the process through which knowledge is shared. Currently, organisations work together with other partners, and it is necessary to share a large amount of knowledge in order to remain competitive and continue improving their performance.

However, collaborating to share knowledge among organisations is complex. Current research shows that when different companies try to collaborate to share knowledge they usually face difficult problems. These problems can be of different types and nature, ranging from diverse organisational cultures to differences in objectives between individuals and organisations (Chua and Banerjee, 2023; Koivisto and Taipalus, 2025).

To better understand these CKM barriers, different frameworks have been proposed to classify and analyse them. Sanchis, Sanchis-Gisbert and Poler (2020) proposed a three-dimensional framework that structures CKM barriers according to three main dimensions: perspectives, levels of collaboration and barrier blocks.

The perspectives represent different viewpoints from which the barriers can be analysed, and they are divided into human, organisational, technological, contextual, and informational aspects. The human perspective involves the people who perform the collaboration and covers the skills, abilities, attitudes, or fears that influence the CKM process. The organisational perspective involves the internal structure and management of organisations, with elements such as leadership, communication flows, strategies, and organisational culture. The technological perspective considers the tools and systems used to support CKM, such as artificial intelligence, information technologies, communication platforms, or data systems that facilitate the exchange and storage of knowledge. The contextual perspective concerns the external conditions of the organisations, such as environmental, social, cultural, or regulatory factors. Finally, the informational perspective focuses on the characteristics of the information and knowledge being shared, such as its accuracy, relevance, availability, and uncertainty, among others.

The levels define where the CKM process takes place, covering from individuals to collaboration within entire supply chains. The framework considers four main levels. The individual one that focuses on knowledge interactions between people. The intra-collaborative level that covers the collaboration inside the same organisation (between departments, teams, or functional units). The inter-collaborative level, which refers to collaboration between different organisations within a supply chain. Finally, the framework defines a novel level, called extra-collaborative level, which involves the knowledge exchanges that go beyond a single supply chain, involving multiple networks, institutions, or broader collaborative ecosystems. This level of collaboration is the most complex due to the large number of actors involved in the CKM process and also due to the variety of interests, structures, and objectives.

With regard to the barriers blocks, they are divided into four: trust, management, environment, and means, which help organise the different barriers that may affect CKM initiatives. In this study, we focus on the management barriers block, which includes the barriers related to how knowledge collaboration is organised,

coordinated, and managed, as shown in Table 1. While the structure follows the three-dimensional framework proposed by Sanchis et al. (2020), some barriers have been slightly updated to better reflect current challenges related to digital collaboration and the increasing use of knowledge-sharing technologies.

Table 1: Management barriers block adapted from Sanchis et al. (2020)

Perspective	Individual	Intra-collaborative	Inter-collaborative	Extra-collaborative
Human	Differences in abilities and skills. Lack of motivation.	Differences in knowledge domains and professional backgrounds.	Strong contrasts in expertise, disciplines and professional cultures.	High diversity of knowledge domains and skills across actors.
Organisational	Self-interest of individuals. Incompatibility between personal objectives.	Prevalence of departmental objectives over organisational goals.	Dominance of individual organisational interests over network goals.	Dilution of shared objectives and strategic misalignment among networks.
Technological	Lack of technological training strategies.	Lack of coordination and management of technological systems.	Technological imbalance between organisations.	Lack of common technological initiatives and low interoperability between digital collaboration platforms.
Contextual	Fear of becoming redundant. Lack of awareness of knowledge strategies and tools.	Conflicts of interest and weak collaborative knowledge culture.	Differences in organisational size and power imbalance between partners.	Confusing interests between networks and lack of shared governance structures.
Informational	Lack of knowledge recording practices.	Lack of documentation policies and knowledge management standards.	Insufficient mechanisms to externalise and structure knowledge.	Complex and dense knowledge externalisation strategies and information overload in digital collaboration environments.

3. Optimisation-based Approach

The optimisation model proposed in this paper aims to support managers when selecting actions to reduce CKM barriers. In many organisations, there are several possible actions that could improve knowledge sharing. However, due to limited resources, it is usually not possible to implement all of them at the same time.

For this reason, managers need to decide which actions should be prioritised. Some actions may have a strong impact on several barriers, while others may only affect a small number of them. At the same time, each action has a cost and requires organisational effort to be implemented. The optimisation model evaluates different combinations of actions and identifies the set of actions that produces the greatest reduction of the barriers while respecting organisational constraints. These constraints include the available budget, the organisation's capacity to implement change and possible relationships between actions.

In addition, the model allows managers to monitor how much each barrier is reduced by the selected actions. This helps decision-makers better understand the results and identify which barriers still require additional attention.

3.1 Model Formulation

The notation used in the optimisation model is summarised in Table 2.

Table 2: Notation of the CKM barriers mitigation optimisation model

Set of indices	
I	Set of candidate solutions (indexed by i, k)
J	Set of barriers (indexed by j)
Subsets of indices	
D	Set of dependency pairs (i, k) where solution i requires solution k to be implemented
E	Set of exclusion pairs (i, k) where solutions i and k cannot be selected simultaneously

Parameters	
c_i	Implementation cost of solution *i*
e_{ij}	Effectiveness of solution *i* in mitigating barrier *j*
w_j	Importance weight assigned to barrier *j*
B	Total available budget for implementing solutions
K	Organisational change capacity. Maximum number of solutions that can be implemented simultaneously
α_j	Minimum desired mitigation level for barrier *j*. Threshold parameter
Decision variables	
x_i	Binary decision variable equal to 1 if solution *i* is selected, 0 otherwise
Output variables	
m_j	Achieved mitigation level of barrier *j*, where $m_j \in [0,1]$

The objective function (1) maximises the overall mitigation impact of the identified barriers. This impact is calculated as the weighted sum of the mitigation levels achieved for each barrier, where the weights reflect their relative importance. One of the main challenges of this model is to make the results easier to interpret for managers, as many of the companies that could use this type of tool do not have strong technical backgrounds. For this reason, the model includes a variable that represents the mitigation level achieved for each barrier. This value is limited to a maximum of one, which corresponds to full mitigation.

$$\max \sum_{j \in J} w_j \cdot m_j \tag{1}$$

The model is subjected to different constraints. The budget constraint (2) ensures that the total cost of the selected solutions does not exceed the available budget. The change capacity constraint (3) limits the total number of solutions that can be implemented at the same time, reflecting that organisations cannot implement multiple initiatives simultaneously.

$$\sum_{i \in I} c_i \cdot x_i \leq B \tag{2}$$

$$\sum_{i \in I} x_i \leq K \tag{3}$$

The mitigation level achieved for each barrier depends on the effectiveness of the selected solutions. For this reason, the model links the effectiveness of the selected solutions with the variable that represents the mitigation level of each barrier (4). In this sense, the model represents the combined effect of multiple solutions taking into account that the mitigation level cannot exceed full coverage, i.e. 1 (5). In addition, the model also includes coverage constraints, which require a minimum mitigation level to be reached for specific barriers that are considered particularly important (6).

$$m_j \leq \sum_{i \in I} e_{ij}\, x_i \qquad \forall j \in J \tag{4}$$

$$0 \leq m_j \leq 1 \qquad \forall j \in J \tag{5}$$

$$m_j \geq \alpha_j \qquad \forall j \in J \tag{6}$$

Finally, the model also considers relationships between solutions. Dependency constraints ensure that some solutions can only be implemented if other solutions are also selected (7). At the same time, exclusion constraints prevent the simultaneous selection of solutions that are incompatible (8). All the variables that represent the selection of solutions are binary, meaning that each solution is either implemented or not (9).

$$x_i \leq x_k \qquad \forall (i,k) \in D \tag{7}$$

$$x_i + x_k \leq 1 \qquad \forall (i,k) \in E \tag{8}$$

$$x_i \in \{0,1\} \tag{9}$$

3.2 Case Study

The case study was conducted in an engineering and information and communication technologies consulting company specialised in the design of intelligent transport systems (ITS) for public and private organisations. The company develops technological solutions related to traffic monitoring, mobility management and transport data analysis.

Projects in this sector usually involve multidisciplinary teams composed of engineers, software developers and technical specialists. In this context, knowledge sharing is very important because experiences and solutions developed in previous projects can help improve future projects.

As part of its digital transformation strategy, the organisation aims to improve its CKM practices. The company is particularly interested in improving the way knowledge generated during projects is captured, stored and shared across teams.

To identify the most relevant barriers and possible improvement actions, three professionals from the organisation participated in the evaluation process. These participants included one senior manager responsible for innovation strategy, one engineer working on ITS design projects and one technical specialist responsible for system implementation. These experts evaluated 12 barriers from the three-dimensional framework proposed by Sanchis et al. (2020). Only barriers related to management were assessed as it is shown in Figure 1.

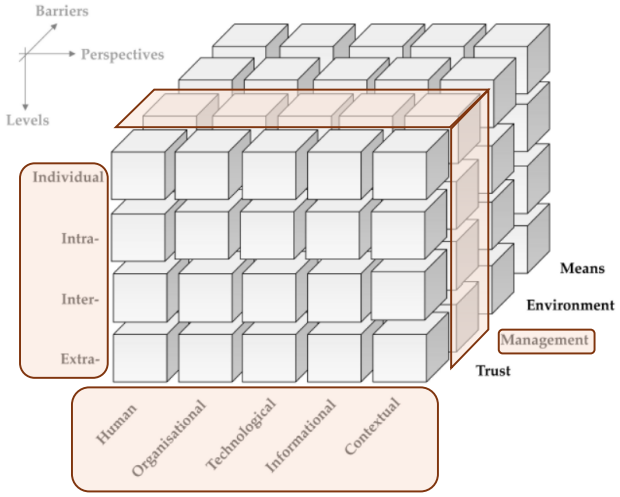


Figure 1: Coverage of the optimisation model based on the three-dimensional framework of CKM barriers proposed by Sanchis et al. (2020)

The company defined the importance of each barrier by assigning a weight on a scale from 1 to 10, where 1 represents a low level of importance and 10 represents a very high level of importance. In addition, the participants were asked to indicate the percentage of mitigation they would like to achieve for each barrier. Table 3 presents both the importance weights (w_j) of each barrier analysed and the coverage thresholds (α_j).

Table 3: Set of barriers analysed in the case study with its importance (weight) and coverage threshold.

Barrier	Description	Weight (w_j)	Threshold (α_j)
B1	Lack of skills and abilities	8	0.4
B2	Self-interest and incompatibility	7	0.3
B3	Lack of knowledge registers	6	0.15

Barrier	Description	Weight (w_j)	Threshold (α_j)
B4	Differences in knowledge fields	7	0.4
B5	Functional *vs* organisational objectives	9	0.5
B6	Lack of technological coordination	7	0.25
B7	Differences in skills between organisations	6	0.3
B8	Conflicting organisational interests	9	0.5
B9	Weak knowledge culture	8	0.4
B10	Disorder in knowledge structures	6	0.1
B11	Strategic misalignment	10	0.5
B12	Difficulty externalising knowledge	7	0.25

Based on this, the company considered eight possible actions that could improve CKM as shown in Table 4. These actions represent initiatives that could be implemented within a short pilot period of two to three months.

Table 4: Possible improvement actions that could improve CKM

Action	Description	Cost (€)
A1	Training workshops on knowledge sharing practices	4,500
A2	Incentive programme for knowledge contributions	3,000
A3	CKM collaboration platform (software licences and configuration)	8,500
A4	CKM governance committee	1,200
A5	Knowledge repository system	6,000
A6	Document management policy and templates	2,000
A7	Strategic alignment workshop	2,500
A8	Internal culture programme promoting knowledge sharing	3,500

Based on the weights given to the selected barriers (Figure 2), the intra-collaborative level has the highest importance (34.4%). This is followed by the inter-collaborative level (24.4%), the individual level (23.3%), and finally the extra-collaborative level (17.8%). This means that most of the important barriers identified by the company are mainly related to collaboration inside the organisation, that has sense as the company works based on projects, and previous company projects may serve as knowledge basis for future ones.

If we analyse the barriers from the perspective dimension (Figure 2), organisational barriers represent the largest part of the total weight (38.9%). Human barriers are the second most important (30.0%). Technological, contextual and informational barriers have a smaller importance. These results indicate that the main difficulties for CKM in the analysed company are more related to organisational alignment and coordination than to technological problems.

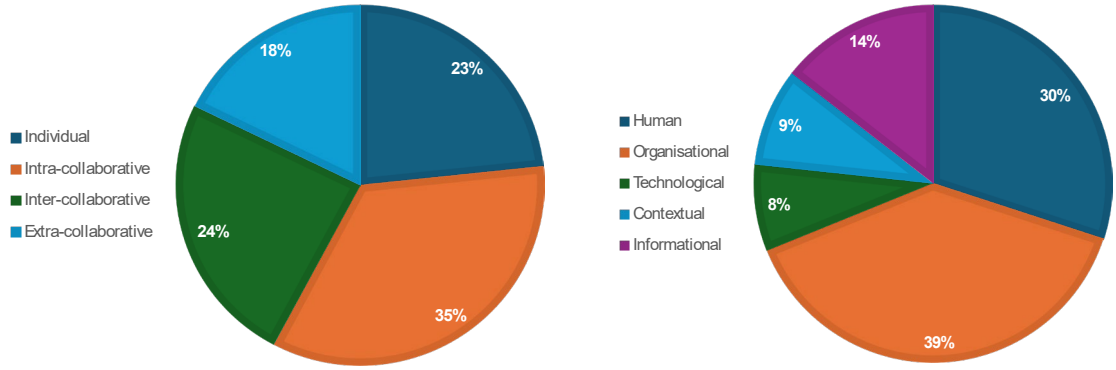


Figure 2: Distribution of barrier weights across collaboration levels and perspectives

The most difficult information for the company to define was the estimation of the effectiveness of each action in reducing the different barriers (Table 5). In addition, it should be noted that this represents a limitation of the study, since the assessments were based only on the information provided by a small group of participants from the company, as well as on their professional experience and knowledge of the organisation's processes. This limitation could be improved in future research by involving a larger number of experts or stakeholders.

Table 5: Effectiveness matrix e_{ij}

Barrier \ Action	A1	A2	A3	A4	A5	A6	A7	A8
B1	0.70	0.10	0.10	0.10	0.05	0.05	0.15	0.20
B2	0.10	0.50	0.05	0.20	0.00	0.00	0.10	0.30
B3	0.10	0.00	0.40	0.05	0.45	0.50	0.05	0.00
B4	0.60	0.05	0.05	0.10	0.00	0.00	0.20	0.30
B5	0.05	0.05	0.05	0.30	0.00	0.10	0.60	0.10
B6	0.05	0.00	0.50	0.20	0.30	0.25	0.05	0.00
B7	0.50	0.05	0.05	0.10	0.00	0.00	0.15	0.20
B8	0.00	0.10	0.00	0.25	0.00	0.00	0.60	0.15
B9	0.15	0.20	0.05	0.20	0.00	0.00	0.10	0.50
B10	0.10	0.00	0.30	0.05	0.35	0.50	0.00	0.10
B11	0.00	0.05	0.00	0.20	0.00	0.05	0.70	0.10
B12	0.10	0.00	0.35	0.10	0.40	0.45	0.05	0.00

The company defined a maximum budget of €15,000 to implement the CKM improvement actions. In addition, there was a constraint related to the organisation's change capacity. The company established a maximum of $K = 3$, which means that only three CKM improvement actions can be implemented at the same time.

The company was also asked whether some of the proposed improvement actions were incompatible with each other or whether some actions needed to be implemented before others. In this regard, the interviewees indicated that actions A3 and A5 require action A6 ($x_{A3} \leq x_{A6}$ and $x_{A5} \leq x_{A6}$). This is because a knowledge repository or a collaboration platform should not be implemented without a basic document management policy. Without clear rules regarding document naming, validation, metadata and document structure, knowledge repositories or CKM platforms can quickly become disorganised.

In addition, the participants identified a dependency between actions A2 and A4 ($x_{A2} \leq x_{A4}$). Specifically, the incentive programme requires the existence of a governance structure. If incentives are introduced without a

governance mechanism, several problems may occur, such as employees uploading irrelevant documents only to obtain rewards or conflicts arising regarding the fairness of the incentive system.

Finally, the company was also asked about possible exclusion relationships between actions. The participants stated that actions A3 and A5 are mutually exclusive ($x_{A3} + x_{A5} \leq 1$). This means that the company can implement either the collaboration platform or the repository system, but not both at the same time. Implementing both solutions would increase costs unnecessarily and could also create confusion about where knowledge should be stored.

4. Results

The optimisation model identifies A1, A4, and A7 as the best set of actions to implement. Since the organisation decided that only three actions could be introduced at the same time, the model searches for the combination that produces the greatest reduction of the barriers while keeping costs under control and meeting the minimum mitigation levels defined for each barrier.

Action A1 that consists of training workshops on knowledge sharing practices supports employees to improve their knowledge and skills. This helps to overcome the barriers related to capabilities and differences in expertise. Action A4 involves the creation of a CKM governance committee which will be in charge of coordinate and monitor the CKM process. In this sense, this action supports the management and organisation of collaborative activities and the better understanding between teams. Action A7, that is the implementation of the strategic alignment workshop, is focused on trying to make that all the members the companies have the same objectives and guaranteeing that all the departments of the company are working to achieve common goals.

It is worth noting that this solution does not include technological tools such as platforms or repositories but the model prioritises actions related to an organisational viewpoint to create the appropriate context to promote knowledge sharing. Considering that the company has a limited budget and its capacity to implement changes is also constrained, the resulting actions seem to be the most efficient ones to reduce the identified CKM barriers.

The total cost of implementing these actions is €8,200, that is the sum of the cost of actions A1, A4 and A7 and it is lower than the budget of €15,000 that the company was willing to invest. This means that the organisation can achieve great mitigation without using all the planned investment what can be addressed to other issues.

Another important aspect of the optimisation model is that it allows the company to evaluate the overall effectiveness of the selected actions. If the mitigation level achieved for each barrier (m_j) is multiplied by its corresponding importance weight (w_j), the resulting value is 55.95, which represents the overall level of barrier reduction achieved by the selected actions. Figure 3 shows the mitigation level achieved for each barrier after implementing the selected actions (A1, A4, and A7). For every barrier, the minimum mitigation threshold defined in the model (α_j) is compared with the mitigation level actually obtained (m_j). As it is illustrated, the selected actions allow the model to reach the minimum required mitigation level for all the barriers considered.

From a managerial perspective, it is worth mentioning that the model selected actions related to training, governance and strategic alignment instead of technological solutions such as, for example actions A3 and A5: knowledge platforms or repositories.

This result suggests that organisations maybe first need to reinforce their organisational aspects instead of investing in advanced and more complex technological tools. If the employees' skills are improved, the company creates coordination mechanisms and aligns organisational objectives, all this can help a lot to improve knowledge collaboration.

In addition, the optimisation model can help managers when they evaluate different improvement alternatives. Instead of relying only on intuition or personal judgement, managers can use the model to analyse different possible actions and see which combination can generate the greatest benefit under the existing constraints.

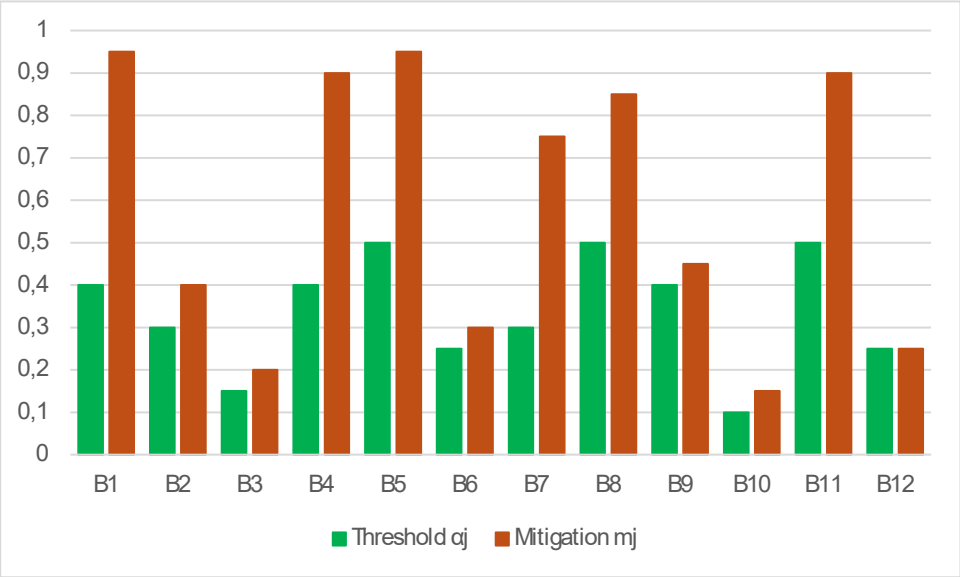


Figure 3: Mitigation level achieved and mitigation threshold

5. Conclusions

This paper proposed an optimisation-based approach to select the optimal improvement actions to reduce CKM barriers. In many organisations, knowledge sharing initiatives face practical difficulties because managers must make decisions with limited resources, limited time, and limited organisational capacity to implement new initiatives. For this reason, it is a very complex task to choose which actions should be implemented.

To solve this, the paper proposed a MILP model that supports company managers to decide about the combination of the most efficient set of actions that can reduce CKM barriers. The model considers the different real aspects that organisations usually face daily, such as implementation costs, budget limitations, organisational capacity to change, and the relationships between actions, i.e. if there is a need for previous actions to be implemented before or if there are actions that cannot be implemented together at the same time. Moreover, the model offers the level of mitigation achieved for each barrier, which makes that managers without expertise in complex mathematical models can understand and interpret easily the results obtained.

The model was validated through a case study of an engineering and ICT consulting company specialised in intelligent transport systems. The results show that the optimisation approach can help organisations identify a small set of actions that produce a significant reduction in the most important CKM barriers. In the analysed case, the model prioritised three actions related to training, governance, and strategic alignment. These actions focus on strengthening the organisational foundations that support knowledge sharing before introducing more complex technological solutions.

Another important aspect to highlight is that the selected actions comply with the minimum mitigation thresholds defined by the organisation. Moreover, the set of actions selected does not achieve the total amount of budget that the company was willing to invest. This evidences that, sometimes, it is not necessary to invest expensive solutions.

The proposed model provides a practical and easy-to-use decision-support tool that can help managers select actions aimed at improving CKM.

However, the study also presents some limitations. In particular, the estimation of the effectiveness of the improvement actions was based on the opinions of only three experts from the company. Future research could involve a larger group of stakeholders in order to obtain more accurate estimates. In addition, future studies could extend the model by incorporating uncertainty in the estimation of action effectiveness, analysing multi-period implementation strategies, or testing the approach in different organisational contexts and industries.

Acknowledgements

The research that led to these findings received funding from the Horizon Europe Framework Programme (HORIZON) with Grant Agreement No. 101177368 “Agile Manufacturing as a Service through AI Autonomous Agents" (MaaSAI).

Ethics Declaration: This study did not require formal ethical approval. The data used in the case study were based on professional assessments provided voluntarily by three employees of the participating company. No personal or sensitive data were collected.

AI Declaration: AI tools were used only to assist with language editing and grammar improvement. The research design, model development, analysis, and interpretation of the results were carried out by the authors.

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Generative AI and Knowledge Creation: Comparing Proposals for Revising the SECI Model

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Abstract: The use of Generative Artificial Intelligence (GenAI) is deeply impacting all Knowledge Management (KM) processes. In particular, due to its ability to generate new content in different forms, the new technology is deemed capable of deeply transforming the knowledge creation process, which is considered the highest and most impactful stage of KM processes. Despite this, a comprehensive understanding of how companies can leverage GenAI to create organizational knowledge is lacking, both empirically and theoretically. Regarding the latter, scholars have recently underlined that prior research has yet to focus on the transformation of the SECI model and Ba theory, the most widely used conceptual frameworks for interpreting the organizational knowledge creation process, in the era of human-intelligence interaction. However, in the last two years, some studies have examined whether the SECI model needs to be revised in light of GenAI. Based on a review of the 19 systematically identified articles on Scopus, the present paper identifies, discusses, and compares the three different conceptual approaches adopted by scholars in dealing with the topic in question: a) applying the SECI model in its original version; b) adapting the original SECI model with small adjustments; c) developing a new SECI-based model. The paper compares the three approaches, highlighting how they assume different notions of the role of GenAI in the knowledge creation process and the types of knowledge involved. The academic and practical implications that arise from the study are discussed in the conclusions.

Keywords: GenAI, Knowledge creation, SECI model, Theoretical framework, Literature review

1. Introduction

It is widely acknowledged that the emergence of Generative Artificial Intelligence (GenAI) is profoundly reshaping all Knowledge Management (KM) processes (Alavi et al., 2024). In particular, due to its remarkable ability to generate new content across various formats, including text, images, code, and multimedia, this technology is deemed capable of fundamentally revolutionizing the knowledge creation process, which is widely recognized as the most sophisticated and strategically impactful stage within KM frameworks (Cerchione et al., 2026). Despite growing interest and emerging applications, a comprehensive understanding of how organizations can leverage GenAI to enhance organizational knowledge creation remains notably absent, both empirically and theoretically (Yan et al., 2026). Concerning the latter, Zhang et al. (2025) have recently emphasized that prior research has yet to systematically address the transformation of the SECI and Ba theory - the most influential and extensively applied conceptual frameworks for interpreting organizational knowledge creation processes (Nonaka and Takeuchi, 1995; Nonaka et al., 2000) - in the emerging era of human-AI interaction and collaboration. Nevertheless, within the past two years, a growing body of scholarly work has begun to critically examine whether the traditional SECI model requires substantial revision or adaptation in light of GenAI's capabilities and implications. Drawing upon a systematic review of the relevant academic literature, this paper identifies, analyses, and critically compares three distinct conceptual approaches adopted by scholars when addressing this pressing issue:

1. Application of the original SECI model without modification. Scholars adopting this approach contend that the original SECI framework remains sufficiently robust and flexible to accommodate and explain the impact of GenAI on organizational knowledge creation processes, requiring no fundamental alterations.
2. Adaptation of the original SECI model with targeted adjustments. Proponents of this approach argue that while the foundational structure of the SECI model remains valid, specific modifications and refinements are necessary to adequately capture and interpret the nuanced ways in which GenAI influences knowledge creation dynamics.
3. Development of a new model derived from the SECI framework. Advocates of this approach maintain that the disruptive nature of GenAI necessitates a substantially revised or entirely reconceptualized model to achieve a comprehensive and accurate understanding of how GenAI fundamentally alters organizational knowledge creation processes.

This study compares these three theoretical approaches from both conceptual and practical application perspectives, focusing on their different assumptions regarding: (a) the specific role GenAI assumes within the knowledge creation process (e.g. as a tool, collaborator, or autonomous agent); (b) the types of knowledge involved; and (c) the management implications that emerge. Rather than proposing a new conceptual framework grounded in existing literature, this paper aims to offer conceptual reflections that may inform and inspire future research on the role of generative AI in knowledge creation.

2. Background: GenAI and Organizational Knowledge Creation

Due to its multifaceted capabilities - including the autonomous creation of virtually any type of content, the sophisticated analysis of massive volumes of data and information, and the provision of intelligent support for creative and innovation processes - GenAI is increasingly recognized as a transformative force with the potential to fundamentally reshape the entire landscape of Knowledge Management (Sumbal and Amber, 2025). In particular, GenAI is unanimously regarded by both scholars and practitioners as capable of radically transforming the way organizational knowledge creation processes unfold, primarily because it can successfully perform complex cognitive tasks previously considered the exclusive domain of human intelligence and expertise (Dai et al., 2026).

This transformative potential explains the surge of scholarly interest in recent years, with an increasing number of KM researchers seeking to systematically analyse and understand the multifaceted effects this technology can exert on organizational knowledge creation processes (Cerchione et al., 2026). However, given that this field of inquiry remains in its infancy, a coherent and comprehensive theoretical framework for understanding these impacts is conspicuously absent.

Addressing this gap, Brown et al. (2024) critically observe that the prevailing discourse surrounding GenAI frequently lacks a robust theoretical foundation, thereby highlighting the urgent necessity for either refining existing theoretical frameworks or developing entirely new conceptual models. Similarly, Schaetzle et al. (2025) emphasize that a structured, theoretically grounded guide on how organizations can strategically integrate these powerful technologies within their KM remains notably absent from the literature.

Focusing explicitly on organizational knowledge creation, He et al. (2026) assert that prior research has yet to systematically address the necessary transformation of the SECI model and Ba theory in the contemporary era of human-AI interaction, particularly within contexts characterized by AI-enabled knowledge processes. They further emphasize that the paramount challenge confronting the field lies in developing theoretical models that are simultaneously theoretically parsimonious - avoiding unnecessary complexity while maintaining explanatory power - and empirically grounded in real organizational practices, thereby accurately capturing the evolving and dynamic nature of knowledge creation in an increasingly AI-integrated technological environment.

However, in recent years, the academic literature has begun to produce important reflections on the need to revisit the foundational theoretical models of KM in light of GenAI's capabilities and implications. Particular attention has been directed toward the SECI model, which remains the most widely recognized, and practically applied framework for understanding organizational knowledge creation processes.

Hence, it is intellectually appropriate and practically useful to conduct a systematic and critical analysis of the trajectories that this theoretical reflection is currently taking, which has motivated the present work.

3. Study Goals and Methodology

This study analyses the state of theoretical reflection regarding the need of revising the SECI model in light of the impacts that GenAI usage can have on organizational knowledge creation processes. It compares perspectives present in the literature on the possibility that the SECI model can still serve as an analytical framework for exploring the transformative potential of GenAI in the domain of knowledge creation.

The study is based on a critical review of papers that have addressed the topic of GenAI and its impact on organizational knowledge creation, using the SECI model as a conceptual interpretative lens. Since scholars have only recently begun to address this topic, relatively few papers were considered in this study. Indeed, a Scopus search using the query "SECI AND (GenAI OR generative AI OR generative artificial intelligence)" yielded only 11 (both journal articles and conference) papers, all of which were included in our study. Unsurprisingly, the first paper dates back to 2024. In addition to these, the study also considered other papers found through a broader Scopus search using the query "SECI AND artificial intelligence". The first article retrieved through this second

search dates back to 2022, confirming that scholarly interest in this topic is very recent. Overall, a total of 19 papers were reviewed.

4. Findings

The analysis of the papers identified three distinct approaches authors use when applying the SECI model to interpret the impact of GenAI on organizational knowledge creation:

- *Adopting the SECI model in its original version*. Authors who follow this approach assume that the original SECI model provides an adequate framework for understanding the impact of GenAI on organizational knowledge creation.
- *Referring to the original SECI model with minor adjustments that do not alter its fundamental structure*. Authors who adopt this approach believe that, with non-radical revisions, the original SECI model can effectively explain the impact of GenAI on organizational knowledge creation.
- *Proposing a new model based on the SECI framework*. Authors who follow this approach argue that a more substantially revised SECI model is necessary to fully understand the impact of GenAI on organizational knowledge creation.

In what follows, these three perspectives will be discussed and subsequently compared with each other.

4.1 Using SECI as is

Scholars following this approach contend that the original SECI model can be applied directly to investigate the impact of integrating GenAI within organizational knowledge creation processes, as it effectively identifies both the benefits and challenges of employing GenAI tools to support the four knowledge conversion modes: socialization, externalization, combination, and internalization.

Reflecting on the evolution of the SECI model of organizational knowledge creation in the age of AI, Ichijo (2022) concludes that the process (and its interpretative model) remains fundamentally unchanged, while its speed changes significantly, because when supported by AI, externalization and combination modes can become faster and more accurate than they currently are.

In the same vein, Sumbal and Amber (2025) employ the SECI model as an interpretative framework to explore how ChatGPT can enhance organizational KM capability through the combination of tacit and explicit knowledge. The authors claim that organizations should adopt a ChatGPT-enhanced SECI model - the original SECI framework in which knowledge conversion processes leverage the functionalities offered by this GenAI tool. Barreto and Abarca (2025) can be added to the authors who follow this approach, as they use the SECI model to identify the factors that contribute to the optimal development of conversion modes through the use of ChatGPT.

Jain et al. (2026) employ the original SECI model to compare and contrast the creative capabilities of GenAI and human intelligence, concluding that this emerging technology can be considered a participant in contemporary knowledge creation models. The findings of their study are summarized in a SECI-based figure that describes the traits, enablers, and challenges of each conversion mode resulting from GenAI integration.

Similarly, Yan et al. (2026) refer to the original SECI model in performing thematic coding on 82 academic articles to analyse how AI facilitates the four key processes of knowledge creation, concluding that although the SECI model remains crucial for understanding organizational knowledge creation, it no longer fully captures the changes brought about by AI. However, the AI-enabled SECI model they propose as an extension of the original is essentially the traditional framework with the addition of AI effects on the individual conversion modes.

Liccardo and Cerchione (2025) use the SECI model to analyse the results of a case study on the influence of GenAI, particularly its benefits and risks, on knowledge generation processes. It should be noted that in the conclusions, the authors underline the need of revisiting and possibly extending the model. Mardarovici et al. (2025) reach a similar conclusion about the need to revise the SECI model after applying it to investigate five cases of AI-enhanced KM systems.

Lastly, Nakash and Bolisani (2026), recalling that recent KM research has examined the impact of AI on the operational application of the SECI model, affirm that it probably should be revised in a form that explicitly incorporates the role of AI.

In summary, a substantial number of scholars (8 papers) have used the SECI model to understand the effects of GenAI on organizational knowledge creation processes, finding it useful for this purpose. Generally, these authors tend to share a rather optimistic vision, which emphasizes benefits more than challenges, of using GenAI to create new knowledge. Although preserving the original structure of the model has the advantage of referring to well-established concepts parsimoniously and linearly expressed, it has the disadvantage of forcing the innovative features of GenAI into a framework that did not anticipate such advanced technological capabilities. As a result, deeper questions about shifts in agency, power relations, and the transformation of the knowledge creation process may not be sufficiently explored.

4.2 Adjusting SECI

Although they still consider the SECI model substantially useful for investigating the impact of GenAI on the knowledge creation process, another group of scholars believes that its interpretative ability can be improved by introducing some minor modifications.

Böhm and Durst (2026) propose an extension of the original SECI model, called GRAI (Generative, Receptive Artificial Intelligence) that considers the machine as a participant capable of playing either an active or passive role. The GRAI model incorporates two actors (human and machine) within the four modes of the original SECI model, resulting in eight different interaction fields (human-to-machine and vice versa in each mode). Essentially, it is a SECI model in which human-machine interactions are explicitly expressed. The model does not include machine-to-machine interactions, although the authors indicate these as a possible future development.

Matsumoto et al. (2024a, b) advance a new knowledge transfer model termed the Human-AI-Collaboration SECI model, characterized by the presence of two cognitive loops. The first loop consists of the process by which humans provide their tacit knowledge to AI and then use and revise the explicit knowledge provided by the AI. The second loop involves the process whereby humans visualize the knowledge accumulated in the AI and then introspect it to enable their tacit knowledge to evolve. This model is logically very similar to the GRAI model.

Dai et al. (2026) draw inspiration from the results of investigating the opinions of fifteen experts about how GenAI affects the four knowledge conversion processes, developing a theoretical extension of the SECI model that includes the concept of “dark knowledge” as an additional dimension that interacts with traditional knowledge conversion modes. This concept, defined by Burnett and Lloyd (2020), refers to the knowledge that AI masters through machine learning that is difficult for humans to understand and interpret. Explicit knowledge acts as a bridge between dark knowledge and tacit knowledge in human-AI interaction, and the transformation of dark knowledge and explicit knowledge is key to the new context of knowledge creation and management. GenAI dark knowledge is integrated with the SECI model in that externalization and combination shape GenAI learning, while dark knowledge influences externalization and combination through the content (explicit knowledge) created by GenAI.

Zhang et al. (2025) propose a new paradigm for the AI-based SECI model in which Dialoguing Ba (referred to as Interacting in the original work of Nonaka and Konno, 1998) is replaced by Interpretation Ba, and Systemizing Ba by Decision-making Ba. The author assumes that AI enables participation in learning processes that ultimately transmit evaluated knowledge to individuals to enhance their decision-making. This is possible because AI not only enhances Originating and Exercising Ba but also deeply transforms Dialoguing and Systemizing Ba, thus generating multiple target decisions for knowledge demanders.

In a somewhat similar way, He et al. (2026) do not modify the original SECI model but extend it by introducing a new form of (AI-mediated) Ba, the Reflective Ba, which is added to the four existing Ba. This “new” Ba acts as a safe cognitive space during the initial emergence of knowledge, where individuals can engage in private exploration, sensemaking, and framing without the immediate pressures of organizational evaluation. It appears to function as a sort of “personal” Ba used to trigger the knowledge spiral.

In summary, these authors (7 papers) converge on the idea that to fully understand the impact of GenAI on the knowledge creation process, the new technology should be integrated into the original SECI model. In the revised framework, GenAI would no longer be seen merely as a passive tool, but rather as an active actor with which humans interact dynamically throughout the different phases of knowledge creation and sharing. Considering GenAI as a new actor leads the authors to highlight that its effective integration into the knowledge creation process requires a human-in-the-loop approach, where humans are actively involved in the AI-driven process, rather than allowing the system to operate fully autonomously. While adjusting the SECI model represents a meaningful theoretical contribution, most revisions remain close to the original SECI logic, often multiplying actors, interaction spaces, or Ba without rethinking the assumptions of knowledge conversion. GenAI is

primarily framed as augmenting or mediating existing human-centered processes, rather than as reshaping the nature, boundaries, and ownership of knowledge itself. These frameworks still leave open questions about the agency, opacity, and power asymmetries introduced by AI systems that operate beyond direct human understanding or control.

4.3 New SECI-based Model

The third approach consists of substantially revising the SECI model and, consequently, developing a new one based on this revision.

Cerchione et al. (2026) argue that GenAI is not just a tool that supports traditional knowledge management, but it has become an active, non-human participant in knowledge creation. To capture this shift, they propose a hybrid SECI model (Figure 1) with two parallel layers: a human dimension (the original SECI model) and a machine dimension, which overlaps with it and covers how data is converted into artificial knowledge and back. In some cases, GenAI naturally fits into the existing SECI framework. For example, it helps users turn tacit ideas into structured outputs (externalization, Figure 1, n. 2) and supports learning through scenario simulation (internalization, Figure 1, n. 4). In other cases, however, GenAI follows a different logic. Conversational prompting mimics some aspects of socialization (Figure 1, n. 1), while GenAI's ability to generate synthetic datasets and identify patterns across them (Figure 1, n. 3) represents a form of combination that works independently of human thinking. These differences suggest that GenAI is not simply joining human knowledge cycles. it is creating new knowledge dynamics through its own, machine-driven loop-

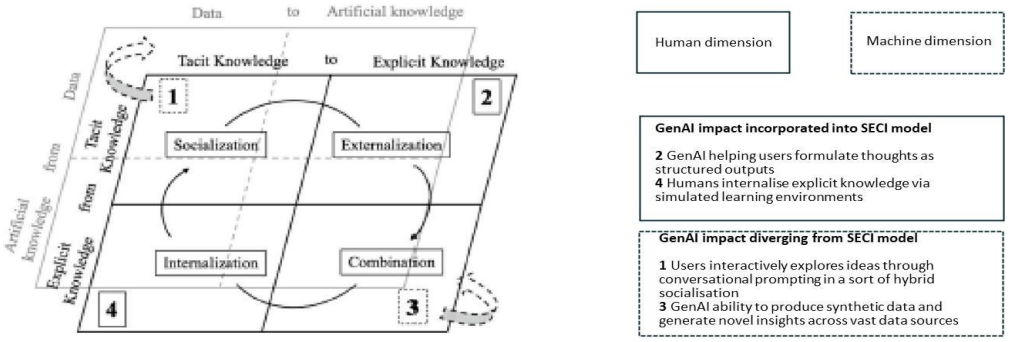


Figure 1: Hybrid SECI model with two dimensions (from: Cerchione et al., 2026)

Based on the experience derived from action research concerning the development of an Informed Artificial Intelligence application, Harfouche et al. (2023) propose the Recursive Theory of Knowledge Augmentation (the KAM model), which explains how tacit and explicit knowledge held by individuals and organizations can be simultaneously enlarged and enriched through the recursive process enabled by human-in-the-loop Informed AI. The model (Figure 2) extends the original SECI model, which the authors still consider essential, by incorporating AI as a new actor and artificial knowledge as a new type of knowledge. Compared to the original SECI model, the KAM model involves five additional knowledge conversion modes (referred to as “situations” by the authors) as follows:

- *Alimentation*, where tacit human knowledge is converted into artificial knowledge.
- *Aggregation*, where explicit knowledge is converted into artificial knowledge.
- *Amplification,* where the knowledge created through AI is converted into explicit human knowledge. This amplification of knowledge is central to human-AI interaction, as humans can learn from the output produced by the AI.
- *Reflection*, where knowledge created through AI is converted into tacit human knowledge. The results produced by AI can stimulate humans’ reflection on their methods and question their knowledge while experiencing new situations.
- *Fusion*, that concerns 1) the recursive transformation of tacit and explicit knowledge that occurred while feeding the AI and 2) the enrichment of knowledge that results from the human learning process that occurs during the interaction of humans with an AI.

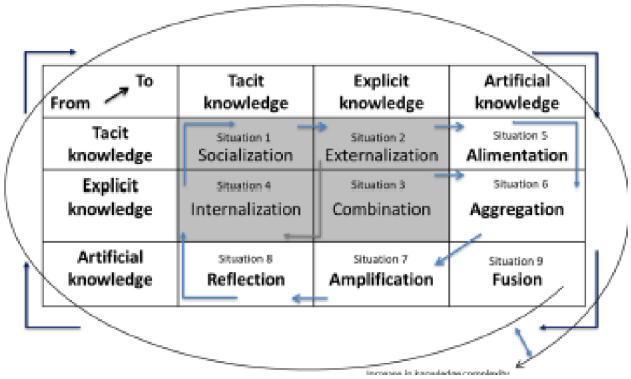


Figure 2: KAM model (from: Harfouche et al., 2023)

The model highlights a two-way relationship between humans and AI. On one side, humans feed AI with their intuition and knowledge, helping it analyze data, recognize patterns, select better responses, and explain its outputs (*first two conversion modes*). On the other side, interacting with AI enriches both the explicit and tacit knowledge of humans *(last two conversion modes)*.

In conclusion it should be underlined that the KM model has not been developed to understand the impact of GenAI on the knowledge creation process, but rather as a "prescriptive" model that should be used as a guide to develop Human-Centric AI. Furthermore, it should be noted that the fusion situation does not involve any conversion from artificial-to-artificial knowledge, contrary to what is represented in Figure 2, and that the authors do not define artificial knowledge explicitly.

Taking into account that recent literature underlines that GenAI can be considered a new actor/player in the organizational knowledge creation process and artificial knowledge a new type of knowledge, Kirchner and Scarso (2026) develop a new SECI-based model, named AKI (Artificial Knowledge Integration), that considers three types of knowledge: tacit, explicit, and artificial, where the latter is the GenAI-generated one (Bratianu and Bejinaru, 2026). In light of this, the model includes nine knowledge conversion processes, as illustrated in Figure 3, and consequently nine Ba.

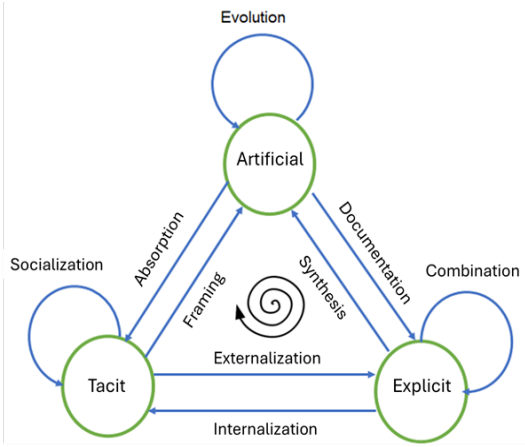


Figure 3: The AKI model of organizational knowledge creation (from: Kirchner and Scarso, 2026)

Unlike the original SECI model, which only considers human-to-human interactions, the AKI model introduces two additional types: human-to-machine and machine-to-machine. As a result, the knowledge creation spiral now evolves through the interplay of three dynamics: human-to-human, human-to-GenAI, and GenAI-to-GenAI. Another key feature of the AKI model is its flexibility. In fact, it can accommodate a wide range of scenarios: from knowledge creation processes that rely heavily on GenAI to those where its role is minimal or absent entirely.

The SECI-MAP model proposed by du Plessis and Britz (2025) differs significantly from the previous ones because it does not modify the SECI model but rather integrates it into the new model as the inner layer of three layers. The outer layer, i.e., the machine layer, capitalizes on the strengths and unique contributions of machines. It consists of two elements: machine intelligence, which refers to the ability of machines to learn and think in a way that mimics human cognition, and representation, which provides the input to the machine learning

process. In the middle resides the human integration layer, which depicts the symbiotic and synergistic partnership between humans and machines. Such an integration is based on creative and experiential thinking as well as analytical and contextual thinking of humans. The basic assumption of the model is that increased potential emerges when humans and machines interact.

In summary, the authors who follow this approach (4 papers) argue that the integration of GenAI into the knowledge creation process introduces a series of new and challenging concepts that cannot be fully captured by the original model. Notions such as artificial knowledge, dark knowledge, human-machine partnership, and the idea of GenAI as an active actor in the knowledge creation process represent novel phenomena that go beyond the explanatory boundaries of the traditional SECI framework. As a result, they advance a substantial revision of the model itself to accommodate the complexity and transformative potential that GenAI brings to the way knowledge is created, shared, and internalized within organizations. While these substantially revised models better acknowledge the transformative potential of GenAI, they also introduce added complexity. The inclusion of new knowledge types, conversion modes, actors, and layers makes them harder to operationalize and to compare across different contexts.

5. Discussion and Conclusions

This study has compared how different conceptual approaches based on the SECI model are used in the literature to investigate the influence of GenAI on knowledge creation processes. As research progresses, there is a growing need to dive into the evolving role of the SECI model in AI-shaped knowledge creation processes.

One particular point emerging from the above analysis deserves to be highlighted. Even scholars who do not propose revising the SECI model (whether completely or partially) agree that GenAI is a new actor in the process and that the knowledge it handles represents a new form of knowledge. Those who do not revise the model, or revise it only in part, believe that the new actor and the new type of knowledge can be incorporated into the original model as additional tools or artefacts; whereas those who deeply revise the model argue that a further dimension must be assigned to the new actor and the new type of knowledge. Regarding the latter, some authors refer to it as “dark knowledge” and others as “artificial knowledge”, but with different meanings. How can this be interpreted?

If we regard GenAI as a new actor, we might consider that, similarly to human actors, GenAI has its own “tacit” knowledge and “explicit” knowledge. The former could be the “dark knowledge” - the knowledge GenAI develops through unsupervised learning - and the latter the “artificial knowledge” - the knowledge GenAI produces in various forms (text, images, etc.) in response to a prompt. This assumption suggests that, just as humans generate explicit knowledge drawing on the tacit knowledge they hold, GenAI produces artificial knowledge drawing on the dark knowledge residing in its "artificial mind", itself shaped through unsupervised learning. Furthermore, as noted by a couple of authors, just as humans learn, updating their pool of tacit knowledge, from the artificial knowledge produced by GenAI, so too does GenAI learn, updating its pool of dark knowledge, through the feedback provided by humans when interacting with it.

5.1 Academics and Managerial Implications

From an academic perspective, this study represents a valuable starting point for researchers who intend to develop a more comprehensive theoretical model of the knowledge creation process that takes into account the distinctive characteristics of artificial knowledge and the growing role of GenAI. By reviewing the existing literature, the study shed light on some fundamental concepts that any future theoretical reflection on the impact of GenAI on knowledge creation cannot afford to overlook. In doing so, it lays the groundwork for a more structured and rigorous academic debate on how traditional frameworks, such as the SECI model, need to evolve in response to the challenges and opportunities posed by artificial intelligence.

The study also offers some managerial insights, with particular reference to the issues related to artificial and dark knowledge, two new components of the knowledge creation process. The first is generated by GenAI to respond to user requests, while the second is “internally” developed by the system (as a result of its training) and is used by the system to generate the first. The responsible use of GenAI requires that users not only carefully verify and critically evaluate the content produced but also develop a genuine awareness of the risks associated with dark knowledge and actively contribute to mitigating them. One concrete way to do so is to provide meaningful and consistent feedback to the system, allowing it to correctly update and enrich its underlying knowledge base over time. This human-in-the-loop dynamic is essential to ensure that the AI system

evolves in a reliable, accurate, and ethically sound direction. Such responsibility becomes especially crucial when organizations develop proprietary GenAI systems grounded in their internal knowledge repositories.

5.2 Future Research Directions

This study did not aim to provide answers, but rather to stimulate the debate on the need to revisit the SECI model and, therefore, to formulate meaningful questions to further deepen the investigation on the impact of GenAI on the knowledge creation process. In light of this, we advance here some possible research questions for future studies.

- What is the role of GenAI in the knowledge creation process? Is it a new actor, or is it still a tool like other software used in knowledge management processes?
- What is the nature of the knowledge possessed and produced by GenAI?
- What are the boundaries between human-created knowledge and GenAI-created knowledge?
- How can humans maintain agency in the creation of hybrid human-AI knowledge?

Finally, it goes without saying that while conceptual reflections are stimulating, empirical validation is needed, something that is currently missing.

Ethics declaration: We did not need ethical clearance for the research referred to in this paper.

AI declaration: We used GenAI tools to correct and refine part of the written text.

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Business Model Canvasses Revisited: From Static Stagnation Towards Dynamic Agile Feedback Cycles

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Abstract: While the Business Model Canvas (BMC) is a ubiquitous tool for strategic visualization, it remains fundamentally a 'static snapshot' unsuitable for the high-velocity requirements of market dynamics and knowledge management alertness. This paper proposes a transition from static stagnation toward a dynamic, cybernetic framework by extending the traditional nine-element structure into a 12-Slot Unified Matrix (SUM). Building on the previous synthesis of sixteen dynamic models of knowledge creation (ECKM 2025), this research introduces three distinct Cybernetic Loop Agile Systemic Processes (CLASP) that transform the canvas into a dynamic iterative cycle. The model repurposes the ninth slot as a Validation Benchmark—a 'Higher Ground' sensor—to trigger feedback cycles. These cycles flow through three novel control layers: Organizational Cohesion (Slot 10) for process adaptation, Evolutionary Agility (Slot 11) for perimeter adjustment, and Scalable Integrity (Slot 12) for project adaptation and trust engineering. By integrating Axiomatic Design principles, the paper demonstrates how these loops manage goals and outcomes and strengthen the institutional knowledge heritage for organizational learning. The result is a dynamic governance system where the 'Functional Intent' of the venture is continuously re-engineered through active feedback, ensuring that the business model evolves in lockstep with the knowledge assets it seeks to leverage.

Keywords: Business model canvas (BMC), Business model innovation (BMI), Knowledge management (KM), Cybernetics, Axiomatic design, Dynamic capabilities, Knowledge co-creation

1. Dynamic KM Models Versus Business Model Canvas/Innovation (BMC/BMI)

Last year's ECKM paper presented not only a 3-dimensional map aligning sixteen renowned dynamic KM-related models (Schmitt, 2025) but also visually integrated a 12-step iterative cycle for developing more personal-centric Knowledge Management Systems (PKMS); its SICECE paradigm (seizing, imbedding, collating, encompassing, curating, and effectuating) reverses and expands Nonaka's SECI & Ba Model (Nonaka, Toyama and Konno, 2000) to address three key issues:

- As most conventional KM models were shaped by last century's information scarcity unable to anticipate today's abundance, they provide little guidance for dealing with the accelerating entropy and infoxication (Cornella, 2000) we are facing.
- As traditional KM models are focusing on organizational applications, they provide little 'digital dividends' (World Bank Group, 2016) for individuals with their diverse abilities, contexts, means, and ends (ACME) and, thus, co-facilitate widening world-wide opportunity divides (Shirazi and Hajli, 2021).
- As a combination of these two factors, they also offer no opportunities for organizations to incentivize their knowledge workers to accept organizational-focussed KMS (OKMS) initiatives due to their dilemma of appropriation-versus-participation perceptions (Rechberg and Syed, 2014).

These related findings and functional requirements are based on a longitudinal design science research trajectory with thirty WoS-indexed publications (Schmitt, 2021), which led to a start-up to realize the system (Schmitt, 2023), and culminated earlier this year in proposing a new memetic/metaphorical digital twin (MDT) category (Schmitt, 2026). The aim of this paper is to expand on the 16-KM-Map which already addressed the synergies with dynamic KM models by integrated six complementing PKMS-focused SICECE scenarios. The focus, hence, shifts to Business Model Innovation (BMI) by addressing the critique concerning the static approach of Business Model Canvasses (BMC). By 'dynamizing' these very popular approaches (especially in the start-up sphere) and by furnishing them with two cybernetic feedback mechanisms, the objective is to exemplify the versatility of the SICECE modelling approach as an enabling element in KM/MDT design spaces.

The Business Model Canvas (BMC) has established itself as the standard for strategic visualization across academic and practitioner domains. Its nine-element structure provides a clear snapshot of how an organization creates, delivers, and captures value. However, the contemporary business landscape is characterized by high-velocity shifts and a critical need for Knowledge Management (KM) alertness. In these volatile environments, the traditional BMC often serves as a 'static snapshot', capturing a moment in time that quickly becomes obsolete.

To address this 'static stagnation', there is a theoretical and practical requirement for a more dynamic framework that can respond to rapid market dynamics. This paper proposes an extension of the conventional structure into a 12-Slot Unified Matrix (SUM). Building upon the synthesis of sixteen dynamic knowledge creation models (Schmitt, 2025), this research introduces a cybernetic approach to business modelling. By incorporating three distinct Cybernetic Loops (CL0, CL1, and CL2) termed Cybernetic Loop Agile Systemic Processes (C.L.A.S.P.) and utilizing Axiomatic Design principles, the model seeks to synchronize business outcomes with an evolving institutional knowledge heritage. The objective is to move beyond simple visualization toward a dynamic governance system where the 'Functional Intent' of the institution is continuously refined through active feedback cycles. An accepted paper (Schmitt, forthcoming) applies this extended dynamic structure while preserving the intuitive grasp of the visual canvas logic; using a perceptual alignment layer, it adds further BMC layers to benefit entrepreneurs and start-up investors based on an accustomed canvas visual experience. Its intention is to exemplify the versatility of the SICECE-driven BMC approach towards a generative Architecture for Canvas Ecosystems (A.C.E.) Framework. While Business Model Innovation (BMI) is typically viewed as a series of discrete strategic shifts, the A.C.E. space would reframe BMI as a continuous, cybernetic process with the SUM providing the structural 'rigging' that motivated and rationalized the concurrent study's canvas expansion into entrepreneurship and start-up investment.

Based on conceptual analysis, systems thinking, and design science research methodologies (Schmitt, 2021), the objective is to move beyond sporadic goal-path-alignments and simple visualizations toward a dynamic governance system where the 'Functional Intent[1]' of the institution[2] is continuously refined and its absorptive capacity[3] is strengthened through active feedback cycles. By dynamizing these logics based on CLASP's cybernetic feedback loops and tuning them to the composition of existing canvasses an Architecture for Canvas Ecosystems (ACE) is established.

2. Literature Review

2.1 Repurposing Static BMCs as Systemic Nodes and Flow Dynamics

Business Model Canvasses (BMC) afford widely adopted tools[4] for businesses to articulate, visualize, and communicate their business models. Their initial nine-element structure offers clarity and simplicity, enabling organizations to map value propositions combining creation and delivery. Although widely used, they provide mainly static snapshot tools suitable for more stable environments (e.g., foreseeable customer needs, low-risk-technological disruption, limited transformational needs). To broaden the economic focus of the original Business Model Canvas (Osterwalder and Pigneur, 2010; Osterwalder *et al.*, 2015), it has been triple-layer-expanded (TLBMC) with an environmental life cycle and an social stakeholder layer (Joyce and Paquin, 2016).

These traditional BMCs, however, represent an inherently static approach. To address fast-changing environments with shifting consumer behaviors in competitive markets typified by technological innovation, other static BMCs have been suggested by expanding the element-count as, for example:

- The Creative Business Model Canvas (11 elements) (Carter and Carter, 2020)
- The Digital Business Model Canvas (DiBMC) (11 elements) (Matricano and Liguori, 2026)
- The Public Governance Canvas (14 elements) (Martins, Mota and Marini, 2019)
- The Flourishing Business Canvas (16 elements) ("Flourishing Business Canvas," no date)
- The Sustainable Project Management Canvas (17 elements) (Schipper and Silvius, 2017)
- The Innovation Canvas (18 elements) (Kline *et al.*, 2013),
- The Business Model Innovation Canvas (19 elements) (Jin *et al.*, 2022),
- The InnoWise Knowledge Canvas (21 elements) (Foster, no date).

[1] This "Functional Intent" is closely linked to the set of Functional Requirements (FR) that the SUM is designed to satisfy and creates a clear bridge between the KM theory and the engineering logic of Suh's axiomatic design principles (Suh, 1995).

[2] Institutions are defined as "snapshots of a subset of the ideational field that persevere while the network itself continues to fluctuate" (Kanengisser, 2014).

[3] Absorptive Capacity has been defined as the "ability to recognize the value of new information, assimilate it, and apply it to commercial ends" (Cohen and Levinthal, 2000).

[4] The BMC structure has even be applied as a taxonomy in the design and classification of product-service systems design methods (Salwin *et al.*, 2022).

A survey among entrepreneurs acknowledged the BMC limitations in capturing complex or rapidly evolving business environments and the resulting demand for regular updates as a resource-intensive requirement (Kupczyk *et al.*, 2024). But, as the 'take-make-dispose' linear economy is considering more sustainable (Minatogawa *et al.*, 2022) and circular (Bocken *et al.*, 2019) approaches, the iterative BMI processes need to be supported by appropriate tools able to frame, fuel, and focus the transformational activities and outcomes.

With a focus on addressing such changes, the Digital Transformation Canvas (DTC) provides a conceptual framework for leading DT processes. The DTC's 11 elements and 43 sub-categories cover (1) DT Strategy [Purpose], (2-6) DT Operational Pillars [People, Process, Platform, Partner, Project], (7-9) DT Value [Product, Performance, Planet], and (10-11) DT Pitfalls [Privacy, Protection]. In these contexts, DT actors may take up multiple roles to effectively combine social (mentor, mentee, networker), generative (pioneer, innovator), and leadership (enabler, manager) responsibilities (Elia *et al.*, 2024). The handling of the key drivers are essential and include knowledge acquisition, retention, recall, use, and transfer (Anohina-Naumeca, 2023). A sustainable BMI matrix (2022) has mapped and benchmarked the BMI tools studied into a dynamic capabilities framework along its sensing, seizing and transforming phases; while the BMCs are placed at the sensing level, the DTC (2024) would have been positioned in the top-tier (Minatogawa *et al.*, 2022).

The study of 928 core-BM publications sheds more light on the spectrum across these three tiers; although the number and landscape of their static structural elements differs considerably, key clusters have been Identified as: Business Model Innovation; Sustainability and Circular Economy; Strategic Foundations and Value; Digital Transformation, Service and Platform Innovation; Energy Efficiency and Resource Optimization which share common characteristics (#123) (Schuricht, 2026):

- #1: Although the visuals are representing static boxes, a linguistic analysis exposed the action verbs applied as the implicit process-oriented operationalizers.
- #2: As explicit cluster-specific flow terminologies are absent, the ability of the underlying generic flow logic to handle the clusters' diverse manifestations and priorities has been verified in a flow analysis.
- #3: A coding exercise assessed the tools' holistic orchestration and balancing capabilities and proved that static elements can be repurposed as dynamic flow nodes which can be continuously managed.

With business models re-interpreted as meaningful nodes populating flow configurations, the emphasis has to shift to the explication of their connecting flow profiles (e.g., network patterns, flow directionalities, exchange types, magnitudes and constraints) (Schuricht, 2026). The #123 identifiers are applied in the following sections to indicate a close association with these three logics and logistics.

2.2 Escalating Systemic Dynamics to Dynamic Agile Feedback Cycles

Table 1 (rows or rubrics 2-4) presents the BMC/TLBMC elements (Osterwalder and Pigneur, 2010; Joyce and Paquin, 2016) elements from 0 (top right element in the canvas layout) to 8 (bottom right element). Row 5 depicts the Perceptual Alignment Layer (PAL) of common denominators added by the author; PAL adds nine generic classification terms for each column to envelop the three BMC terms (rows 2-4) and to create a distinct but complementing semantic space to synergetically position elements of further rubrics. The sequence 0-8 clearly explicates the process-orientation (#1) which is passed on to the PAL.

Table 2 presents the 12-slot-SICECE Model (row 2) which serves as the iterative flow in a novel Personal Knowledge Management System approach (PKMS) (Schmitt, 2025). The top-row (#2) shows the 12-Slot Unified Matrix (SUM) providing the columns with unique identifiers (a-l) which have been applied in row 3 to point out the CLASP's three cybernetic loops (based on (Beer, 1979; Argyris and Schön, 1997)) already build into the iterative SICECE-cycle:

- *CL0:* The iterative loop for learning and authorship activities. In the BMC context, this represents the pathway for adhering to a given procedure.
- *CL1:* The tactical feedback loop prompted by content consolidation to awaken the system's curating facilities for actuating process options.
- *CL2:* The strategic feedback loop for adjusting system perimeters (e.g., heuristics and boundaries) and adapting the project via new collaboration choices.

Table 2 (row 4) also accommodates a rubric depicting the Axiomatic Design Stages (CA, FR, DP, and OV) with their intermittent design matrices (DM) (Suh, 1995). As an iterative cycle, this method – like the BMC – has no explicit built-in 1st or 2nd cybernetic cycles which would allow for process or project changes; it just assumes to repeat the a-h-loop (adhering to the procedure) until the planned job is finalized without need for any 1-2-CL-

interventions. The accepted paper referred to earlier (Schmitt, forthcoming) is proposing to integrate these i-l interventions (#3) to complete the full mathematical 'rigging' of the SUM by axiomatic design principles.

In addition to aligning the sixteen Dynamic KM models to six SICECE scenarios (Schmitt, 2025), Table 2 (row 5 and 6) demonstrates how the extended (indicated by +) notions of KM building blocks (Probst, 1998) and KM Schools (Earl, 2001) closely align to the 12-step SICECE cycle. The next section focuses on the synthesis of these two tables as an ACE pre-requisite (Architecture for Canvas Ecosystems).

3. Towards an Architecture for Canvas Ecosystems (ACE)

Figure 1 shows the integration of table 1 into table 2 in the conventional canvas outline (0 as i, 1-8 as a-h left) with three new additional elements (jkl). Although the BMC sequence (see references to the TLBMC terms) stayed intact, its conventional starting position 0 (customer segments) has been absorbed by slot i; it became the quasi 'ideal sensor or vantage point' of the BMC purpose for Validation Benchmarking. Like in real-life BMC applications, if customer segments change, a new BMC assessment exercise should be triggered.

This slot i, hence, has different roles depending on the context of its accommodating rubric. In the case of the dynamic dBMC, it represents a signal which triggers an awakening or alarm to prompt a reaction or intervention (e.g., the assumptions of market conditions may have been wrong); the operator must decide to let it go and resume business-as-usual (CL0), or initiate CL1 or CL2 interventions. In a case, where routines are in place these processes are automated; when the centralized PKMS repository receives contributions from community members (slot h has produced, and slot i verifies its outcome acting as an audit gateway), it starts its curation activities with its pre-defined handling procedures.

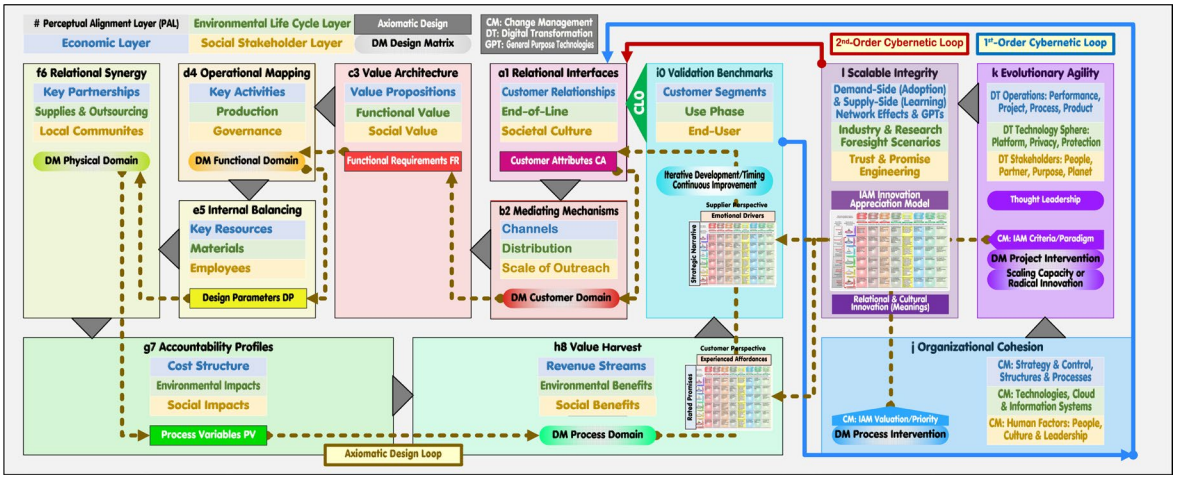


Figure 1: Traditional BMC Layout with TLBMC (left) and cybernetic loop extensions (right)

By integrating the BMC 0 with the SICECE i slot, both, the 9-element and 12-slot logic, are maintained and redundancy of separate 0 and i elements is avoided; position i is where the iterative pathway is either advanced as usual (a), or the need for interventions or contingency planning have to be at least considered, triggering minor (j CL1) or major (kl CL2) activities (#1). This includes what has been termed KM alertness in the abstract and introduction; a term indicating an aim beyond just market sensing but embracing the strengthening of absorptive capacity and organizational capability to sense and respond to knowledge shifts. In this sense, the CL1 and CL2 also act as a mechanism for maintaining an 'Institutional Knowledge Heritage' (#2).

Table 1: BMC/TLBMC (Osterwalder and Pigneur, 2010; Joyce and Paquin, 2016) with Perceptual Alignment Layer (PAL)

Rubrics/Slots	0 -> I	1 -> A	2 -> B	3 -> C	4 -> D	5 -> E	6 -> F	7 -> G	8 -> H
Economic Layer	Customer Segments	Customer Relationships	Channels	Value Propositions	Key Activities	Key Resources	Key Partnerships	Cost Structure	Revenue Streams
Environmental Life Cycle Layer	Use Phase	End-of-Line	Distribution	Functional Value	Production	Materials	Supplies & Outsourcing	Environmental Impacts	Environmental Benefits
Social Stake-holder Layer	End-User	Societal Culture	Scale of Outreach	Social Value	Governance	Employees	Local Communities	Social Impacts	Social Benefits
Perceptual Alignment Layer (PAL)	Validation Benchmarks	Relational Interfaces	Mediating Mechanisms	Value Architecture	Operational Mapping	Internal Balancing	Relational Synergy	Accountability Profiles	ValueHarvest

Table 2: SICECE Model, Axiomatic Design, Cybernetic Loop Agile Systemic Processes (CLASP) (based on: (Schmitt, 2025), (Suh, 1995; Beer, 1979; Argyris and Schön, 1997)

SUM: 12-Slot Unified Matrix	A 1	B 2	C 3	D 4	E 5	F 6	G 7	H 8	I 9	J 10	K 11	L 12
SICECE Cycle	Seizing	Stewarding	Imbedding	Immersing	Collating	Collaborating	Encompassing	Edifying	Curating	Consolidating	Effectuating	Easing
Cybernetic Loops (CL) C.L.A.S.P.	CL h/j/l -> Pathway Advancing	->	->	->	->	->	->	CL0 (h->a) Procedure Adhering	-> Prompt Awakening	CL1 (j->a) Process Actuating	-> Perimeter Adjusting	CL2 (l->a) Project Adapting
Axiomatic Design (Suh)	Customer Attributes (CA)	Customer Resourcing Design-Matrix	Functional Requirements (FR)	Functional Options Design-Matrix	Design Parameter (DP)	Physical Projections Design-Matrix	Operative Variables (OV)	Product Fitness Design-Matrix	-	-	-	-
Digital Trans-formation Canvas (Elia *et al.*, 2024)	DT 10 Pitfalls [Privacy]	DT 11 Pitfalls [Protection]	DT 4 Operational Pillars [Platform]	DT 3 Operational Pillars [Process]	DT 7 Value [Product]	DT 5 Operational Pillars [Partner]	DT 2 Operational Pillars [People]	DT 7 Value [Performance]	DT 6 Operational Pillars [Project]	DT 1 Strategy [Purpose]	DT plus DT vs. Digital Dividends for All	DT 9 Value [Planet]
KM Building Block Alignment (Probst, 1998)	Knowledge Measurement (B8)	Heritage Knowledge (B8-B1)	Knowledge Goals (B1)	K-Identification & Acquisition (B2 & B3)	Knowledge Development (B4)	Memetic K.-Representation (B5+ & B6+)	Knowledge Preservation (B6)	Decentralized KM Revolution (B4+ Impact)	Knowledge Community (B1+ & B4+)	Knowledge Reengineering (B5+ & B6+)	Knowledge Use (B7)	Knowledge Distribution (B5)
KM School Alignment (Earl, 2001) Connectivity & (Focus): S-Social (Collaboration) I-Informational (Content)	I System School (technocratic) Externalization & Internalization: Domain-specific Lessons Learnt & Best-Practices	I Commercial School (economic) Combination: Intellectual Capital & Intangible Products	+S: 'Generative' School +I: 'Negentropic' School	S Strategic School (behavioural) Optimal Resource Allocation: Knowledge Strategy & Business Plans	S Cartographic School (technocratic) Socialization: Relationship Capital & Smart Maps 'who knows what'	S Organizational School (behavioural) Socialization: Connectivity & Collaboration Intranet & Groupware	S Spatial School (Behavioral) Socialization: Creative Con-versations & Physical/Virtual Spaces 'Ba'	+I: Manufactu-ring Systems (SCM ERP CRM) As-Built-Genealogies (e.g., Bill of Parts/Labor)	+I: Operations School (feeding KMS) Product & Process Specs: Encapsulated & Org. Know-How & Workflows	I Engineering School (technocratic) Process Re-Engineering: Task-related Learning & Continuous Improvements	S & I Integration & Scaling Knowledge Weaving (Tengö et al., 2017)	Knowledge-based System Evolution General Purpose Technologies (Cantner and Vannuccini, 2012)

3.1 The Integration of Suh's Axiomatic Design Principles

The term 'Functional Intent' mentioned earlier is not only closely linked to the CL0 (j: maintenance and stability for Organizational Cohesion), CL1 (k: incremental innovation for Evolutionary Agility), and CL2 (radical re-engineering for Scalable Integrity). It is also correlated to the axiomatic design principles (Suh, 1995):

- *The Independence Axiom* - Maintain the independence of Functional Requirements (FRs): This axiom refers to the separation of concerns within a system. It postulates that multiple Functional Requirements (FRs) should be mapped to Design Parameters (DPs) in an un-or-de-coupled manner. The goal is to ensure that each DP can be adjusted to satisfy its corresponding FR without unintended interference with other requirements. From a cybernetic perspective, this structural independence ensures that feedback loops are clearly aligned. This alignment prevents 'systemic oscillation'—a failure state where a correction in one part of the process inadvertently destabilizes another.
- *The Information Axiom* – Minimize the information content of the design: This is Occam's Razor for systems; among designs that satisfy independence, the one with the least information is best because it maximizes the probability of success. From a cybernetic perspective, this minimizes entropic potential and conserves the attention required for system comprehension or management.

These principles and the a:CA-c:FR-e:DP-g:OV sequence are included in Figure 1 (icons shown in h-l account for the proposed intervention elements addressed in the concurrent study (withheld for review)) as they directly govern the fulfilment of 'Functional Intent.' This integration provides the mathematical 'rigging' for the SUM; by decoupling 'Functional Intent' from physical implementation and operation, an institution can iterate and adapt without risking systemic collapse. In this axiomatic context, the SUM is not merely an expansion of the traditional canvas; it is a 'decoupled' architectural system (ACE) grounded in Suh's Axiomatic Design (Suh, 1995). Traditional multi-element canvasses often suffer from 'coupled' logic, where a change in one area—such as a revenue shift—triggers a cascading and unmanaged collapse of other operational elements—or where the consideration of too many flow profiles causes visual/mental confusion (#3). The SUM slots h-l are dedicated nodes facilitating systemic governance:

- *Organizational Cohesion (j):* This node functions as the system's internal stability controller. Drawing on Heisig's synthesis[5] (Heisig, 2009) and Leavitt's diamond model[6] (Leavitt, 1962), Slot j manages the interdependencies between human, structural, managerial, and technological knowledge assets. Within the context of the CL1 (Tactical) Loop, it acts as a stabilizing mechanism to ensure that process adjustments do not destabilize the organization's core operational flow. It is here that 'Process Actuating' occurs, aligning internal resources with the feedback sensed at the Slot i validation benchmark.
- *Evolutionary Agility (k):* This node serves as the system's strategic interface with changing environments. It facilitates structural adaptation—the capacity to reconfigure boundaries and heuristics. By adhering to the Information Axiom, it ensures that 'Perimeter Adjustments' minimize systemic entropy.
- *Scalable Integrity (l):* This final slot represents overarching governance and identity. It ensures the 'Institutional Knowledge Heritage' is preserved across contexts. It acts as the strategic filter for 'Project Adaptation', ensuring radical changes do not compromise foundational integrity while generating positive GPT[7] externalities (Cantner and Vannuccini, 2012).

[5]Heisig arrived at his conclusion by comparing 119 KM Frameworks from around the world and their respective "success-critical context factors" which resulted in a total of 424 terms made use of categorized into four main clusters: human factors (culture, people, and leadership), organizational aspects (structures and processes), management processes (strategy and control) as well as information technology. He further observed, "A broad consent prevails over the fact that a one-sided implementation of only one of these factors does not correspond to KM as a holistic effort. The task of KM is to arrange these factors in such a manner that the KM activities can be achieved as smoothly as possible" (Heisig, 2009).

[6]Leavitt's Diamond Model postulates that change may affect four components and, hence, has to be approached from four different perspectives: human factors, structure, technology, managerial, and operative tasks (representing the four points of a diamond) (Leavitt, 1962).

[7]General Purpose Technology (GPT) characteristics with their focus on pervasiveness, improvement, and innovation spawning enables the system and their models to scale effectively, while 'Trust Engineering' is formalized as the consistent, reliable delivery of the 'Functional Intent' to all stakeholders and a means to generate positive GPT externalities from supply-side learning and demand-side network effects (Cantner and Vannuccini, 2012)

3.2 Cybernetic Loop Mechanics: The h-j-l to a Feedback Signal

The 12-Slot Unified Matrix (SUM) operationalizes dynamic governance by utilizing Slot i (Validation Benchmarks) as a systemic sensor. When the 'Functional Intent' is evaluated at this 'Higher Ground' position, one of three CLASP cybernetic loops is triggered:

- *CL0 (Operational Loop:* i -> a): The 'Advancing Pathway' loop. When Slot i confirms alignment with Functional Requirements (FRs), the system signals a continuation of the existing trajectory. Knowledge is refined through iterative 'Learning-by-Doing', moving from Slot i back to Slot a.
- *CL1 (Tactical Loop:* j -> a): Activated when Slot i detects a 'Perceptual Mismatch'. The signal flows to Slot j to 'Actuate' a process adjustment, re-aligning internal assets (Leavitt's Diamond) before the system restarts at Slot a.
- *CL2 (Strategic Loop:* l -> a): The highest intensity loop, governing 'Project Adaptation'. Triggered by fundamental environmental shifts, the signal moves to Slot l to re-engineer the 'Functional Intent' itself, adjusting perimeters (Slot k) before initiating a radical adaptation cycle starting back at Slot a.

3.3 Axiomatic Alignment of the Feedback Cycles

By separating these loops, the Architecture for Canvas Ecosystems (ACE) adheres to the Independence Axiom. Each loop addresses a specific level of systemic complexity—Operational (CL0), Tactical (CL1), or Strategic (CL2)—ensuring that a correction in one layer does not cause unintended 'Systemic Oscillation' in another. This 'Mathematical Rigging' allows the institution to manage high-velocity knowledge shifts while maintaining a coherent and traceable Institutional Knowledge Heritage.

4. Discussion

In this framework, the 'Functional Intent' represents the domain of what the institution wants to achieve, while the slots represent how it is achieved. This decoupling allows for Knowledge Management (KM) Alertness through:

- *Decoupled Iteration:* Re-engineering specific slots (e.g., Slot 11) without disrupting core stability (Slot 3).
- *Traceability:* CLASP Cybernetic loops (CL012) mapping the transition between intent and operation.

The SUM acts as a 'Station Platform' where dynamic models of knowledge creation arrive and depart, ensuring that the knowledge heritage is systematically integrated into the institutional memory. This transforms static 'snapshot' canvases into 'living' dynamic tools, enabling institutions to move beyond static planning toward dynamic foresight and timely interventions. The plan is to integrate this logic into the 3D-Mapping mentioned which already accommodates the more generic SICECE Model where this 'Station Platform' becomes the hub offering departure and arrival gates for those other dynamic models of knowledge creation.

The stated objective, hence, has been met by evolving static linear cause-effect relationships to dynamic continuous adaptability, a familiar 'snapshot'-focus to iterative pivotabilities, and often once-off rapid fire-and-forget exercises to a more rationalizable integration of learning and transformational feedback cycles. By incorporating dynamic extensions (logically and visually), the static sBMCs with their inherent '123-potentials are transformed into 'living' dynamic dBMC tools and credentials. By embedding adaptability and resilience into the canvas itself, the dBMC enables institutions to move beyond static planning toward dynamic foresight, strategic risk-managing scenarios, and timely interventions. Accordingly, the dBMC is particularly relevant for business ventures and start-up investors operating in volatile, uncertain, complex, and ambiguous (VUCA) contexts, where agility and trustworthiness are essential. As mentioned in the introduction, an accepted ECIE paper (Schmitt, forthcoming) transforms this dynamic structure into an Architecture for Canvas Ecosystems (ACE) and provides an Illustrative Scenario which adds further complementing dynamic dBMC layers for start-up investment and entrepreneurial perceptions.

Acknowledgements

I would like to express my deepest appreciation to the staff and institutions of the Economic Development Board (edbmauritius.org), the Mauritius Research and Innovation Council (mric.mu), and La Plage Factory Africatech Business Incubator (laplage.io). The EDB's/MRIC's policies and National SME Incubator Scheme allow entrepreneurs from Mauritius or abroad (like me) to be considered for initially operating in partnership with one of the accredited Mauritian business incubators under the MRIC's aegis.

Ethics Declaration: No ethical clearance for the research was necessary.

AI Declaration: As AI tools are increasingly used by reviewers, I applied Gemini to also check my completed submission to confirm that my proposed solutions are indeed novel in the context of academic research as well as professional applications. To the best of my knowledge, after verifying the AI-generated results, this approach has not been previously pursued in academic or commercial realms.

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Scaling Human Capabilities: A Learning Architecture for Knowledge Management

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Abstract: Artificial intelligence is fundamentally changing the nature of knowledge work by providing greater support for the generation, organisation and retrieval of knowledge. Consequently, organisational performance is becoming more dependent on human capabilities such as ownership, collaboration and responsible judgement. While existing learning approaches address individual aspects of this challenge, they rarely combine effectiveness, sustainability and scalability. This study therefore asks which learning architecture can systematically develop collaborative human capabilities while enabling organisation-wide implementation. The development methodology combines a literature review with an action research project and an exploratory pilot evaluation to develop and evaluate the proposed Learning Architecture. The literature review examined peer learning, learning psychology, neuroscience, organisational learning and adult education in order to identify design principles for the development of collaborative capabilities. These findings were then translated into an iterative action research process involving researchers, executives and trainers. The resulting learning approach was then evaluated in six pilot projects involving participants from different organisations. The study developed a Learning Architecture comprising four complementary design elements: Learning Circles as the collaborative learning format. A Learning Cycle as the didactic process. A shared but adaptable curriculum. The Learning Journey as the organisation-wide implementation framework. Together, these elements combine structured organisational orientation with decentralised self-organisation. Participants gave positive evaluations of the learning environment, particularly the self-organisation of the Learning Circles. Knowledge acquisition, reflection, practice and peer feedback were also evaluated positively, whereas workplace tasks were seen as the weakest. Participants further reported perceived improvements across all outcome dimensions, with the strongest effects observed for collaboration within work teams. The study contributes to contemporary knowledge management by proposing a Learning Architecture that systematically connects individual collaborative learning with organisation-wide capability development. It argues that, as explicit knowledge and increasing parts of professional tacit knowledge become more accessible through digital systems, competitive advantage increasingly depends on collaborative capabilities through which knowledge is interpreted, evaluated and responsibly applied in organisational practice. The study provides a structured and scalable mechanism that links knowledge management and organisational learning while preserving decentralised collaborative practice. Although the exploratory pilot does not permit conclusions about long-term behavioural or cultural change, it provides initial empirical support for the proposed conceptual framework and establishes a foundation for future longitudinal research.

Keywords: Knowledge management, Organisational learning, Peer learning, Learning circles, Human capabilities

1. Introduction: Transforming Technology and Transforming People

Artificial intelligence is reshaping knowledge work by increasingly supporting analysis, automation and the management of knowledge. As a result, organisations increasingly depend on distinctly human capabilities such as ownership, collaboration and responsible judgement (Hofmann, 2023; Alavi, Margherita and Massaro, 2024). For organisations, this shifts the challenge from introducing new technologies to systematically developing these human capabilities across the workforce. The representative TÜV Professional Development Study (2026) confirms this trend and identifies social skills as the most important future competencies in every sector of industry in Germany. Wittich (2026) found ownership and collaboration to be the soft skills most frequently requested by employers.

This shift is also relevant for knowledge management. Even when knowledge can be generated, organised and distributed through AI-supported systems, its effective use depends on how people interpret, share and apply it in their day-to-day work. These capabilities are closely associated with tacit knowledge, behavioural routines and social interaction. This is challenging for KM as these capabilities are difficult to develop through documentation or conventional knowledge transfer alone. The present study consequently examines how human capabilities relevant to knowledge work can be developed through a structured and scalable learning architecture.

Existing learning formats address individual aspects of this challenge but combine effectiveness, sustainability and scalability only to a limited extent. Town halls and microlearning can reach large groups but rarely provide sustained opportunities for behavioural practice. Workshops can create intensive learning experiences, but the transfer of learning into everyday work remains challenging (Blume et al., 2010; Baethge, Severin and Weiß, 2013). Business coaching can support lasting individual development but is difficult to implement across an

entire organisation because of its resource requirements (Kotte et al., 2016). Peer learning offers workplace relevance and scalability, yet many formats provide insufficient common structure for the systematic development of shared behavioural capabilities (Schmitt et al., 2026). Organisations therefore still lack a learning approach that combines effectiveness, sustainability and scalability. This paper therefore addresses the following research question:

Which learning architecture can support the systematic development of ownership, collaboration and organisational culture while combining effectiveness, sustainability and scalability across the organisation?

2. Method

2.1 Literature Review

A targeted narrative literature review was conducted to establish the theoretical foundation of the study. The review first examined existing peer-learning approaches and their potential for structured, organisation-wide implementation. It then analysed research from learning psychology, neuroscience and organisational learning to identify how soft skills, mindset and collaborative behaviour can be developed effectively. In addition, literature from management and adult education was reviewed to define the learning curriculum and its scope for different target groups.

2.2 Action Research

The findings of the literature review were transferred into an action research project to develop a scalable Learning Architecture. Following established principles of action research (Lewin, 1946; Coghlan and Brannick, 2014), five researchers, three executives and twelve trainers collaborated throughout the development process, combining scientific perspectives with practical experience.

The Learning Architecture evolved through iterative cycles of design, implementation, evaluation and refinement. Two collaborative concept workshops produced the initial learning design. The first drafts of the learning modules were iteratively reviewed, tested and refined, resulting in an elaborate participant guide. A spin-off organisation then adapted the Learning Journey for two target groups and coordinated two pilot implementations. Findings from both pilots informed the final refinement of the participant guide.

The author participated throughout the project as a member of the action research team and subsequently became a partner in the spin-off organisation. This dual role provided continuous access to the development process but may also have introduced researcher bias, which should be considered when interpreting the findings.

2.3 Pilot Evaluation

The Learning Journey was evaluated in two programme variants, which were implemented in six pilot projects. The companies involved were recruited through the MAINPROJECT network at Aschaffenburg University of Applied Sciences. A total of 82 participants took part in the programmes. The analyses reported in this paper were based on 43 completed final questionnaires (52%).

Participation was voluntary and questionnaires were completed anonymously. Companies approved the programmes as part of their HR development activities. Where employee representation bodies (works councils) existed, the questionnaire was approved prior to implementation.

This study's questionnaire was specifically developed based on the Learning Journey's learning objectives and design principles. It comprised 20 items organised into the three evaluation dimensions shown in Table 1, as well as two demographic questions.

All Learning Journey variants followed the same Learning Architecture, shared the same learning objectives and were based on a common curriculum. They differed only in the scope and wording of the content to reflect the requirements of two target groups. As the study evaluates the Learning Architecture rather than individual programme variants, all responses were analysed as a single dataset using the same questionnaire.

Table 1: Example questionnaire items for the three evaluation dimensions

Dimensions	Example statement	Scale
Perceived behavioural improvement	The learning journey has significantly improved collaboration within the team.	1 (strongly disagree) – 5 (strongly agree)
Fit of the didactic Learning Cycle	The exercises helped me to explore different perspectives and develop approaches for everyday situations.	1 (strongly disagree) – 5 (strongly agree)
Support of the learning environment	Self-organisation (scheduling, time management, moderation) within the Circle worked well throughout the entire learning journey.	1 (strongly disagree) – 5 (strongly agree)
Demographic information	What is your role within the company?	A Employee without managerial responsibility. B Employee with partial shared responsibilities in project management. C Manager with personal responsibility for staff.

Although questionnaires were completed at several measurement points during the programmes, only the final responses were analysed as the study focuses on participants' overall assessment of the Learning Architecture.

3. Results: Learning Architecture

3.1 Learning Circles

The literature review identified Learning Circles as a promising format. Based on peer learning, it is highly scalable, enabling broad participation while keeping costs low. Unlike many other peer-learning approaches, the concept combines self-organisation with structured content. This allows participants to build on their own experiences while developing shared organisational principles and linked behavioural practices (Sinnayah et al., 2024; Graf & Liebhart, 2024; Schmitt et al., 2026).

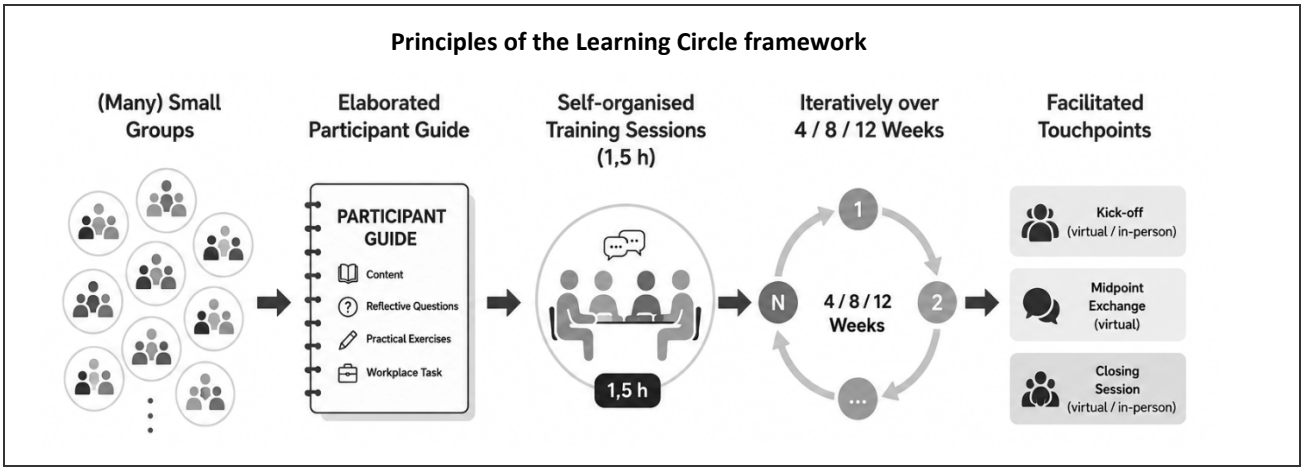


Figure 1: The Learning Circle concept illustrating the basic elements (Source: Own illustration)

Furthermore, Learning Circles organise integrate learning into everyday work through recurring collaborative sessions, which support the establishment of routines (Hodgson, 2023; Wijga, Beausaert and Kyndt, 2025). Initial evidence also suggests medium-term effects. Augner et al. (2024) evaluated John Stepper's "Working Out Loud" which focuses primarily on professional visibility and networking. Its underlying Learning Circle Concept is comparable and participants still reported measurable behavioural improvements six months after completing the programme.

3.2 Learning Cycle

The review on learning psychology and neuroscience provided the foundation for the didactic Learning Cycle. Current research indicates that the development of soft skills is a complex relearning process. Communication,

collaboration and mindset are largely shaped by established behavioural routines embedded in unconscious patterns of action (Kullmann and Seidl, 2005; Schmitt, 2011; Roth, 2018). Developing these capabilities requires more than knowledge transfer. It requires a didactic process that systematically combines knowledge with reflection, practice, workplace task, peer feedback and reinforcement (Argyris and Schön, 1999; Heckhausen and Heckhausen, 2010; Roth and Ryba, 2016; Rogers, 2016). Based on these findings, the action research team developed the Learning Cycle shown in Figure 2:

Sequences of the didactic Learning Cycle

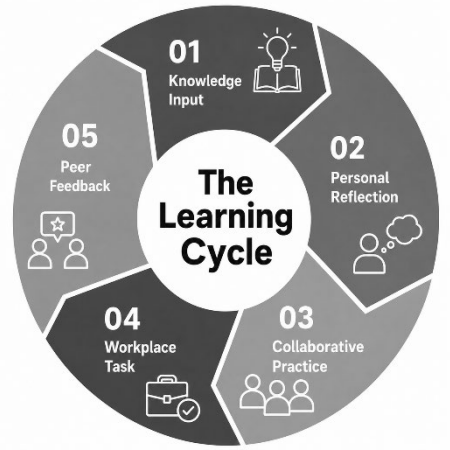


Figure 2: The didactic Learning Cycle illustrating the iterative sequence. (Source: Own illustration)

First, new knowledge is introduced to establish a shared understanding of the content. Participants then reflect on their own experiences, connecting the new knowledge with their existing perspectives and everyday work. Practical exercises allow them to experience new behaviours in a safe environment before transferring them into their daily practice underpinned by workplace tasks.

At the beginning of the following session, participants share their experiences, reflect on the workplace task and provide peer feedback. The cycle is repeated in each Learning Circle session, introducing new content while progressively reinforcing new behaviours with the aim of establishing sustainable routines.

3.3 Learning Scope

The Learning Journey content was developed during the action research process on the basis of current soft-skills curricula and aligned with recent analyses of contemporary workplace challenges (Beck and Cowan, 2008; Münchner Kreis, 2020; Erpenbeck and Sauter, 2024). The curriculum covers communication competencies alongside related topics such as dealing with change, handling mistakes, and self-management. At an advanced level, the curriculum also explores systems thinking and leadership.

As adult learning must build on existing competencies and challenge participants without overwhelming them, the programme was adapted for different target groups (Langheiter, 2022). While the underlying Learning Architecture remained unchanged, the language, thematic depth and practical examples were adapted to the participants' prior knowledge and professional responsibilities. The objective was to establish a common curriculum that would support a shared organisational culture at different stages of professional development.

The “Teamwork” Learning Journey is designed for participants with little or no prior experience of modern teamwork. It comprises eight learning sessions and can be extended by four additional “Team@Work” sessions, which cover video-based collaboration. During the pilot projects, 50 participants from three companies completed this Learning Journey.

The “New Work Mindset”' Learning Journey consists of twelve learning sessions. It is intended for experienced professionals and managers who have received prior training in communication skills. During the pilot projects, 32 participants from three companies completed this Learning Journey.

Each session combines thematic input with practical exercises based on either case studies or the participants' own professional experience.

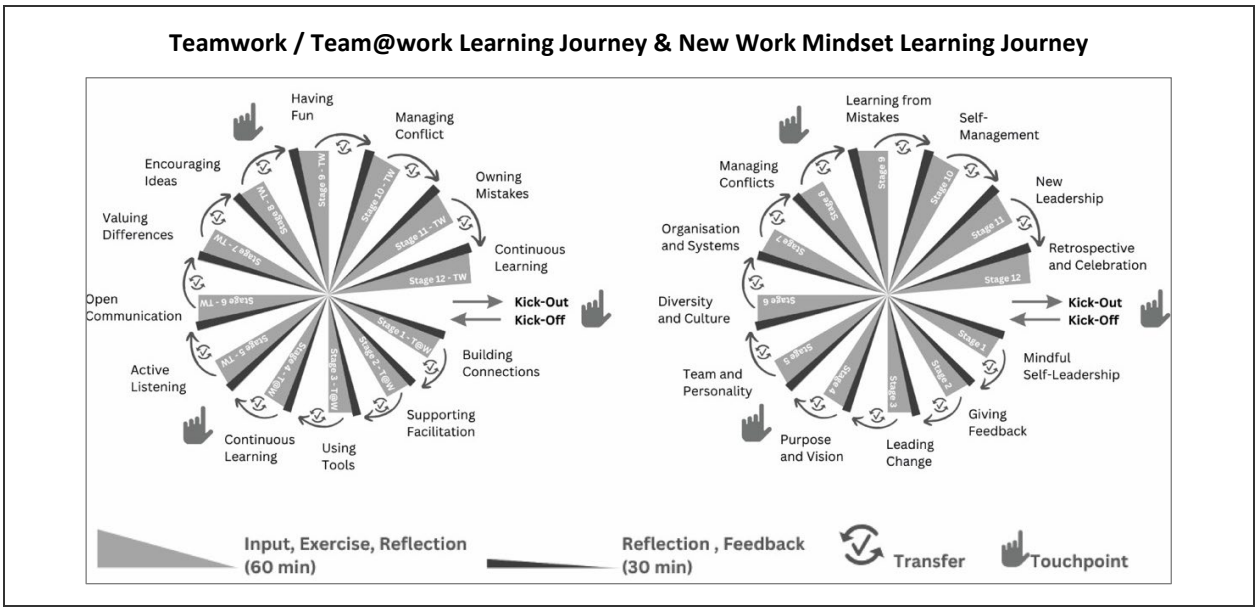


Figure 3: Content and structure of the two Learning Journeys variants. (Source: Own illustration)

3.4 Learning Journey

The Learning Journey integrates the Learning Circles, the Learning Cycle and the curriculum into a coherent Learning Architecture. It combines self-organised peer learning with recurring facilitated touchpoints.

The programme begins with an interactive "Kick-off" involving all participants and facilitated by an internal HR professional or an external coach. During the Kick-off, participants are assigned to Learning Circles of four to six members. Any number of Learning Circles can participate simultaneously in the same Learning Journey. A participant guide, designed according to modern storytelling principles, structures the entire programme. It provides orientation through structured content and a clear sequence of reflection questions, practical exercises and workplace tasks.

Each Learning Circle follows its own schedule, typically meeting every one or two weeks for a 90-minute learning session. While the sessions are organised independently, all Learning Circles participate in facilitated touchpoints after approximately every four sessions. Supported by regular motivational emails, these touchpoints provide opportunities for reflection, questions and shared learning across the different Learning Circles. The Learning Journey concludes with a joint "Kick-out", where participants reflect on their experiences and share their learning.

4. Results: Pilot Evaluation

The following results are based on the final questionnaires completed by 43 participants across the pilot programmes. Table 2 summarises the characteristics of the participants.

Table 2: Participants by Learning Journey variant and participant characteristics

Learning Journey	n	Role at workplace	n	Organisational tenure	n
Team@Work	6	A Employee without managerial responsibility	26	Less than 1 year	4
Teamwork	17	B Employee with partial shared responsibilities in project management	7	Up to 5 years	20
New Work Mindset	20	C Manager with personal responsibility for staff	10	Up to 10 years	6
				More than 10 years	13
	43		43		43

The completed questionnaires (n = 43) contained valid responses for all reported items. The only exception was the knowledge item within the evaluation of the Learning Cycle, for which one response was missing (n = 42).

The data were analysed using descriptive statistics. Means and standard deviations were calculated for each item and for the aggregated dimension. Given the exploratory nature of the pilot study and the limited sample size, no inferential statistical analyses were conducted.

4.1 Perceived Improvements

The first part of the questionnaire focused on four complementary dimensions linked to the objectives of the Learning Journey.

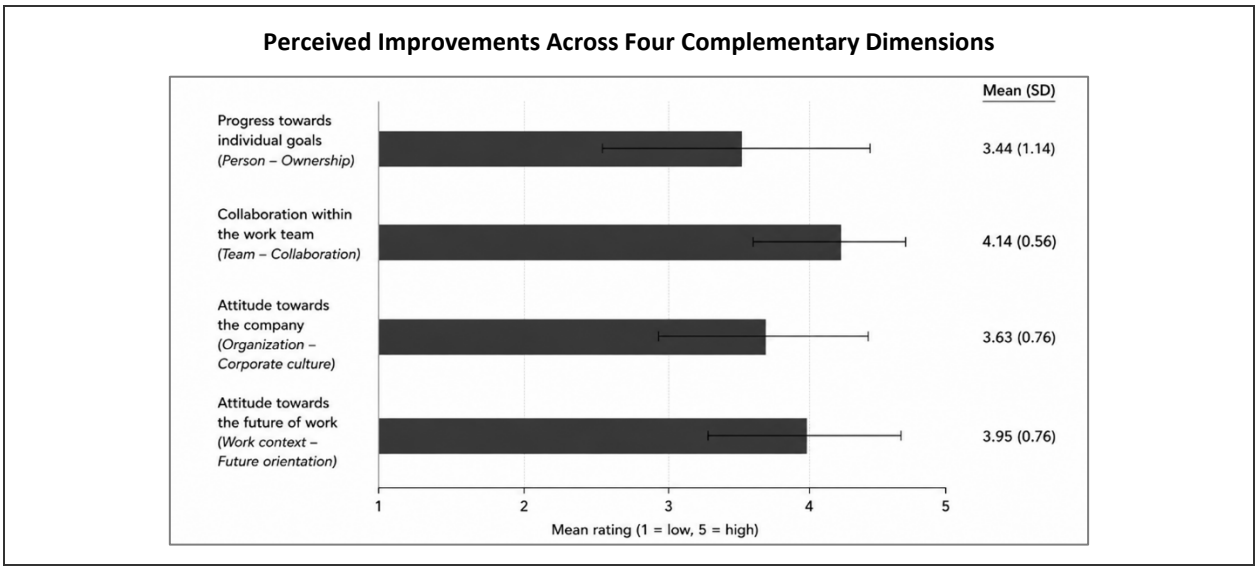


Figure 4: Perceived improvements reported by participants (n = 43). Ratings are based on a five-point Likert scale (1 = low, 5 = high). Error bars indicate ±1 standard deviation

The results show positive perceived improvements across all four dimensions, ranging from the individual to the organisational level. The highest perceived improvement was reported for collaboration within the work team (M = 4.14, SD = 0.56).

4.2 Learning Process

The second part of the questionnaire evaluated the didactic learning sequence underlying the Learning Journey. The five dimensions correspond to the five stages of the Learning Cycle.

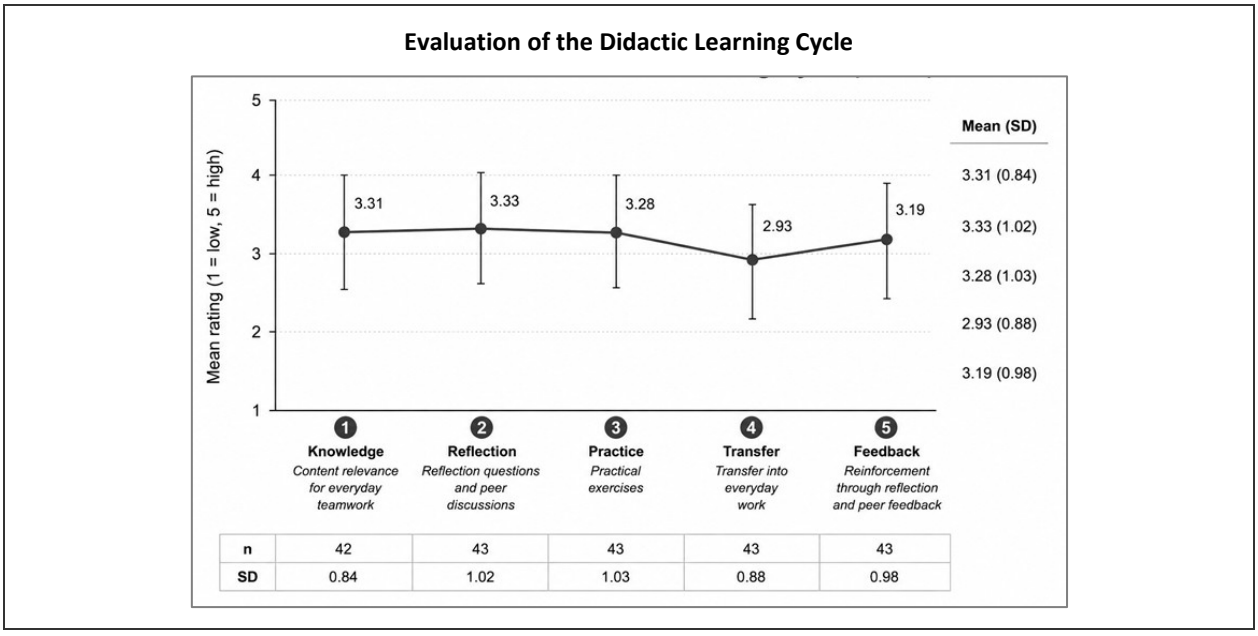


Figure 5: Integrated evaluation of five learning stages (n = 43). Ratings are based on a five-point Likert scale (1 = low, 5 = high). Error bars indicate ±1 standard deviation

The results show positive evaluations for knowledge acquisition, reflection, practice and feedback. Ratings for the workplace task were comparatively lower and remained close to the neutral midpoint of the scale.

4.3 Learning Environment

Another part of the questionnaire evaluated three complementary elements of the Learning Architecture supporting the Learning Journey.

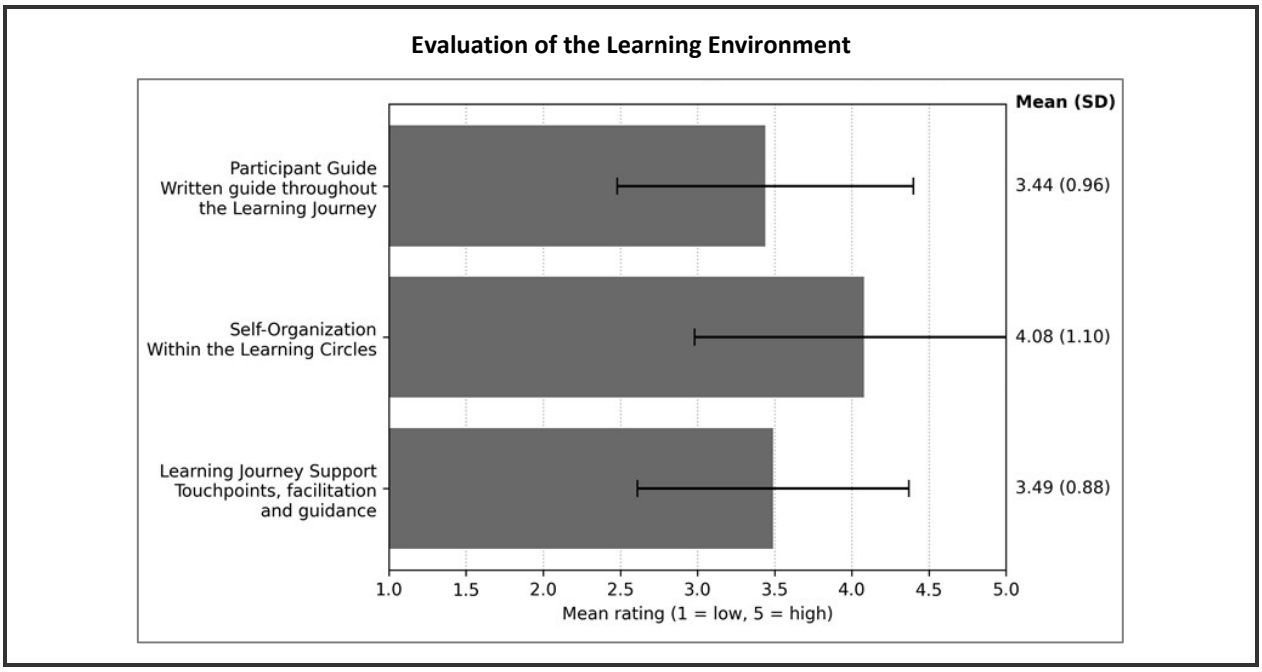


Figure 6: Integrated evaluation of the learning environment supporting the Learning Journey (n = 43). Ratings are based on a five-point Likert scale (1 = low, 5 = high). Error bars indicate ±1 standard deviation

The results show positive evaluations across all three elements of the learning environment. The highest ratings were reported for the self-organisation of the Learning Circles.

5. Discussion

Taken together, the literature review, action research and pilot evaluation describe the development and initial evaluation of a Learning Architecture comprising four complementary design elements. The positive evaluation of the Learning Environment suggests that structured organisational orientation and decentralised self-organisation are complementary. Participants rated the self-organisation of their Learning Circles particularly highly, despite working largely without continuous facilitation. This finding is consistent with research emphasising trust, psychological safety and repeated social interaction as central conditions for collaborative knowledge processes (Pasipamire et al., 2025). At the same time, the literature review revealed that self-organisation alone is insufficient for supporting organisation-wide development through collaborative learning. Unlike many well-established peer-learning approaches, the Learning Circles developed in this study combine decentralised collaboration with a shared curriculum. This enables participants to connect their own workplace experiences with common organisational principles and development objectives (Schmitt, 2025; Schmitt et al., 2026).

A similar pattern emerges for the Learning Cycle. Participants evaluated knowledge acquisition, reflection, practice and peer feedback consistently positively, whereas workplace tasks received comparatively lower ratings. This finding reflects the well-documented challenge of transferring learning into everyday work (Blume et al., 2010; Baethge et al., 2013). The overall pattern suggests that workplace transfer should not be understood as the responsibility of a single learning element. Rather, the continuos iteration of reflection, practice and feedback appears to create a broader transfer process over time. This interpretation is consistent with Taylor's (2007) understanding of tacit knowledge, which develops through repeated action and shared practice rather than through information alone. The particularly positive ratings for collaboration within work teams provide

initial empirical support for this interpretation, suggesting that transfer may emerge from the iterative Learning Cycle as a whole rather than from workplace tasks in isolation.

The learning scope represents the third design principle of the Learning Architecture. Rather than standardising learning content, its common curriculum establishes shared developmental principles while allowing language, thematic depth and practical examples to be adapted to different target groups. This finding is consistent with Langheiter's (2022) argument that effective adult learning must connect new content with existing competencies and professional experience. At the organisational level, Hodgson's (2023) understanding of routines provides an important theoretical explanation for this design. Rather than defining routines as repeated behaviours, he conceptualises them as organisational capacities that enable context-sensitive action across different situations. The Learning Architecture follows this logic by providing common orientation without prescribing identical behaviour. Through recurring collaborative learning practices, participants repeatedly engage with shared principles of ownership, collaboration and responsible judgement while interpreting and applying them within their own professional contexts (Schmitt, 2011). The positive evaluation of attitudes towards the future of work provides an initial indication that such repeated collaborative practice may contribute not only to behavioural improvements but also to broader mindset development.

Taken together, these findings highlight the study's key contribution: integrating social learning, didactic structure, a shared curriculum, and organisational implementation into a coherent Learning Architecture. The four design elements fulfil complementary functions. Together, they provide a common organisational orientation while maintaining decentralised responsibility for learning, reflection, and workplace application. This integrative perspective situates the study within the ongoing debate surrounding the relationship between knowledge management and organisational learning. Khadir and Durst (2025) distinguish between the two fields based on their respective primary focus. Knowledge management focuses on how people create, interpret, share, and apply knowledge in their day-to-day work. In contrast, organisational learning examines how these individual learning processes become embedded in organisational capabilities and performance. Rather than treating these concepts as competing perspectives, the authors argue that they should be understood as complementary. The Learning Architecture developed in this study operationalises this relationship by systematically connecting individual collaborative learning with organisation-wide capability development.

This human-centred understanding of knowledge management becomes increasingly relevant in AI-supported knowledge work. As Alavi et al. (2024) argue, generative AI increasingly supports the retrieval, organisation and externalisation of knowledge. Consequently, the strategic challenge shifts from knowledge availability towards the human capabilities required to interpret, contextualise, judge and collaboratively apply increasingly available knowledge. Kauffeld et al. (2025) underpin this orientation when they argue: “Fostering strong networking and social exchange behaviour within organisations can accelerate transformative efforts and facilitate the integration of learning outcomes into broader change processes.” The study directly addresses this challenge by providing a structured organisational framework through which these capabilities can be developed collectively.

This interpretation is also consistent with the broader development of knowledge management research. Since the work of Nonaka and Takeuchi (1995), the field has progressively extended its attention beyond managing explicit and tacit knowledge towards the organisational processes through which knowledge is created, shared and applied (Hamzah et al., 2025). Recent contributions further emphasise the human and organisational conditions that enable knowledge to become effective in practice. Kucharska et al. (2025) similarly shift attention from knowledge resources towards collaborative organisational capabilities by relating the absorption of tacit knowledge to agile mindset and organisational experience. Building on this perspective, Nakash (2026) conceptualises contemporary knowledge management as an organisational architecture that provides coherent orientation rather than a collection of isolated practices. The Learning Architecture proposed in this study operationalises this perspective through a learning-oriented design that systematically connects individual learning processes with organisation-wide capability development. The pilot findings provide initial empirical support for this theoretical interpretation. Although the exploratory design and reliance on self-reported perceptions do not permit conclusions about sustained behavioural or cultural change, the findings provide initial empirical support for the proposition that an organisation-wide orientation architecture can create the conditions under which collaborative capabilities may gradually develop.

6. Limitations

As this was an exploratory pilot evaluation based on a limited sample, the findings should be interpreted with appropriate caution. The questionnaire was developed specifically for this study and has not yet been independently validated, and the response rate of 52% means that self-selection bias cannot be excluded.

Furthermore, the study relies on participants' self-reported perceptions and therefore cannot demonstrate behavioural change, organisational outcomes or causal effects. The Learning Architecture was also developed through an action research process in which the author participated throughout the project and subsequently became a partner in the spin-off organisation responsible for its implementation. While this close involvement enabled continuous refinement of the Learning Architecture, it may also have introduced researcher bias.

Consequently, the findings should be understood as initial evidence supporting the coherence and perceived relevance of the proposed Learning Architecture rather than its long-term effectiveness. Future research should therefore examine the Learning Architecture using longitudinal designs and validated behavioural measures. Such studies would provide a stronger basis for evaluating whether the Learning Journeys contribute to sustained collaborative capabilities, organisational routines and, ultimately, organisational culture.

7. Conclusion

This study set out to identify a Learning Architecture capable of systematically developing ownership, collaboration and related human capabilities while combining effectiveness, sustainability and scalability. The proposed Learning Architecture provides a possible answer to this challenge by integrating collaborative peer learning, a structured didactic process, a shared curriculum and an organisation-wide implementation framework.

The discussion suggests that this contribution addresses a growing challenge within contemporary knowledge management. While explicit knowledge and increasing parts of professional tacit knowledge can be documented, organised and made accessible through digital systems and generative AI, the collaborative capabilities required to interpret, evaluate and responsibly apply this knowledge remain inseparable from human practice. They develop through repeated social interaction and become embedded in the routines and shared orientations of organisational members.

This is where the proposed Learning Architecture becomes relevant. By systematically linking individual collaborative learning to organisation-wide capability development, it provides a practical approach through which knowledge management and organisational learning can reinforce each other. At the same time, the architecture addresses a limitation of many existing learning approaches by combining the conditions required for capability development with organisational requirements such as orientation, sustainability and scalability. Collaborative capabilities can be developed systematically across large numbers of participants through shared content, recurring collaborative practice and decentralised self-organisation, without reducing learning to standardised training.

This exploratory pilot study provides initial empirical support for the conceptual proposition. Further longitudinal research is required to investigate whether these patterns lead to sustained collaborative capabilities, organisational routines and, ultimately, organisational culture.

Acknowledgements

The pilot study was funded by MAINPROJECT from Aschaffenburg University of Applied Sciences hosted by Prof. Dr. Wolfgang Alm and Prof. Dr. Georg Rainer Hofmann. The introduced Learning Journey guides are published by Lernwelt Designstudios hosted from the author together with Katja Leimeister, Meike Schumacher, Ivonne Grabinski and Oliver Staudt.

Ethics Declaration: Companies joined voluntarily and approved the programmes with their employees as part of their organisational development activities. Employees were invited to participate by their respective companies and were informed that completion of the questionnaires was optional. Where employee representation bodies (works councils) existed, the questionnaire was reviewed and approved prior to its use. According to the applicable institutional regulations of Aschaffenburg UAS, no formal ethical approval was required for this anonymous voluntary evaluation study.

AI Declaration: AI-tools (DeepL and ChatGPT) were used for language refinement, grammar checking and design of figures. All scientific concepts, methodological decisions, data analyses, interpretations, figures and editorial decisions were developed, verified and approved by the author, who takes full responsibility for the content of this manuscript.

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Developing Knowledge-based Dynamic Capabilities for Shared Value Creation in Circular Supply Networks

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Abstract: This paper examines the development of knowledge-based dynamic capabilities (KBDCs) within a circular supply network and their role in enabling shared value creation. It analyses the interplay among knowledge acquisition, knowledge generation, and knowledge combination capabilities as they emerge through interorganizational collaboration and investigates how these capabilities contribute to economic, environmental, and social value outcomes. An exploratory case study was conducted within a circular supply network in Poland comprising grain producers, distributors, feed manufacturers, farms, and processors engaged in circular exchanges of materials, services, and by-products. Data were collected through in-depth interviews, focus groups, study tour observations, and internal documents. The findings indicate that all forms of KBDCs, such as knowledge acquisition, generation, and combination, are actively developed through collaboration among network actors. High relational embeddedness, manifested through trust, joint problem-solving, and mutual commitment, is identified as the central enabler of KBDC development. Knowledge acquisition is enhanced through interactions that enable actors to assimilate strategic, operational, and contextual knowledge. Knowledge generation arises from collective efforts orientated toward circularity, whereas knowledge combination is facilitated through the integration and reconfiguration of knowledge flows across the network. These processes foster shared value creation, manifested in economic efficiency and supply chain resilience, environmental restoration through regenerative production and closed-loop practices, and social benefits such as local skill development and community education. The study advances understanding of how KBDCs support shared value creation within circular supply networks by elucidating the interplay among distinct knowledge capabilities and demonstrating that collaborative interactions underpin their development. Contributes to the knowledge management literature by showing how KBDCs emerge from joint interactions and are reinforced through industrial network relationships in a circular economy context. The study illustrates how organisations can embed environmental and social objectives into their strategic core by leveraging KBDCs to develop circular solutions and simultaneously achieve economic, environmental, and social value.

Keywords: Knowledge-based dynamic capabilities, Shared value, Value co-creation, Inter-organisational collaboration

1. Introduction

Circular supply networks have received attention in academic research as networks seek to integrate circularity with larger sustainability and value-creation goals. Scholars have examined these networks through various lenses, including industrial ecology, green supply chain management, comprehensive sustainability frameworks, and circular economy approaches (Amir et al, 2022). However, despite this expanding literature, the field remains conceptually underdeveloped. Circular supply networks are commonly viewed as contexts in which value arises from regenerative resource flows, waste minimisation, and the reuse of outputs as inputs in new value cycles. In these contexts, value creation goes beyond strictly economic results to also include ecological restoration and social benefits.

This broader perspective aligns with shared value, which stresses creating economic, environmental and social value simultaneously (Sibińska and Krawiec, 2023). In circular supply networks, shared value arises when firms increase competitiveness while reducing ecological harm, supporting communities, and strengthening long-term network relationships. It also relies on continuous learning and on capabilities that enable organisations to acquire, create, and integrate knowledge across organisational boundaries. The knowledge-based view treats knowledge as a core organisational resource shaped by social interaction (Grant, 1996), while knowledge-based dynamic capabilities (KBDCs) emphasise the ability to obtain, generate and combine knowledge in dynamic environments (Phalswal et al, 2024). The development of KBDCs in circular supply networks remains underexplored, especially regarding how inter-organisational interactions shape knowledge-acquisition, generation and combination capabilities and how these processes support shared value creation. In summary, research on circular supply networks has examined circular practices and sustainability outcomes but offers limited insight into the knowledge mechanisms that produce these outcomes. Addressing this gap is crucial because circular supply networks rely on collaboration among multiple actors and such collaboration is likely to be central to mobilising and transforming distributed knowledge.

The present study investigates how knowledge-based dynamic capabilities develop within a circular supply network to enable shared value creation. Drawing on an exploratory case study of a circular agri-food supply network in Poland, the paper examines how knowledge acquisition, generation, and combination emerge

through inter-organisational collaboration and how these capabilities support economic, environmental and social value outcomes. The study addresses the following research question: *How do inter-organisational interactions foster knowledge-based dynamic capabilities' development for shared value creation in networks?* By addressing this question, the paper aims to improve understanding of how KBDCs evolve to support circular collaboration and to explain how shared value emerges from interactions among actors in the network.

2. Theoretical Background

Research on circular supply networks is growing, but the field remains conceptually fragmented. Existing studies adopt environmental perspectives from industrial ecology and green supply chain management, holistic sustainability frameworks that integrate economic, social, and environmental outcomes, and circular economy principles focused on regenerative resource cycles (Taghikhah, Voinov and Shukla, 2019; González-Sánchez et al, 2020; Aryee et al, 2025). Despite this diversity, circularity is widely recognised as one of the key mechanisms to advance the transitions of the circular supply network by reducing waste and resource consumption. They do so through closing, slowing, narrowing, intensifying, or dematerialising material loops, and by embedding circular strategies into supply chain management to strengthen sustainability performance (Geissdoerfer *et al.*, 2018; Lahane, Kant and Shankar, 2020).

Within the circular supply chain network, value creation becomes the guiding logic. Firms aim to propose, create, deliver, and capture value through long-lasting product use, remanufacturing, refurbishing, the use of renewable resources, and reductions in environmental and social costs (The Ellen MacArthur Foundation, 2013). Circular flows ensure that production outputs are reintegrated as inputs for new value cycles rather than treated as waste (Vlajic, Mijailovic and Bogdanova, 2018).

Circular supply networks provide a foundation for shared value creation, whereby economic, social, and environmental value emerge simultaneously within a networked context. Shared value encompasses organisational efforts to enhance competitiveness while generating societal and environmental benefits (Sinthupundaja, Kohda and Chiadamrong, 2020; Sibińska and Krawiec, 2023). Economic value creation (EVC) denotes the capacity of network participants to endure, prosper, and function effectively to achieve growth and financial viability while introducing new products and services (Paulraj, 2011). Social value creation (SVC) refers to benefits delivered to society or local communities, such as improved well-being and safety, increased awareness and protection of people's rights, and significant progress in alleviating social problems (Maletič, Maletič and Gomišček, 2018). Environmental value creation (EnVC) relates to reductions in ecological harm, the elimination of waste and pollution, and overall environmental improvement (Maletić, Maletić and Gomišček, 2018).

Creation of shared value in circular supply networks requires continuous learning and the development of dynamic capabilities that facilitate effective interorganisational relationships. These capabilities are grounded in the knowledge-based view (KBV), which positions knowledge as a central organisational resource shaped through social interactions both within and across firm boundaries (Grant, 1996). Bratianu and Bejinaru (2020) extend this perspective by conceptualising knowledge as "knowledge dynamics," highlighting processes of knowledge transformation that support the evolution of an organisation's knowledge base.

Dynamic capabilities emerge through repeated interactions that produce new knowledge and stimulate capability development (Prieto and Easterby-Smith, 2006). Faccin et al (2019) describe knowledge-based dynamic capabilities (KBDCs) as a firm's ability to obtain, generate, and combine knowledge to exploit opportunities in dynamic environments. Furthermore, Zhen et al (2011) distinguishes three forms of KBDCs as knowledge-acquiring capabilities (KACs), knowledge-creation capabilities (KCCs), and knowledge-combination capabilities (KCCs). The acquisition of knowledge encompasses the processes and routines of recognising and acquiring internal and external knowledge (Cohen and Levinthal, 1990) and covers creative searching and strategic sense-making (Pandza and Thorpe, 2009). The generation of knowledge is defined as the practices of organising the ability to develop and enhance new knowledge creation (Nonaka, 1994). Integration and application of internal and external knowledge is the focus of knowledge combination capabilities (Bindra et al., 2023). The development of KBDCs within circular supply networks remains underexplored. A central question concerns how interorganisational interactions (Perna *et al.*, 2022; Guercini, La Rocca and Perna, 2024) shape the emergence of knowledge-acquisition, knowledge-creation, and knowledge-combining capabilities. Understanding these developments is essential to explain how KBDCs contribute to shared value within circular network settings.

3. Methodology

An abductive research approach examined how knowledge acquisition, generation, and combination capabilities develop for shared value creation in circular supply networks (Dubois and Gadde, 2002). Iteration between empirical evidence and theory generated new insights. This approach suited the exploratory research question and the limited prior work linking circular supply networks to shared value creation (Sibińska and Krawiec, 2023) and to knowledge-based dynamic capabilities (Bindra et al., 2023). As no universally accepted framework for measuring shared value exists (Dembek, Singh, and Bhakoo 2016), this study defined shared value as the aggregate of firms' economic, social, and environmental impacts and assessed it by adapting Bloom and Smith's (2010) rating approach to organizational performance in these three areas. A single exploratory case study analysed a circular supply network centred on a grain and cereal producer in Poland. Beyond cereal and grain production, the network redistributes waste streams and by-products for animal feed, thus operationalising circular flows (Montag, 2022). Network actors jointly create economic, environmental, and social value. The analysis focuses on stakeholders most directly involved in shared value creation, enabling in-depth examination of the interactions shaping KBDCs (see Table 1).

Table 1: Overview of circular supply network actors

Name of the actor	Organisation's core activities	Role of the actor within the network
Grain Food Producer and Distributor	The company manufactures organic and conventional grain products.	The focal company that integrates all other supply network organisations in waste management processes to produce food products.
Food Waste Processor	A feed manufacturer that uses grain-based raw materials to produce feed for poultry, swine, and cattle.	It acquires grain by-products from network companies to produce feed and brokers the sale of by-products and finished products to farms.
Feed Manufacturer	A feed manufacturer that uses grain-based raw materials to produce feed for cattle.	It uses products supplied by other manufacturers in the network to produce feed.
Farmland	A medium-sized farm that grows winter and spring crops and raises cattle.	It provides the raw materials such as wheat to the grain food producer.
Buckwheat Processor	The company specialises in purchasing, producing, and selling buckwheat and millet groats.	It provides buckwheat and millet and transportation services to grain producers and Distributors.
Farm Apiary	This family-owned business sources high-quality varietal honeys and other bee products.	It is a supplier of honey and bee products and materials to the grocer and distributor of grains.
International Group of Agricultural Producers and Processors	This international group of enterprises produces cereals, oil crops, potatoes, sugar beets, milk, dairy cattle, and other products.	It supplies wheat and oil products as raw materials and delivers grain harvest waste and by-products for cattle feed.

Source: Author's own work

Primary data were collected between July 2024 and December 2025 through ten in-depth interviews, a study visit to the Grain Food Producer and Distributor, and participant observation. Organisations and informants were selected via purposive and snowball sampling based on recommendations from the focal organisation's management. Data collection comprised three stages: (1) an exploratory interview with a company representative to map network actors and key circular practices in grain production and waste utilisation; (2) a study visit to directly observe technological and production processes and clarify circular flows; and (3) additional supplier interviews to deepen insights into interactions, shared practices, and collaboration. Four interviews and the observation were conducted in person, six interviews were conducted via MS Teams due to distance. All interviews were recorded and transcribed to ensure confirmability and transparency (Guba and Lincoln, 1994). The interview protocol addressed organisational roles in circular processes, resource deployment, and interaction episodes in shared value creation.

The primary data came from multiple actors in the circular supply network. For the grain food producer and distributor, material included four in-depth interviews (CEO, Sales Director, Purchasing Specialist, Production and Technological Director); study visit with observations (CEO, Production and Technological Director, production staff); seven internal documents; and one external source (web pages). For the Food Waste Processor, data comprised an in-depth interview with the cofounder and two external sources (website, industry

report). In-depth interviews were also conducted with the General Director of the Feed Manufacturer, the owner of the Farmland actor, the General Director of the Buckwheat Processor, and the Vice President of the Management Board of the Farm Apiary. For the International Group of Agricultural Producers and Processors, data included an in-depth interview with the CEO and one external source (website).

The analysis employed abductive reasoning and systematic combining (Dubois and Gadde, 2002), iteratively moving between the empirical material and the evolving theoretical framework. Data collection and analysis were conducted in parallel, whereby preliminary interpretations informed subsequent rounds of inquiry. Drawing on interview transcripts, field notes, and secondary documents, the study first generated a descriptive account of circular practices. It then examined interaction episodes in terms of their outcomes to identify manifestations of shared value creation, building on established conceptualisations (Sinthupundaja, Kohda and Chiadamrong, 2020). Given the absence of a universally accepted approach for measuring shared value (Dembek, Singh, and Bhakoo, 2016), economic, social, and environmental value creation was assessed using Bloom and Smith's (2010) rating of organizations' economic, social, and environmental achievements. The empirical material was coded into three categories of knowledge-based dynamic capabilities derived from the proposed framework (Zheng, Zhang and Du, 2011).

4. Results

The findings show that knowledge-based dynamic capabilities (KBDCs) develop through repeated interactions within the circular supply network and are closely tied to shared value creation. The results are organized into three themes: KACs and shared value creation, KGCs and shared value creation, and KCCs and shared value creation.

4.1 Developing Knowledge Acquiring Capabilities (KACs)

The study identifies three types of knowledge-acquisition capabilities: technical, process, and marketing. These capabilities develop through repeated inter-organisational interactions that help actors identify, access, and assimilate external knowledge from multiple sources. Technical knowledge mainly arises from interactions focused on creating environmental value by improving environmental conditions. These improvements include greater crop resilience, better soil analysis, and compliance with ecological standards, which support ecosystem protection.

The findings show that developing process knowledge acquisition capabilities depends on interaction mechanisms among network actors, such as meetings and quarterly quality audits. These mechanisms create economic value by helping firms detect supplier bottlenecks, improve raw material and quality assurance systems, better align products with customer and market requirements, and strengthen operational and strategic decisions and processes.

Marketing knowledge acquisition enables network actors to recognise market requirements, achieve higher parity with prevailing standards, and thus create economic value. In addition, marketing knowledge about farmers' needs, feed applications, and market conditions supports social value creation such as regional development and stabilises network relationships (see Table 2).

Table 2: Developing knowledge acquisition capabilities in shared value creation processes

Episodes of interactions	Shared Value Outcomes	Actors involved	KACs development
Meetings and technician seminars with farmers and experts	Enhancement of crop survival and mitigation of plant stress (EnVC)	International Group of Agricultural Producers and Processors Grain Food Producer and Distributor	Learning advanced technical knowledge and remote sensing analysis methods
Meetings and quarterly quality audits	Boosting product quality and cutting waste through better inputs (EVC)	International Group of Agricultural Producers and Processors Buckwheat Processor Grain Food Producer and Distributor Farm Apiary	Identifying supplier capacity bottlenecks in raw materials and acquire external knowledge on global standards.

Episodes of interactions	Shared Value Outcomes	Actors involved	KACs development
Gathering collectively market and industry data	Improving product quality and providing the parity standards to the industry (EVC)	Grain Food Producer and Distributor International Group of Agricultural Producers and Processors	Collective acquisition of market, laboratory, packaging, quality information and knowledge
Performing laboratory tests	Ensuring safe, high-quality products and stronger alignment and trust (EVC)	Grain Food Producer and Distributor Farmland	Acquiring knowledge on raw material quality and customer requirements
Participation in regional festivals and agricultural events	Promote regional development by using local suppliers (SVC)	Grain Food Producer and Distributor Farmland	Acquiring knowledge of organic certification and market requirements
Regular meetings with local farmers	Economic and financial support for farmers through stabilised by-product purchase contracts (SVC)	Grain Food Producer and Distributor Farmland Food Waste Processor Feed Manufacturer	Acquiring knowledge about farmer needs, feed applications and market conditions
Communication and meetings on certification standards	Protecting ecological integrity (EnVC)	Grain Food Producer and Distributor Farm Apiary	Acquiring knowledge about ecological certification, quality testing, and cross-border logistics

Source: Author's own work

4.2 Developing Knowledge Generation Capabilities (KGCs)

Capabilities to acquire process, technical, and marketing knowledge foster new knowledge and expertise. The cability to generate novel knowledge is closely tied to building expertise in circular solutions, as actors collaboratively design new solutions, routines, and process know-how in response to environmental challenges and emerging opportunities. Instead of merely transferring existing knowledge, these interactions create new agronomic, technological, and organisational knowledge within the network. Collaborative experimentation has been shown to promote reciprocal learning in the development of environmentally value creation. Social value creation that is exemplified by joint workforce development programmes, is supported through the strengthening of community engagement, the enhancement of awareness of circularity, and the generation of knowledge about innovative regenerative production solutions. Economic value creation is facilitated by the generation of novel technological and process-related knowledge, which in turn underpins market diversification, reduced input utilization, enhanced production capacity, improved cost efficiency, and decreased operational downtime (see Table 3).

Table 3: Developing knowledge generation capabilities in shared value creation processes

Episodes of interactions	Shared Value Outcomes	Actors involved	KGCs development
Kick-off meeting on diverse multi-species crops	Soil quality and resilience improvement (EnVC)	International Group of Agricultural Producers and Processors Grain Food Producer and Distributor	Development of proprietary expertise in soil management and crop rotation
Joint experimentation	Market diversification and lower inputs (EVC)	International Group of Agricultural Producers and Processors Grain Food Producer and Distributor	Creation the specialistic knowledge on low-input cultivation protocols
Creation of production plant	Developing new production capacity and reducing waste (EnVC) to improve economic competitiveness (EVC)	Grain Food Producer and Distributor Farmland	Generating new technological and process knowledge to innovate grain cleaning and processing

Episodes of interactions	Shared Value Outcomes	Actors involved	KGCs development
Establishing of a reuse policy	Realize cost savings (EVC) and environmental advantages (EnVC)	Grain Food Producer and Distributor Farmland	Generating new process knowledge on using by products as inputs to new processes.
Co-organising and co-funding a local workforce empowerment programme	Local community's development through recruiting and training local workers in circular practices (SVC)	Grain Food Producer and Distributor Farmland Buckwheat Processor	Building community engagement and knowledge in circular and regenerative production solutions
Jointly negotiation cooperation procedures	Transparent transactions and stable business relationships (EVC)	Grain Food Producer and Distributor Farmland Buckwheat Processor Farm Apiary International Group of Agricultural Producers and Processors	Developing new quality assessment and procurement protocols
Collaborative management of production breakdowns	Reduction of downtime and adjustment of production schedules (EVC)	Grain Food Producer and Distributor Farmland Food Waste Processor Feed Manufacturer	Developing new routines for problem-solving and production adjustment

Source: Author's own work

4.3 Developing Knowledge Combination Capabilities (KCCs)

Regarding the development of knowledge combination capabilities, the findings show that this development is linked to generating knowledge and enhancing expertise on circular issues. KACs enable actors to recognise and absorb agronomic, technical, market, and regulatory knowledge through audits, meetings, testing, and ongoing exchanges. KCCs then allow actors to integrate heterogeneous knowledge across organisational boundaries, combining operational, technological, and market-related knowledge from different organisations and functions. KCCs are primarily associated with economic value creation.

The integration of farmers' experiential knowledge with corporate standards, as well as the synthesis of multi-country procurement knowledge, contributes to increased income, enhanced supply stability, and improved competitiveness. Similarly, the combination of technical data enables actors to reduce input use, stabilise business operations and promote more sustainable soil management, thereby fostering environmental value creation. Moreover, the integration of accounting, logistics, and production-related knowledge reduces costs, strengthens quality assurance, improves efficiency, and enhances both organisational and economic synergies across the network (see Table 4).

Table 4: Developing knowledge combination capabilities in shared value creation processes

Episodes of interactions	*Shared Value Outcomes*	*Actors involved*	*KCCs development*
Contributing to national meetings and participating in trade shows	Rising incomes, stable supply, and greater competitiveness (EVC)	International Group of Agricultural Producers and Processors Grain Food Producer and Distributor Food Waste Processor Feed Manufacturer Farmland	Integrating farmer knowledge with corporate standards and multi-country procurement expertise

Episodes of interactions	*Shared Value Outcomes*	*Actors involved*	*KCCs development*
Integrating technical data	Reduced inputs and yield stability (EVC) and sustainable soil cultivation (EnVC)	International Group of Agricultural Producers and Processors Grain Food Producer and Distributor	Aggregating multi-source data for business decisions
Business process consolidation meeting	Lower admin costs; better synergy; long-term economic value (EVC)	Grain Food Producer and Distributor Feed Manufacturer	Integrating accounting, logistics, and production knowledge into organizational routines
Jointly negotiations with external parties	Cost savings, better quality assurance, and industry standardisation (EVC)	International Group of Agricultural Producers and Processors Grain Food Producer and Distributor	Cross-company knowledge sharing in quality, procurement, and logistics
Joint logistic management system	Improvement of mutual logistics efficiency (EVC)	Grain Food Producer and Distributor Feed Manufacturer	Integrating schedules and logistical knowledge

Source: Author's own work

5. Discussion

This study examines how inter-organisational interactions build knowledge-based dynamic capabilities for shared value creation in a circular supply network. In specific, the study makes three theoretical contributions.

Firstly, this study advances debates on knowledge-based dynamic capabilities (KBDCs) in inter-organizational networks (Bindara et al, 2023). The findings show that knowledge acquisition, generation, and recombination build cumulatively through repeated collaboration among network actors. Relational embeddedness is the key condition enabling these capabilities at the network level. The configuration of KBDCs examined here rests on reciprocity, which drives the creation of new knowledge and specialized expertise. The results further indicate that actors integrate and coordinate knowledge through socially embedded interactions that allow them to address circular challenges and market demands. This aligns with prior business network research (Perna et al., 2022; Guercini, La Rocca and Perna, 2024) while offering a deeper understanding of how circular network settings foster KBDCs.

Secondly, this study advances the KBDCs framework (Zheng et al, 2011) by offering refined insights into the dynamic interplay among KACs, KGCs, and KCCs, thereby clarifying the mechanisms through which one type of capability shapes, enables, and transforms another. The findings indicate that knowledge acquisition exerts a direct and positive influence on the development of both knowledge generation and knowledge combination capabilities. Although dynamic capabilities exhibit common foundational characteristics across organisations, they vary in the ways in which they are enacted and deployed (Eisenhardt and Martin, 2000). These processes indicate that KBDCs develop in a relational way, in which the activities of acquiring, creating, and integrating knowledge reinforce one another and strengthen capabilities.

Thirdly, the study reveals new aspects of shared value creation in circular supply networks (Amir et al, 2022) by emphasizing the role of KBDCs. Prior research has focused on circularity, regenerative resource flows, and sustainability outcomes, but has offered limited insight into the knowledge mechanisms that enable these outcomes. It has suggested that circular supply networks create value by closing resource loops and reducing environmental and social costs, while the knowledge-based view sees knowledge as a strategic resource shaped through social interaction (Grant, 1996). Building on these perspectives, this study shows that shared value creation in circular supply networks depends not only on material recirculation, but also on knowledge-intensive interaction. Circularity is enacted through episodes in which actors access external knowledge, co-develop new solutions, and integrate dispersed expertise into coordinated practices.

6. Conclusions

This study examines how knowledge-based dynamic capabilities (KBDCs) develop through inter-organisational interactions in a circular supply network and how they enable shared value creation. The results show that knowledge acquisition, generation, and combination capabilities build through repeated collaboration among

network actors and jointly support economic, environmental, and social value. KBDCs in circular supply networks are interaction-driven and relationally embedded. By tracing how specific interaction episodes generate different KBDCs and shared value outcomes, the study clarifies the micro-level mechanisms linking inter-organisational collaboration, knowledge dynamics, and shared value creation at the network level.

Based on a single case, the study nevertheless offers analytical transferability beyond the analysed network. The identified mechanisms as interdependent knowledge acquisition, generation and combination capabilities, and the centrality of relational embeddedness, are not specific to the agri-food sector and are likely relevant to other circular and sustainability-oriented inter-organisational networks. However, transferability is limited by the specific institutional and relational context of the studied network. Less mature or more transactional networks may display different capability dynamics. Future research could use comparative and longitudinal designs across diverse network configurations and institutional environments to test whether these patterns hold, especially in circular networks with different technologies, power structures, or degrees of formalisation.

Practically, the findings suggest that managers in circular supply networks should invest in relational and knowledge-management processes. Regular knowledge exchange, joint experimentation, collaborative problem solving and integrating dispersed operational and sustainability knowledge are critical for strengthening circular practices and shared value outcomes.

Acknowledgements

The research is financially supported by Marketing Department of the University of Lodz, Poland. The author alone is responsible for what is presented.

Ethical Declaration: This study did not require ethical clearance.

AI Declaration: AI-assisted writing (Writefull Software) was employed for grammar checking and paraphrasing in some areas. All interpretations were conducted by the author.

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Development of a Structure of User Rights in a Knowledge-sharing Environment

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Abstract: The issue of knowledge sharing in projects connected to the free-culture movement is linked to egalitarianism and the lack of formal social roles. This should distinguish them from bureaucratic organizations, where the source of authority is position, not knowledge. However, on Wikipedia, the most recognizable project of this movement, the initially flat user-rights structure has become greater over time. This article presents the variation within the user-rights structure in the largest language versions of Wikipedia. Previous research into the power structure within the Wikipedia community has focused on the effectiveness of teamwork, the formation of network structures and the influence of cultural factors on the activity of individuals in administrative roles. This article compares the user-rights structure across 42 language versions of Wikipedia. For this purpose, publicly available statistical data were analysed concerning the number of user groups (UGs) with different types of user rights and the activity of administrators. The next stage of the research involved comparing the relationships between these variables and the Power-Distance Index, as defined by Hofstede. Analysis of statistical data has shown that larger language versions of Wikipedia with a high number of administrators tend to have a talled organizational structure. Both the number of bureaucrats — individuals formally responsible for assigning Wikipedians to specific UGs — and the number of UGs were increasing. A comparison of variables relating to a power structure with Hofstede's Power-Distance Index (PDI) allowed to accept the hypotheses that a higher PDI correlates with 1) less frequent use of blocking and 2) less frequent removal of user pages by administrators. Furthermore, a weak negative correlation was observed between the PDI score and the number of users with administrator rights, though only in the case of smaller Wikipedia communities. This may imply that a greater power distance limits interference in people's actions, or that in cultures with a higher PDI, behaviour requiring intervention by those with the power to exclude are less common.

Keywords: Wikipedia user rights, Knowledge-sharing environment, Hierarchical structure, Online communities, Power distance

1. Introduction

In the late 20th century, it was assumed that the dynamics of new social movements were shaped by the values and needs of the middle class who preferred anti-hierarchical attitudes (Klandermans and Tarrow, 1988). Perhaps a legacy of this approach is the focus of researchers on the emergence of a new axiological order. This was the case when Wikipedia began to gain success as a project initially created by communities associated with the free-software movement. From the mid-2000s, studies began to emerge focusing primarily on the sharing of knowledge in a decentralized volunteer community (see: Lessig, 2008; Levinson, 2009). Tapscott and Williams (2008) indicated that such communities self-organize and that it is sufficient to create the right conditions for them to develop their own projects.

The social structure of these communities was usually not the focus of attention. The community of users creating Wikipedia was often reduced to the notion of an amorphous collectivity or crowd (Feldstein, 2011). However, collaborating on a project such as Wikipedia requires agreeing on and sometimes negotiating rules, thus seeking to establish a certain framework for how things are done. This in turn, contributes to relatively frequent interactions between users and to the formation of ties between them. Therefore, the users who contribute to Wikipedia should be treated as a community, not as a crowd. When communities create their own social networks, they demand transparency, and a number of options for dealing with key issues begin to emerge (Dobusch and Kapeller, 2018).

Previous research into the structural aspects of how the Wikipedia community functions has focused primarily on the coordination of team efforts (Kittur, Lee and Kraut, 2009; Morgan et al., 2013; Rezgui and Crowston, 2018) and on the analysis of elements of the network structure (Iba et al., 2010; Park et al., 2015; Qin, Cunningham and Salter-Townshend, 2015). The hierarchical structure and power relations were discussed in relation to issues concerning reputation and the role of authority figures in motivating volunteers to take action (Klapper and Reitzig, 2018), while attention was also drawn to the cultural factors influencing Wikipedians' activity, including the power distance (Pfeil, Zaphiris and Ang, 2006; Hara, Shachaf and Hew, 2010; Chandra and Maiti, 2018; Konieczny, 2020). However, these studies neglected the processes by which the hierarchical order took shape.

This article aims to examine how the hierarchical structure is shaped in the largest language versions of Wikipedia, while taking cultural diversity into account. Drawing on the findings of previous research, the author at hand sought to answer the following questions: (1) What is the structure of user permissions in the largest language versions of Wikipedia? (2) Does the power to exclude users depend on the Power-Distance Index (PDI) as defined by Hofstede (Hofstede, Hofstede and Minkov, 2010)? To answer these questions, a quantitative analysis was carried out on data concerning user-rights groups, as well as the frequency of particular administrative actions, in 42 of the largest language versions of Wikipedia.

2. Literature Review

Although Wikipedia does not have a formal structure based on the division of labour, a hierarchical structure is evident, stemming from the fact that some users have exclusionary power. Users who are granted administrator (sysop) rights can, among other things, block other users from editing, delete content, or prevent pages from being edited by users without the appropriate user rights. A significant proportion of earlier studies drew attention to the connection between certain aspects of power, mainly exclusionary power and organizational culture. One of the first studies to use Hofstede's cultural dimensions theory found that the higher the PDI score, the less frequently content was removed from articles. However, these studies were limited to four language versions and analysed changes in a small number of articles (Pfeil, Zaphiris and Ang, 2006). The findings were attributed to the fact that, in cultures with a high PDI, people are less likely to interfere with the work of others. Later studies on a larger sample of language versions showed that "bold editing" of popular articles is not dependent on the user's editing experience. New users, who typically have fewer user rights, tend to be more daring in this regard in the Polish, Russian, Chinese and Swedish versions (Chandra and Maiti, 2018), yet the countries they come from vary significantly in terms of PDI scores (*Country Comparison Tool*, 2026).

However, PDI proved to be a variable whose impact on the Wikipedia community can be considered to be limited. For example, studies of Wikipedia communities in East Asian countries have found no correlation between user activity and the distance to power. The study analysed 15 language versions of Wikipedia (Konieczny, 2020). Research into the relationship between PDI and the removal of administrators' rights found that no such relationship is apparent when the issue is examined using a single model. However, in Western and Asian cultures, as the PDI score increases, the proportion of current administrators relative to former administrators rises, whereas in Orthodox and Islamic cultures it falls (Skolik & Karczewska, 2021). In contrast, Park et al. (2015), who analysed 12 language versions, found only a partial correlation between PDI and egalitarianism.

Some of the research into administrator rights focused on emotional responses. Blocking users from editing Wikipedia pages is sometimes a measure to prevent conflicts. Hara, Shachaf and Hew (2010) noted that more polite comments from participants on article talk pages are found in cultures with a higher PDI. They analysed 120 talk pages in four language version. The issue of conflict resolution may be particularly relevant in cultures with a lower PDI, where such conflicts may arise more frequently. Extensive research analysing more than 640,000 talk pages on the English Wikipedia showed that less experienced users are more likely to intervene in conflicts, especially when those conflicts become heated. At the same time, interventions are desirable when the person intervening has legitimacy to act based on competence (Klapper and Reitzig, 2018).

The size and structure of a team can affect the effectiveness of teamwork. It has been suggested that larger teams can provide greater benefits when the work is routine, whereas smaller benefits when teamwork requires a high degree of coordination. Such coordination may, for example, be necessary when onboarding new users who are still learning the basics while editing articles supervised by experienced users (see Kittur, Lee and Kraut, 2009). Coordination is also important when collaborating on WikiProjects, which are internal Wikipedia projects dedicated to specific subject areas. Some of them require users to work together relatively closely. In most cases, however, there is a clear division between the centre and the periphery: the most active Wikipedians coordinate the work of peripheral users, thereby limiting their own contribution to content development (Morgan et al., 2013). Later studies found that the existence of central hubs (leaders) who coordinate activities over a long period of time enables WikiProjects to function effectively (Qin, Cunningham and Salter-Townshend, 2015).

Descriptions of how new users become involved in editing assume that they gradually adopt the principles of collaboration and later take on roles of greater importance to the community, such as that of an administrator. This approach was consistent with the general characteristics of online communities from a netnographic perspective (Kozinets, 2015). On Wikipedia, in order to be granted administrator rights, a user must be trusted,

as these rights are awarded through a vote by the community of active Wikipedians. It is generally accepted that, in order to foster greater commitment to new roles, identifying with the values of the Wikipedia community is more important than the reputation gained through contributions to the project (Goldspink, 2009). A different approach to this issue is presented by authors who analyse variations in contributions to articles selected based on quality. Usually, in such cases, there are a small number of editors who contribute the most content to these articles and make the most edits. They are referred to as coolfarmers. They are in contrast with egoboosters, who spend a great deal of time developing their own user page (Iba et al., 2010).

In the works cited above, the decentralized generation of knowledge, the networked structure and the absence of a top-down hierarchy were highlighted as strengths and as an alternative to traditional organizational models. Nevertheless, Wikipedia shows a tendency towards the formation of increasingly complex structures, within which dozens of user groups with corresponding bundles of user rights can be identified. The created user rights levels led to the lengthening of the "advancement progression pathway". Over time, the different language versions began to diverge in how they implemented new user rights. However, these processes have not been systematically studied to date.

3. Materials and Methods

This study was conducted across 42 language versions of Wikipedia, the largest in terms of the number of active users. Some analyses included versions in the official languages of individual countries, which enabled comparisons of variables with Hofstede's cultural dimensions theory. The sample included the following language versions: Arabic (arwiki), Azerbaijani (azwiki), Bulgarian (bgwiki), Bengali (bnwiki), Czech (cswiki), Danish (dawiki), German (dewiki), Greek (elwiki), English (enwiki), Spanish (eswiki), Estonian (etwiki), Persian (fawiki), Finnish (fiwiki), French (frwiki), Hebrew (hewiki), Croatian (hrwiki), Hungarian (huwiki), Armenian (hywiki), Indonesian (idwiki), Italian (itwiki), Japanese (jawiki), Georgian (kawiki), Kazakh (kkwiki), Korean (kowiki), Lithuanian (ltwiki), Latvian (lvwiki), Malay (mswiki), Dutch (nlwiki), Norwegian (nowiki), Polish (plwiki), Portuguese (ptwiki), Romanian (rowiki), Russian (ruwiki), Slovak (skwiki), Slovenian (slwiki), Serbian (srwiki), Swedish (svwiki), Thai (thwiki), Turkish (trwiki), Ukrainian (ukwiki), Vietnamese (viwiki), Chinese (zh wiki).

For each language version, data was collected on the number of members of individual user groups (UGs) with specific bundles of user rights, while using a dedicated special page (*User Group Rights*). This data was related to the early period of 2026. This made it possible to identify the diversity of the power structure within the Wikipedia community. To identify variation in the use of power to exclude, data was first collected for each of the language versions studied on the number of administrators, the number of new users (new accounts making edits in that version) and the number of pages created. For this purpose, publicly available data was used from a page on Wikimedia Commons (*Data:Wikipedia statistics*, 2026) and from a special statistical data page maintained by the Wikimedia Foundation (*Wikimedia Statistics*). Subsequently, using the XTools (*Admin Stats*), data was collected on the frequency with which particular administrator tools were used, including the frequency of page deletions and the blocking of other users. The data used for the analysis covered the whole of 2025.

The PDI data for individual countries was obtained from a dedicated website containing up-to-date Hofstede's cultural dimensions indices (*Country Comparison Tool*, 2026). Data collection and analysis were carried out in January and February 2026.

The first stage of the data analysis involved the examination of the structural relationships between variables relating to UGs. Earlier studies showed that community size (active users) clearly correlates with the number of administrators (Skolik and Karczewska, 2021). Similarly, the number of active users correlates with the size of contributions (number of bytes added) and the number of edits made (Skolik, 2025). This study posits two hypotheses regarding the relationship between exclusionary power (of administrators) and the structure of user rights:

> *H1: The greater the number of administrators in Wikipedia language versions, the greater the number of user groups.*
>
> *H2: The more administrators there are in a given language version, the more pronounced the tendency for more users to be granted bureaucrat rights, which allow them to grant administrator rights.*

Confirmation of H1 could indicate that a greater number of supervising administrators is required to ensure greater diversity of user rights. Furthermore, this could also mean that more administrators could delegate some of their rights to other users more efficiently. Conversely, a larger number of bureaucrats translates into

significantly greater potential for granting user rights, including administrator rights. The community usually approves the granting of such rights: administrators are elected by vote, and the granting of bot flags requires the approval of other bot operators. Therefore, the tasks usually performed by bureaucrats involve formally assigning a user account to the appropriate category and only a small number of individuals are needed for this. If H2 were to be confirmed, this could also signal a trend towards expansion the organizational structure.

To investigate the relationship between cultural factors and the power of exclusion, the following research hypotheses were formulated:

H3: As the Power-Distance Index (PDI) increases, fewer users may be granted administrator rights.

H4: The higher the PDI, the less likely administrators are to block users.

H5: The higher the PDI, the less likely administrators are to delete pages.

Confirmation of H3 would indicate that a high PDI can limit access to exclusionary power. Conversely, accepting H4 and H5 would confirm previous research by Pfeil, Zaphiris and Ang, which suggested that a higher PDI is associated with less willingness to interfere in the actions of others (2006). Since PDI relates to individual countries, language versions whose communities originate from more than one country were omitted from the analyses: enwiki, dewiki, eswiki and arwiki.

4. Results

Among the 42 language versions examined, 60 different UGs were identified, with the following present in each version: users (people with registered accounts in the project); administrators; interface administrators and bots. Interface administrators are a relatively new user group added in 2018, for users with sufficient technical expertise to edit system JS and CSS files. The 40 language versions also included the following groups: bureaucrats (users authorized to assign other users to a specific user group) and “IP block exemptions” (users authorized to log in and edit content from IP addresses that have been blocked). Although a bureaucrat is needed to grant user rights, two versions (rowiki and hywiki) had no users with this role. Ten established user groups had no members in any language version.

The highest number of UGs (28) occurred in enwiki, while the lowest (6) in hywiki. Some UGs had only one right, e.g. the extended confirmed users could only edit pages protected as “Require extended confirmed access”, while the file movers could only rename media files. By contrast, the administrators have the largest number of user rights in every language version, although the number assigned to this group varies: at the time of the study, it was 81 in plwiki, 79 in ewiki and 76 in eswiki. In addition, anyone with a Wikipedia account has around 20 user rights, depending on the version.

Some language versions include UGs that permit delegation of user rights. This means that the user does not need to obtain administrator rights in order to carry out some tasks freely. These additional rights lengthen the “career progression pathway”. For example, the reviewer role has been introduced in eight language versions, allowing articles to be designated “free from vandalism”. Administrators, who can grant and revoke this right, monitor the quality of the work of the editors who hold it.

This study assumes that a larger number of UGs requires a larger number of administrators. Statistical tests carried out on 42 language versions of Wikipedia revealed that there is a clear correlation between the two variables in this case. For $p < 0.000001$, Spearman’s rho correlation is 0.689786. Thus, H1 can be accepted. These relationships are shown in Figure 1. This result suggests that as the community seeks to have more administrators, there is a tendency to create new bundles of user rights.

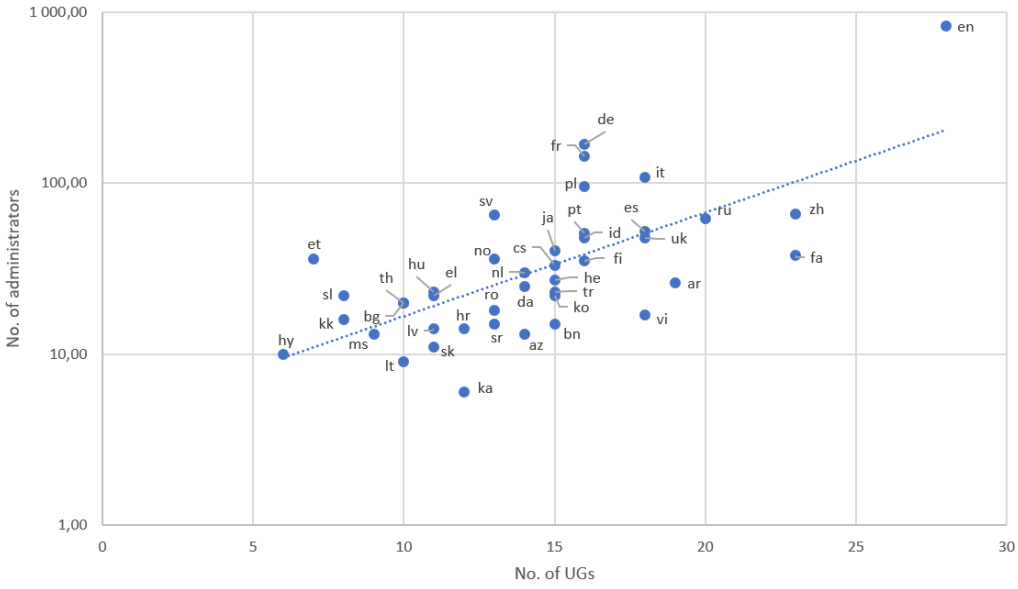


Figure 1: The relationship between the number of administrators and the number of user groups; N = 42

The relationship between the basic UGs may also indicate the expansion of the hierarchical structure. H2 posits that as the number of administrators increases, so too will the number of bureaucrats. The statistical test carried out also supported its acceptance. At p = 0.000036, Spearman's rho correlation is 0.604903; therefore, there is a relatively strong statistical relationship between the variables, which is presented in Figure 2. It is worth noting some exceptions to the trend in the case of ltwiki and skwiki, where there was only one bureaucrat. Another exception to this trend is the eswiki, where anyone granted administrator rights is automatically granted bureaucrat rights as well, which sets this language version apart in terms of the trust it places in its users.

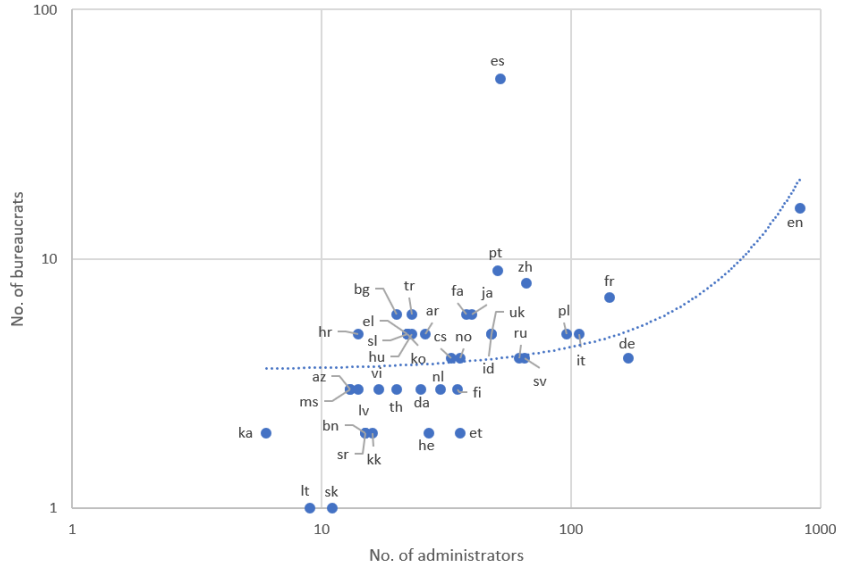


Figure 2: The relationship between the number of administrators and the number of bureaucrats; N = 40

In the subsequent part of the study, variables relating to exclusionary power in selected language versions of Wikipedia were compared with the PDI scores for individual countries. After excluding four language versions (edited by communities from a larger number of countries with different PDIs), no statistically significant correlation was found between these variables. Considerable dispersion was particularly evident in the case of the largest of the language versions analysed. Accordingly, hypothesis testing was carried out for Wikipedia language versions involving fewer than 10,000 users. Following this adjustment, it was found that there was a weak negative correlation: for p = 0.042674, Spearman's rho correlation was -0.360499. Therefore, H3 can be

accepted for populations with fewer than 10,000 active Wikipedians. Interestingly, in this case, it was the total number of administrators that correlated with the PDI score, rather than their percentage. These relationships are illustrated in Figure 3.

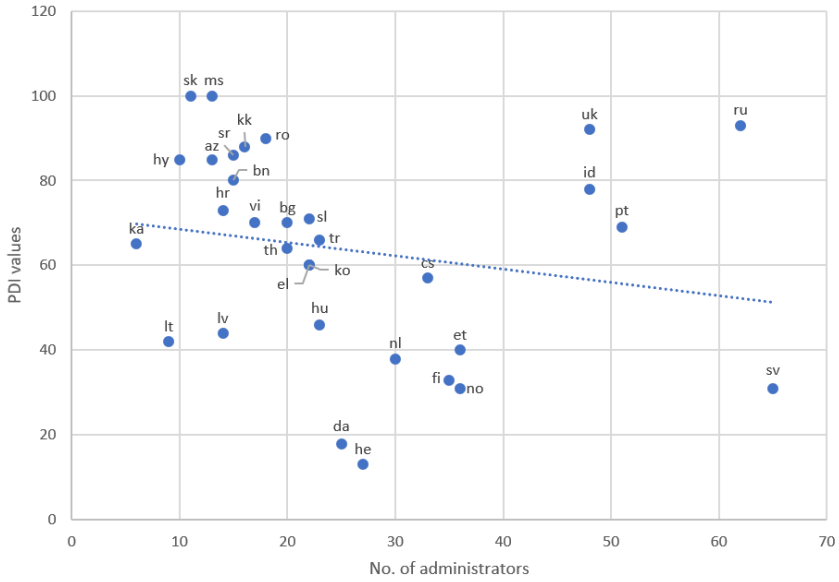


Figure 3: The relationship between the number of administrators and PDI values; N = 32

Additionally, a considerable deviation from the trend line can be observed, among others, in the case of ruwiki. If this version was excluded, the relationship might be stronger. Since 2025, there has been a significant decline in the number of active users on ruwiki, resulting from restrictions on online activity in Russia. This community used to be much larger.

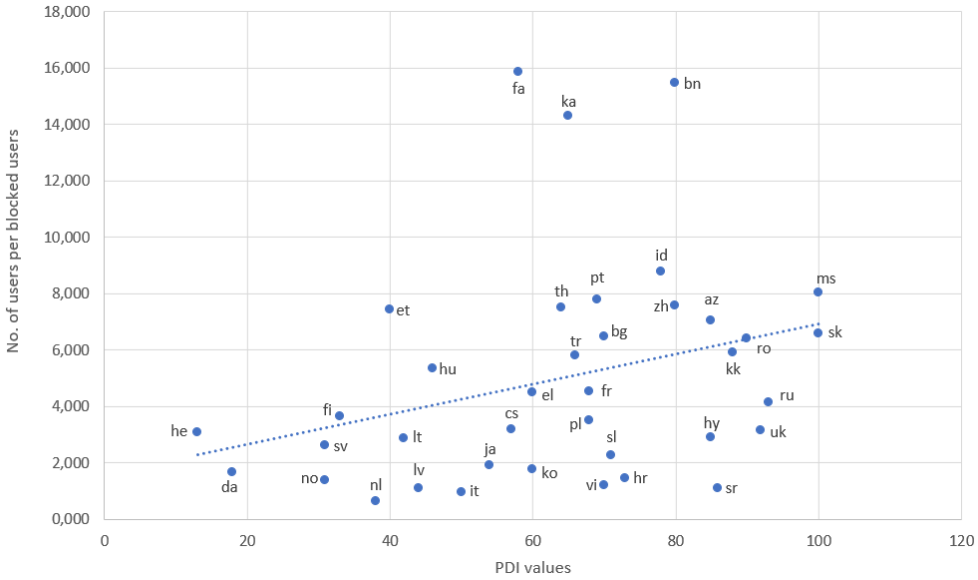


Figure 4: The relationship between the ratio of new users to blocked users and PDI values; N = 38

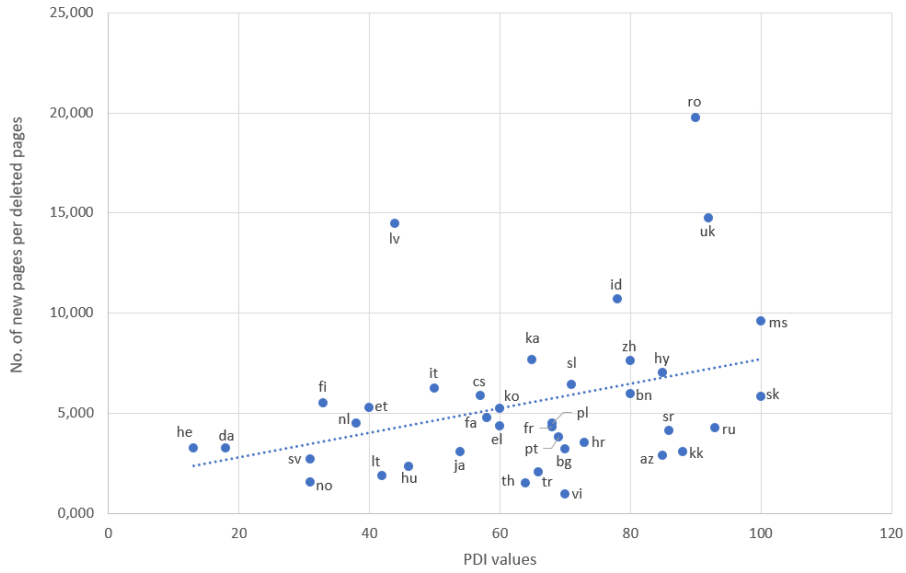


Figure 5: The relationship between the ratio of new pages to deleted pages and PDI values; N = 38

The final part of the study involved testing H4 and H5 across 38 language versions (excluding enwiki, dewiki, eswiki and arwiki). When exercising power to exclude, the most common practice is to remove new pages and block new users. Consequently, for H4, the PDI values were compared with the ratio of new users to blocked users, and for H5, the PDI values were compared with the ratio of new pages to deleted pages. Both hypotheses were accepted. For the former hypothesis, Spearman's rho correlation is 0.373160 with p = 0.021026; whereas in the case of the latter, Spearman's rho correlation is 0.339883 with p = 0.036816. These relationships are presented in Figure 4 and Figure 5. Importantly, the PDI values did not correlate with the components of these variables: new pages, deleted pages, new users or blocked users, nor with other tasks performed by administrators. It was also noted that page deletions occurred most frequently on thwiki, kkwiki, trwiki, kawiki, ltwiki, arwiki and nowiki (accounting for over 85% of administrator actions), while user blocks occurred relatively most frequently on nlwiki, itwiki, lvwiki, dawiki, cswiki, jawiki and eswiki (accounting for over 20% of administrator actions). No similarity was observed between Hofstede's cultural dimensions within either of the two groups.

5. Discussion and Conclusions

Although the structure of user rights in the studied language versions of Wikipedia includes 60 different UGs, the prevailing discourse on the exercise of power within Wikipedia is usually limited to administrator accounts. Becoming an administrator was supposed to be "no big deal". However, it became clear even in the early years that this posed a serious challenge for Wikipedians (Burke and Kraut, 2008). As the rights assigned to administrators grew, candidates were required to know how to use them. This also led to the creation of further user groups that could only use some of the administrator rights. Research suggests that the number of UGs increases when a particular version already has a large number of administrators. Therefore, delegating user rights to specially created groups helps to reduce the workload of administrators.

This is also the case with the granting of user rights, which was previously the prerogative of bureaucrats, as administrators can now assign users to specific UGs. Consequently, on the one hand, the structure of user rights is more tall, while on the other hand, the base of the hierarchical pyramid is broadened. As more UGs are formed, there is a need for a broader understanding of how to monitor the quality of the work carried out by the users assigned to such groups. Having more administrators may allow for greater specialization in this area.

However, the number of administrator groups in the various language versions has not increased when looking at trends following the year 2010, when the number of UGs began to rise. Although their rights primarily relate to the elimination of inappropriate content and behaviour, they are also expected to contribute to the creation of the encyclopedia's content. A significant proportion of administrators are actively involved in coordinating operations within smaller collaborative networks, as noted in previous studies (Morgan et al., 2013; Qin, Cunningham and Salter-Townshend, 2015). This involvement is important enough that Wikipedia communities

call for resignation from the function of an administrator when administrators become insufficiently active in the project. Further research could make it possible to capture the relationship between informal collaboration networks and the hierarchical user-rights structure.

Although PDI would seem to be a cultural dimension that should affect the power structure, capturing the relationship in this respect proved difficult. A particularly interesting case was the negative correlation between PDI and the number of administrators in Wikipedia versions with fewer than 10,000 active Wikipedians. It can be presumed that if communities do not reach a certain critical size, the considerable power distance limits the number of users who are granted administrator rights. In turn, the relationships between PDI and the less frequent use of exclusionary power may confirm the earlier suppositions of researchers that a higher PDI favours weaker tendencies to interfere in the actions of others. However, this may also be the effect of less frequent destructive behaviour in communities recruited from countries with a higher PDI, if greater politeness is indeed present in them (Hara, Shachaf and Hew, 2010). Ttherefore this would probably also lead to greater respect for someone else's work.

The weak relationships between PDI and the developed user-rights structure may result from Wikipedia's organizational culture becoming stronger than the national cultures from which Wikipedians originate. As Park et al. (2015) emphasized, online cultures may differ significantly from offline cultures. This indicates that further research into cultural diversity should focus more on endogenous factors. This study identified a fairly clear distinction between instances where administrators focus largely on deleting pages and those where they more frequently block other users. These could be two philosophies of dealing with the problem of undesirable content: focusing on deleting articles or focusing on blocking the users who publish it.

One limitation of the present study is that the analysis focused on the current structure of user rights. The correlations observed could therefore result from temporary fluctuations. An analysis of data from previous years would make it possible to determine whether such a suspicion should be ruled out. Conversely, replacing the traditional cultural dimensions used in subject-related literature with dimensions based on Wikipedia's system of norms and values would make it possible to describe the diversity across a larger number of projects.

Ethics Declaration: I declare that the study is based on publicly available data and open-source data and, as such, the nature of this study did not warrant review by an ethics committee.

AI Declaration: I declare that I did not use AI in this article; the entire text was written manually.

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Enacting Explainability: Knowledge Practices Around Generative AI in a Consulting Firm

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Abstract: As generative AI becomes embedded in knowledge-intensive work, organizations face a central paradox: AI systems produce influential outputs while their inner workings remain opaque. Although explainability research has largely focused on technical methods, less attention has been given to how organizational actors practically make sense of and govern AI-generated knowledge. This study adopts a knowledge-practice perspective to examine how explainability is enacted in everyday work within a mid-sized consulting firm. The study is based on a qualitative case design involving nine semi-structured interviews with AI practitioners, clients, and an AI expert. Rather than treating explainability as a technical property, the analysis explores how consultants interpret, validate, and operationalize AI outputs in the absence of formal governance structures. The findings show that explainability is enacted as a situated and role-dependent knowledge practice. First, employees assess outputs pragmatically, focusing on whether they "make sense" in context rather than seeking insight into model internals. Second, prompting emerges as a form of tacit expertise developed through trial-and-error learning, functioning as an informal mechanism for influencing and interpreting outputs. Third, actors rely on local validation routines such as re-running prompts and cross-checking information to manage uncertainty and maintain trust. Finally, the absence of internal guidelines results in individualized and uneven practices, indicating that knowledge about AI use is created but not institutionalized. From a Knowledge Management (KM) perspective, the study contributes by conceptualizing explainability as an emergent knowledge practice shaped by situated sensemaking, tacit skill development, and informal governance. It extends knowing-in-practice research by illustrating how organizations cope with opaque digital systems when formal knowledge infrastructures lag behind technological adoption. For KM practice, the findings highlight the need for lightweight governance mechanisms, shared prompting norms and role-adapted guidelines that support collective knowledge development around AI use.

Keywords: Knowledge practices, Organizational knowing, Generative AI, Explainability, Knowledge governance

1. Introduction

Generative artificial intelligence (AI) is rapidly becoming embedded in knowledge-intensive work, transforming how organizations produce, interpret, and apply knowledge. In domains such as consulting, employees increasingly rely on AI systems to generate analyses, summaries, and recommendations that directly influence professional outputs. These systems are increasingly embedded in organizational processes, particularly in knowledge-intensive sectors such as consulting (Lari and Manu 2024). However, organizations face significant challenges in implementing and integrating AI into existing practices, including issues related to governance, trust, and organizational readiness (Raftopoulos 2024). This growing reliance introduces a fundamental tension: while AI systems can produce highly useful and persuasive outputs, their internal workings are often difficult to interpret for end users. This creates challenges for understanding, validating, and justifying AI-generated knowledge in organizational contexts (Miller 2019; Rai 2020).

Existing research on explainability has primarily approached this issue from a technical perspective, focusing on methods that make machine learning models more transparent or interpretable (e.g., Lundberg and Lee 2017; Ribeiro et al. 2016). While such approaches are important, they often assume that explainability is a property that can be engineered into the system itself. In practice, however, many widely used AI tools, particularly generative AI systems, remain effectively "black-boxed" from the perspective of everyday users. As a result, the challenge of explainability is not resolved solely through technical design but emerges as a practical concern in how users make sense of and work with AI outputs (Burrell 2016).

From a Knowledge Management (KM) perspective, this raises important but underexplored questions. KM research has long emphasized that knowledge is not only stored in systems, but enacted through practice, shaped by context, and embedded in social interaction (Alavi and Leidner 2001). More recent work highlights how digital technologies, including AI, are reshaping knowledge processes by augmenting human capabilities while also introducing new forms of uncertainty and complexity. For instance, Jarrahi et al. (2023) argue that AI

should be understood as a partner in knowledge work, requiring new forms of human–AI collaboration and sensemaking. Similarly, Alavi et al. (2024) emphasize that generative AI challenges traditional KM assumptions by altering how knowledge is created, validated, and governed.

Despite these advances, little is known about how explainability is enacted in everyday organizational practice. While AI research often focuses on improving model transparency, and KM research examines knowledge processes more broadly, limited attention has been given to how organizational actors actually produce "explainability" when working with AI systems whose inner logic is not accessible. We lack insight into how users interpret AI outputs, develop trust, and establish defensibility in contexts where formal explanations are limited or absent.

This study addresses this gap by adopting a knowledge-practice perspective to examine how explainability is enacted in AI-enabled knowledge work. Rather than treating explainability as a technical feature, the study conceptualizes it as a situated and socially embedded practice through which actors render AI outputs understandable, usable, and justifiable. This perspective aligns with knowing-in-practice approaches in KM, which view knowledge as something that is performed, negotiated, and situated in action rather than simply transferred or stored (Nicolini et al. 2003; Orlikowski 2002).

We conducted a qualitative case study of a mid-sized consulting firm where generative AI tools are increasingly integrated into daily work processes. Through semi-structured interviews with employees, clients, and an AI expert, we explore how actors interpret, validate, and operationalize AI-generated outputs in the absence of formal governance structures and standardized practices.

The following research question guided the study: *How do organizational actors enact explainability as a knowledge practice when working with opaque AI systems?*

By addressing this question, the paper makes two primary contributions. First, it contributes to KM theory by conceptualizing explainability as a knowledge practice shaped by situated sensemaking, tacit skill development, and informal governance. Second, it provides empirical insight into how organizations cope with the challenges of AI-enabled knowledge work when technological capabilities outpace formal knowledge infrastructures. In doing so, the paper bridges AI explainability research and KM scholarship, highlighting the importance of organizing knowledge practices alongside technical systems for responsible and effective AI use.

2. Theoretical Framing: Knowledge Practices and Explainability in AI-enabled Work

2.1 Knowledge as Practice in Organizations

KM research has increasingly moved beyond viewing knowledge as an object that can be stored, transferred, or codified, toward understanding knowledge as something that is enacted in practice. Early KM work emphasized the role of information systems in capturing and distributing knowledge (Alavi and Leidner 2001). At the same time, a complementary stream of research has emphasized that knowledge is inherently situated, socially embedded, and inseparable from action (Brown and Duguid 2001; Polanyi 1962).

The knowing-in-practice perspective conceptualizes knowledge not as a static resource but as an ongoing accomplishment emerging through everyday work activities (Orlikowski 2002). From this perspective, knowing is enacted through situated action, shaped by context, experience, and interaction among actors. Similarly, practice-based approaches emphasize that knowledge is developed and expressed through routines, tools, and embodied skills within specific organizational settings (Nicolini 2011). These perspectives shift attention from formal knowledge structures to the micro-level practices through which knowledge is produced, interpreted, and validated. In uncertain and complex settings, actors rely on tacit knowledge, judgment, and situated sensemaking rather than formal knowledge representations. Knowledge practices, therefore, include not only formalized procedures but also informal routines, heuristics, and workarounds that enable actors to navigate ambiguous situations. This perspective is especially relevant in complex and distributed work settings, where knowledge must be coordinated across multiple actors and teams (Dingsøyr et al. 2018).

2.2 AI and the Transformation of Knowledge Work

The increasing integration of AI into organizational processes is reshaping how knowledge is created and used. AI systems can generate content, synthesize information, and support decision-making, thereby augmenting human capabilities in knowledge-intensive work. However, this transformation also introduces new challenges for KM.

Recent research suggests that AI should be understood as a collaborator in knowledge work rather than merely a tool. Jarrahi et al. (2023) argue that effective use of AI requires new forms of human–AI partnership, where users interpret and contextualize AI outputs rather than passively receiving them. In this sense, AI systems participate in knowledge processes, but do not replace the need for human judgment and interpretation.

In addition, generative AI challenges traditional assumptions about knowledge creation and validation. Alavi et al. (2024) highlight that AI-generated outputs blur the boundaries between knowledge creation and knowledge retrieval, raising questions about authorship, reliability, and governance.

As AI systems become more capable, the locus of knowledge shifts to distributed human–AI configurations, creating new challenges for knowledge evaluation and trust. Users may need to act on AI-generated outputs without fully understanding how they were produced or justified.

2.3 Explainability Beyond Technical Transparency

The challenge of understanding AI systems has been widely discussed in the literature on explainable artificial intelligence (XAI). Much of this research focuses on developing methods that make machine learning models more interpretable, such as feature attribution techniques and model-agnostic explanations (Lundberg and Lee 2017; Ribeiro et al. 2016). More broadly, XAI aims to increase the transparency and interpretability of AI systems (Gerlings et al. 2021). While these approaches contribute to technical transparency, they do not fully address how explanations are used and interpreted in organizational contexts.

Recent work on generative AI suggests that explainability challenges are further amplified in these systems due to their probabilistic and generative nature, requiring new conceptual approaches to understanding AI outputs (Schneider 2024). In such contexts, users often interact with AI systems whose internal reasoning remains inaccessible, placing greater emphasis on how outputs are interpreted and evaluated in practice.

Scholars have increasingly emphasized that explainability is not only a technical issue, but also a social and cognitive one. Miller (2019) argues that explanations must be meaningful to human users, taking into account how people understand and evaluate information. Similarly, Rai (2020) highlights that explainability should be considered in relation to user needs, decision contexts, and organizational requirements. From this perspective, explainability can be understood as a process rather than a property. Burrell (2016) distinguishes between different forms of opacity in machine learning systems, noting that even when technical transparency is improved, systems may remain difficult to interpret for non-experts. This suggests that explainability cannot be fully "designed into" AI systems but must also be constructed through interaction and use. This perspective opens up a practice-based understanding of explainability, where explanations are enacted through interaction rather than solely embedded in technical systems.

2.4 Toward a Knowledge-practice Perspective on Explainability

Despite this growing recognition of the human-centered nature of explainability, there remains limited integration between XAI research and KM theory. In particular, little attention has been paid to how explainability is enacted as part of everyday knowledge practices in organizations.

Drawing on a knowledge-practice perspective, this study conceptualizes explainability as an emergent organizational accomplishment. Rather than being located within the AI system itself, explainability is produced through the practices by which actors interpret, validate, and communicate AI-generated outputs. This includes the use of tacit skills, such as prompting, as well as informal routines for verifying and contextualizing results.

This perspective highlights three important aspects. First, explainability is situated: it depends on the specific context in which AI outputs are used and evaluated. Second, it is relational: different actors require different forms of explanation depending on their roles and responsibilities. Third, it is organizational: the extent to which explainability practices are shared, standardized, or institutionalized depends on the presence of governance structures and collective norms.

By framing explainability as a knowledge practice, the study bridges KM and AI research, shifting the focus from technical transparency to the organizational processes through which AI-generated knowledge becomes meaningful and actionable. This provides a foundation for analyzing how organizations cope with the challenges of AI-enabled work when technological capabilities outpace formal knowledge infrastructures.

3. Research Context

This study is based on a qualitative case study conducted in a mid-sized Norwegian consulting firm operating in digital transformation, data analytics, and technology advisory services. The company has actively adopted generative AI tools in both internal and client-facing work, making it a relevant setting for examining AI-enabled knowledge practices. Consultants use AI for tasks such as drafting reports, generating analyses, summarizing information, and supporting problem-solving activities, with outputs often contributing directly to client deliverables.

At the time of the study, AI adoption was widespread but largely driven by individual experimentation rather than formal organizational initiatives. As a result, employees displayed varying levels of AI use and expertise, ranging from frequent application in analytical and advisory work to more selective use for information retrieval, drafting, and idea generation. The organization had not yet established formal guidelines or standardized procedures for AI use, and employees relied largely on individual experience and informal practices. This provided a suitable setting for exploring how explainability is enacted in contexts where AI systems are widely used, yet formal knowledge governance structures remain under development.

4. Research Method

The study adopts a qualitative case study approach, which is well suited for exploring knowledge practices in organizational settings (Yin 2018). Data were collected through nine semi-structured interviews with practitioners from a consulting firm, two client representatives, and an AI expert. Participants had varying levels of experience with generative AI, enabling insights across roles and contexts (Table 1).

Interviews focused on participants' experiences of using AI in their work, including how they interpreted, validated, and communicated AI-generated outputs. Semi-structured interviews enabled participants to elaborate on their experiences while ensuring comparability across interviews (Kvale and Brinkmann 2009; Myers and Newman 2007). Interviews were conducted digitally, recorded, and transcribed. Limited follow-up questions were conducted via email to clarify selected findings.

The data were analyzed using an iterative thematic analysis informed by abductive reasoning (Langley 1999). Initial coding focused on how participants described understanding, validating, and explaining AI outputs. Codes were grouped into broader themes through comparison and categorization (Miles et al. 2018). Guided by a knowledge-practice perspective, the analysis identified five themes: explainability as situated judgment, prompting as tacit skill, local validation practices, role-dependent knowing, and absence of institutionalization.

As a single-case study, the findings are intended for analytical rather than statistical generalization (Yin 2018). The case provides insight into how explainability is enacted as a knowledge practice in AI-enabled work.

Table 1: Overview of interview participants in the study

Participant Group	N
AI Expert	1
Clients	2
Practitioners	6

5. Findings

5.1 Explainability as Situated Judgment

Across participants, explainability was rarely described in technical terms. Instead, it was understood as a practical judgment about whether AI-generated outputs were meaningful and appropriate for the task at hand. Rather than seeking insight into how models function internally, participants emphasized their ability to assess outputs based on experience and contextual relevance.

As one participant explained:

> *"Explainability, for me, is about whether the answer makes sense in the context I'm working in."*

Similarly, another noted:

> *"I don't really need to understand the model. I just need to be confident that what it gives me is usable."*

These accounts suggest that explainability is enacted through situated sensemaking. Participants draw on prior knowledge and contextual understanding to evaluate outputs, shifting attention from algorithmic transparency to the plausibility and usefulness of results.

5.2 Prompting as Tacit Skill

A central aspect of working with AI systems was the ability to formulate effective prompts. Participants consistently described prompting as something learned through experience rather than formal training. This competence was developed iteratively through trial and error and refined over time.

One participant described this process: "You learn by trying different things. Over time you figure out how to ask in a way that gives better answers."

Another emphasized the importance of formulation:

> *"It really depends on how you phrase it. If the prompt is unclear, the output is unclear."*

Prompting thus functions as a form of tacit knowledge. It is not easily articulated or standardized, but embedded in practice and individual experience. This skill becomes particularly important in contexts where AI systems are opaque. Instead of accessing explanations from the system, users shape and interpret outputs through their ability to interact effectively with it. At the same time, the development of prompting competence appears uneven across participants. Some reported a high degree of confidence and experimentation, while others relied on more basic usage patterns. This suggests that explainability is partly dependent on individual capability, reinforcing its practice-based nature.

5.3 Local Validation Practices

In the absence of formal explanation mechanisms, participants described a range of informal strategies for assessing the reliability of AI-generated outputs. These practices included re-running prompts, comparing outputs across tools, and manually verifying information.

One participant explained:

> *"If I'm unsure, I'll run the same prompt again or tweak it slightly to see if I get the same result."*

Another highlighted the need for caution:

> *"Sometimes it sounds very convincing, but when you look closer, it's not correct."*

These practices constitute local validation routines. Rather than relying on system-provided explanations, participants actively test and verify outputs through iterative interaction. This involves comparing results, checking consistency, and applying professional judgment. Such practices represent a form of epistemic work, where users take responsibility for establishing the credibility of AI-generated knowledge. Explainability is therefore not only about interpretation, but also about validation. It emerges through a combination of interaction with the system and external verification processes.

5.4 Role-dependent Knowing

The findings also indicate that explainability is not uniform across participants but varies depending on role and context. Different actors require different forms and levels of explanation, reflecting their responsibilities and use of AI outputs.

As one participant noted:

> *"For some people, it's enough to get a short answer, while others need more detail to trust it."*

Another emphasized the difference between technical and non-technical perspectives:

> *"If you're working closely with the technology, you might want more insight. But for others, it's more about whether it works."*

This highlights that explainability is relational and audience-dependent. What counts as a sufficient explanation depends on who the user is, what they need to accomplish, and how the output will be used. For consultants, explainability is often tied to the ability to justify outputs to clients, while clients themselves may focus on clarity and usability rather than technical detail. Explainability is therefore not a fixed property, but negotiated across different roles and contexts.

5.5 Absence of Institutionalization

Despite the widespread use of AI tools, participants reported a lack of formal organizational structures guiding their use. There were no standardized procedures, shared guidelines, or formal training related to explainability.

One participant stated:

> *"We don't really have any guidelines. People just use it in their own way."*

The absence of institutionalization results in individualized and uneven explainability practices. While this allows flexibility and experimentation, it also creates inconsistencies in how AI outputs are interpreted and validated. From a KM perspective, knowledge about AI use is generated but not systematically shared or embedded in organizational practices. Taken together, the findings suggest that explainability is enacted through interconnected knowledge practices rather than embedded in AI systems. The following section develops a framework to conceptualize how these practices operate across individual, relational, and organizational levels.

6. Discussion

6.1 Explainability as Knowing-in-practice

This study examined how explainability is enacted in AI-enabled knowledge work. The findings suggest that explainability is not primarily embedded within AI systems but emerges through situated practices of interpretation, interaction, and validation. This extends explainable AI research, which has largely focused on technical mechanisms for increasing transparency (Lundberg and Lee 2017; Ribeiro et al. 2016), by showing how explainability is realized in organizational settings.

The findings align closely with knowing-in-practice perspectives in KM (Orlikowski 2002). Explainability is achieved not through access to model internals, but through the practices by which users interpret outputs, refine prompts, and validate results. Prompting emerges as a form of tacit knowledge, while local validation routines illustrate how credibility is established through practice rather than formal verification systems.

Rather than replacing human knowing, AI introduces new forms of uncertainty that require interpretation and judgment. This reflects broader KM insights into the importance of experiential and embodied knowledge in complex work settings (Nicolini 2011).

6.2 A Practice-Based Framework of Enacted Explainability

Building on these insights, this study proposes *a practice-based framework of enacted explainability* (see Figure 1). The framework conceptualizes explainability as an organizational accomplishment emerging through interconnected knowledge practices. It highlights how explainability is enacted across three levels: micro, relational, and organizational, each shaping how AI outputs are interpreted, validated, and applied in practice.

The figure illustrates how explainability in AI-enabled work emerges across three interconnected levels: situated knowledge practices at the micro level, role-dependent knowing at the relational level, and knowledge governance at the organizational level. When AI systems are opaque, explainability is produced through the interaction of these levels rather than embedded within the system itself.

At the micro level, explainability is enacted through situated knowledge practices, including contextual judgment, tacit prompting competence, and local validation routines. At the relational level, explainability is shaped by role-dependent knowing, as different actors require different forms of explanation depending on their responsibilities and contexts of use. At the organizational level, explainability is influenced by governance structures that shape how practices are shared, coordinated, and institutionalized. Together, these levels illustrate that explainability is not located within the AI system itself but distributed across a network of practices, roles, and structures.

The framework proposes that when AI systems are opaque, explainability shifts from being a system-level property to becoming a distributed organizational accomplishment. The three levels should not be understood as independent. Situated practices are shaped by role-specific expectations, while both are influenced by the presence or absence of governance structures. At the same time, repeated practices may become shared routines that gradually influence organizational norms and governance arrangements. Explainability therefore emerges through ongoing interactions between individual action, social context, and organizational structures. By conceptualizing explainability in this way, the framework extends knowing-in-practice perspectives by showing how new forms of knowing emerge in response to technologically mediated uncertainty.

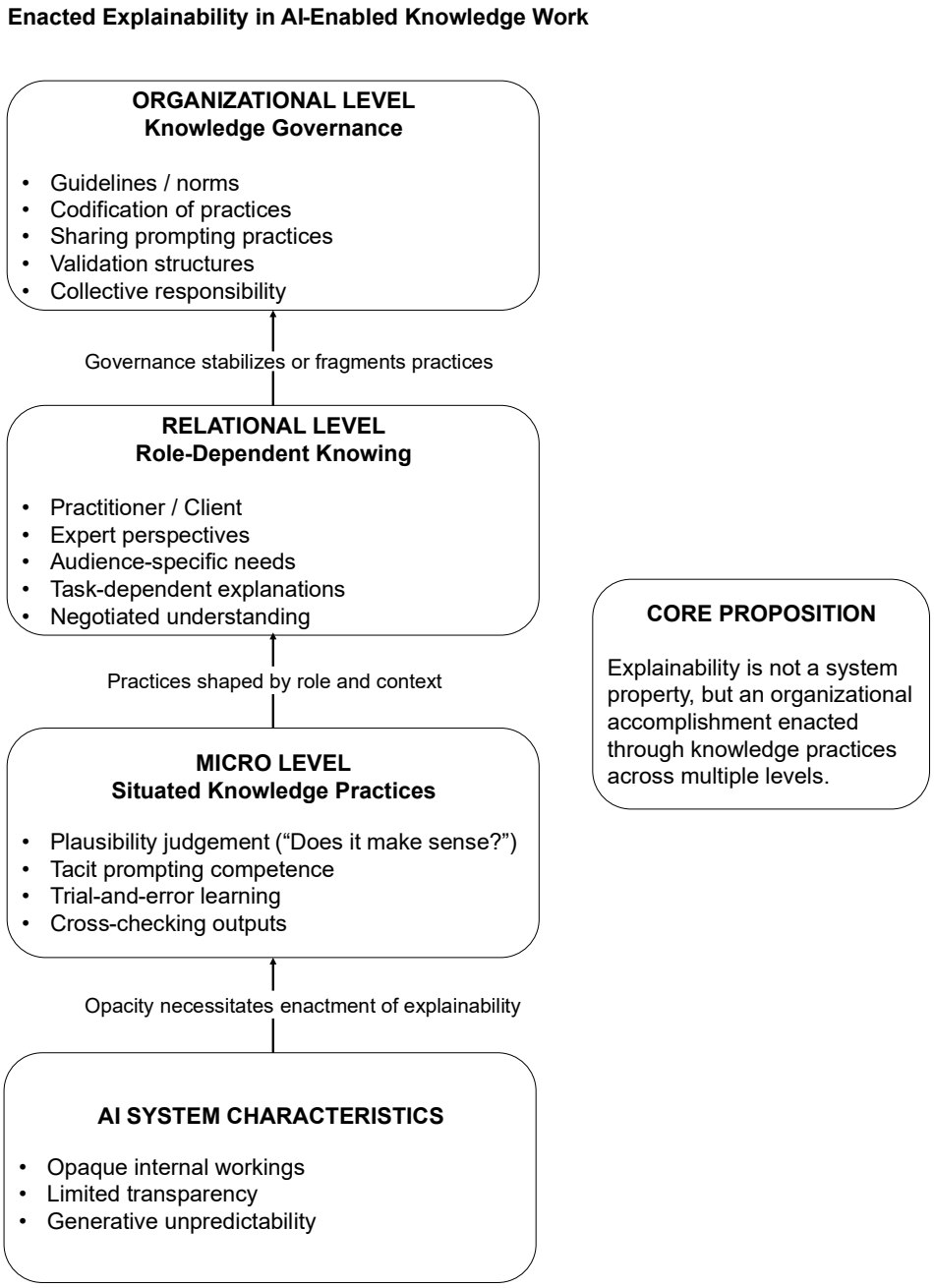


Figure 1: A Practice-Based Framework of Enacted Explainability in AI-Enabled Knowledge Work.

6.3 Implications for KM Theory

The study contributes to KM theory in three ways. First, it extends knowledge-practice perspectives by introducing explainability as a distinct form of knowing-in-practice. While prior research has emphasized how knowledge is enacted in organizational contexts, this study shows how explainability becomes an ongoing accomplishment when working with opaque AI systems. Second, the findings demonstrate the continuing importance of tacit knowledge in AI-enabled work. Prompting emerges as a competence developed through experience rather than formal training, suggesting that AI adoption reconfigures rather than replaces tacit knowledge. Third, the study highlights the role of knowledge governance in shaping AI use. The absence of shared norms and guidelines results in fragmented practices, underscoring the need for KM mechanisms that support the coordination and institutionalization of AI-related knowledge.

This finding aligns with recent research on responsible AI, which highlights the challenges of translating high-level principles into organizational practice (Akbarighatar et al. 2025). More broadly, it underscores the

importance of coordinating knowledge practices across organizational actors in complex knowledge work environments (Dingsøyr et al. 2018).

While situated judgment, tacit prompting competence, and local validation routines enable productive use of opaque AI systems, they also introduce risks. When explainability relies heavily on individual expertise and informal practices, organizations may experience inconsistencies in how AI outputs are interpreted, validated, and communicated. In consulting environments, such variability may create challenges related to accountability, quality assurance, and organizational learning. This suggests that explainability should be viewed not only as an individual capability but also as an organizational capability requiring coordination and governance.

These contributions align with recent calls to integrate AI more explicitly into KM research (Alavi et al. 2024; Jarrahi et al. 2023). In doing so, the study extends knowing-in-practice perspectives by conceptualizing explainability as a distinct form of knowledge work in AI-enabled contexts.

6.4 Implications for Practice

The findings also have important implications for organizations seeking to manage AI-enabled work. First, organizations should recognize that explainability cannot be addressed solely through technical solutions. Even when explainability tools are available, users must still interpret and apply outputs in context. Supporting explainability therefore requires attention to how employees work with AI in practice. Second, the study highlights the importance of developing shared knowledge practices. This includes establishing guidelines for prompting, validation, and communication of AI outputs. Such mechanisms can help reduce variability and improve the consistency of AI use across the organization. Third, organizations should consider how explainability needs differ across roles. Rather than adopting one-size-fits-all solutions, organizations should develop role-adapted approaches that reflect different requirements for understanding and justification. Overall, managing AI in knowledge-intensive work is not only a technical challenge, but also a KM challenge. Organizations must develop structures and practices that enable users to work effectively with AI-generated knowledge.

7. Conclusion, Limitations and Future Research

This study has examined how explainability is enacted in AI-enabled knowledge work, shifting the focus from technical transparency to everyday organizational practice. Drawing on a qualitative case study, the findings show that explainability is not primarily achieved through access to model internals, but through situated knowledge practices such as contextual judgment, tacit prompting, and local validation routines. These practices are shaped by role-dependent needs and remain unevenly developed in the absence of formal governance structures. By conceptualizing explainability as a knowledge practice, the study contributes to KM research by extending knowing-in-practice perspectives into the context of generative AI. The proposed framework highlights that explainability emerges across multiple levels, micro, relational, and organizational, demonstrating that managing AI is not only a technical challenge, but also a matter of organizing how knowledge is produced, interpreted, and validated in practice. For organizations, the findings underscore the importance of supporting shared knowledge practices around AI use. Rather than relying solely on technical solutions, organizations should develop lightweight governance mechanisms, promote collective learning, and adapt explainability practices to different roles and contexts. As AI continues to evolve, future research should further explore how knowledge practices and governance structures co-develop with emerging technologies. Understanding this interplay will be essential for enabling responsible and effective use of AI in knowledge-intensive work.

This study is based on a single-case design, which limits the generalizability of the findings. Future research could explore similar dynamics in other organizational contexts or industries to assess the broader applicability of the framework. In addition, the study focuses primarily on user practices, rather than the design of AI systems themselves. Future research could examine how technical and organizational approaches to explainability interact, particularly in contexts where explainability tools are more actively integrated into workflows.

Ethical Declaration: Ethical clearance was not required for this research study.

AI declaration: Generative AI, ChatGPT (OpenAI), was used to assist with proofreading of this paper. The final text were critically reviewed and validated by the authors, who take full responsibility for the content of this publication.

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Factors Influencing Knowledge Sharing, Cooperation, and Relationship Building Between Academia and Business

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Abstract: Building relationships between businesses and research centres enables the creation of synergies that stimulate development and the flow of best practices. A key element of cooperation and the development of science-business relationships is the sharing of knowledge, which leads to the transformation of intellectual capital into organizational and market value; Technology Transfer Centres (TTCs) serve as intermediaries in the flow of knowledge between the academic community and the business sector. The aim of this article is to identify factors that facilitate cooperation between enterprises and scientific research centres, as well as factors limiting such cooperation, with a focus on the Kuyavian-Pomeranian region in Poland. The research conducted was part of a larger research project dedicated to improving the process of transferring and commercializing innovative solutions between science and the economy. The study covered enterprises from the Kuyavian-Pomeranian region in Poland and TTC units operating in Poland. Data were collected through computer-assisted telephone interviews (CATI), and the research tools consisted of questionnaires developed based on literature reviews. The study determined the significance for both groups of respondents of the factors identified by the research team as either facilitating or limiting cooperation between enterprises and scientific research centres. The findings can be used by businesses, universities, and research centres alike to better tailor their offerings and improve cooperation processes.

Keywords: Cooperation, Relationship building, Knowledge sharing, Technology transfer centres (TTCs)

1. Introduction

The modern global economy increasingly relies on intangible assets, which form the foundation of innovation and competitiveness. In the era of the knowledge-based economy, innovation is no longer viewed as the result of isolated actions by individual entities, but rather as the effect of synergy arising from a dense network of connections between the scientific sector and industry (Drewniak et al., 2023; Słupska et al., 2019; Bergman, 2010). Additionally, in recent decades, there has been a shift from a closed innovation model to an open model, in which organizations deliberately leverage external knowledge flows to accelerate innovation processes (Viederyte, 2020). In this context, the role of research centres has evolved beyond traditional functions of teaching and conducting basic research to include active participation in socio-economic development (Plata, 2024; Pukin, 2019). Businesses, in turn, increasingly view universities as strategic partners that provide not only a well-educated workforce but also unique expert knowledge (Bejerano et al., 2023; Almeida, 2021; Brodny and Tutak, 2022).

This article attempts to identify the factors that facilitate and limit cooperation between businesses and research institutions, with a focus on the Kuyavian-Pomeranian region in Poland. Despite numerous studies on cooperation between businesses and research centres, a research gap remains regarding the analysis of factors that facilitate and limit such cooperation, particularly when considering the diverse perspectives of the participants in the cooperation process.

2. Theoretical Background

In a knowledge-based economy, companies face ever-increasing pressure to seek innovative solutions and enhance their competitiveness. Acquiring the right knowledge- and skill-based resources—ones that are not at risk of becoming obsolete quickly—has become a key determinant of success for modern companies (Drewniak et al., 2023; Słupska et al., 2019). Knowledge resources in enterprises include so-called internal organizational knowledge and external knowledge. The former is knowledge accumulated over many years of the enterprise's development and encompasses established standards, patterns of behaviour and operations, as well as patents, licenses, inventions, and improvements (Nonaka et al., 2000). External knowledge, on the other hand, lies at the boundary between the enterprise and its environment (Gold et al., 2001). It is acquired

through building relational competencies and learning from one another. Nowadays, a company's competitive advantage is based not only on its internal resources but is also shaped by the outcomes of cooperation with its environment (Słupska, 2023). This compels companies to deliberately manage knowledge flows both into and out of the organization to accelerate market innovation (Viederyte, 2020). Additionally, internal knowledge resources form the foundation of absorptive capacity, which determines an organization's readiness to recognize the value of external knowledge and to effectively assimilate and commercially exploit it (Viederyte, 2020; Ryszko, 2015; Dell'Anno and Del Giudice 2015).

Academic research centres are identified as a strategic source of knowledge, providing talent and unique expertise (Reichert, 2019). Perkmann et al. (2013) describe universities' engagement in industry cooperation primarily as formal activities, such as collaborative research, contract research, and consulting, as well as informal activities, such as providing ad hoc advice and networking with practitioners. It is precisely these informal channels that often prove more effective from the perspective of tacit knowledge transfer, which conflicts with the tendency toward formalization and bureaucratization of cooperation evident in the policies of many universities. Universities actively provide resources in the form of talent and scientific research, facilitating the co-creation of knowledge among partners through intermediary services, shared organizational structures, and access to researchers and research infrastructure. Additionally, universities have a natural inclination to explore the frontiers of knowledge and discover new opportunities and technologies, as well as interdisciplinary approaches to problem-solving (Reichert, 2019). Therefore, building relationships between businesses and research centres enables the creation of synergies, which in turn stimulates the development and exchange of best practices (Jasińska, 2019). It should be noted, however, that the academic approach, based on openness and long-term cognitive exploration, conflicts with corporate logic, which seeks to appropriate results and ensure rapid implementation (Tzavidas, et al., 2020). Technology Transfer Centres (TTCs) act as intermediaries in the processes of knowledge flow between the academic community and the business sector, helping to partially alleviate these tensions. Their primary task is to build "technological bridges" that enable the commercial exploitation of research results (Bergman, 2010; Abbas et al., 2018). However, TTCs are often underfunded, operate under varying institutional conditions, and have their own internal limitations that affect their effectiveness in mediating between the distinct organizational cultures of science and business (Siegel et al., 2003).

A key element of cooperation and the development of science-business relationships is knowledge sharing—that is, the process of exchanging information and experiences that enables the transformation of individual intellectual capital into organizational and market value (Ryszko, 2015; Bylok, 2025). Despite obvious benefits, such as increased innovation, cost reduction, and access to financing, the process of building relationships between academia and business faces significant barriers related to, among other things, organizational differences, lack of trust, and communication difficulties (Dell'Anno and Del Giudice 2015; Fan and Beh, 2024; de Wit-de Vries et al., 2019). The literature has long emphasized that the motivation to share knowledge is not self-evident. Opportunistic behaviour, fear of losing a competitive advantage, or informal mechanisms for appropriating research results can effectively block cooperation even in the presence of formally concluded agreements (Dell'Anno and Del Giudice, 2015; Fan and Beh, 2024). Another important aspect of the cooperation between businesses and research institutions under consideration is the effectiveness of knowledge transfer. Knowledge transfer focuses on the practical application of research results and innovations in economic practice and aims to commercialize knowledge and solve specific industrial problems by providing new discoveries and technologies (Bejerano et al., 2023; Loučanová, 2025). The effectiveness of knowledge transfer depends largely on the so-called absorptive capacity of enterprises and the desorptive capacity of research centres, that is, their readiness to effectively transfer and utilize new solutions (Dell'Anno and Del Giudice 2015). However, the concept of desorption capacity remains less developed theoretically and empirically compared to absorption capacity, which constitutes a significant gap in the existing body of research. In summary, cooperation between research institutions and enterprises is a multidimensional process of exchanging resources, knowledge, and technology, which in a modern knowledge-based economy is evolving toward interactive co-creation (OECD, 2019).

3. Research Methodology

The completed studies form an integral part of a research project titled "Improving the Transfer and Commercialization of Innovative Solutions Between Science and the Economy." They were conducted in late 2024 and during the first months of 2025. The project included four main studies: a survey of companies in the Kuyavian-Pomeranian region of Poland, a study of TTCs in Poland, 10 case studies of the best TTCs in Poland, and three expert panels.

The survey of enterprises was conducted using two purposively selected samples, taking into account the minimum sample size. The first sample consisted of small and medium-sized enterprises, and the second sample consisted of large enterprises. A proportional distribution was applied, consistent with the number of entities, across the strata of manufacturing, service, and commercial enterprises. The list of entities was prepared based on data from the Statistical Office. The research tool was a questionnaire developed based on the relevant literature. The division into manufacturing, commercial, and service companies applied to each sample separately. In the group of small and medium-sized enterprises, the estimated sample size was 367. In the group of large enterprises, the estimated sample size was 66. The margin of error was set at 5% for SMEs and 10% for large enterprises. The group of respondents consisted of management representatives. Data were collected during computer-assisted telephone interviews (CATI).

The TTCs study planned to survey 100 entities. The majority of the surveyed entities were TTCs affiliated with the Association of Academic Technology Transfer Centres (PACTT). Due to their large number (93), the study was expanded to include non-affiliated TTCs. The research tool was a questionnaire developed based on the relevant literature. Among the TTCs affiliated with PACTT, 79 entities were ultimately surveyed, while 21 TTCs were not affiliated with PACTT. Respondents included TTCs managers or specialists with expertise in the studied area concerning TTCs cooperation with enterprises, as well as the transfer and commercialization of innovative solutions. Data were collected through computer-assisted telephone interviews (CATI).

This article presents excerpts from a survey of businesses and a TTCs study in the form of a mini-report on the factors influencing cooperation between businesses and research institutions. The survey on these factors included identically worded questions in the questionnaires, which made it possible to gather information from both parties involved in the cooperation. Due to the length of this article, the results of the business survey are presented in aggregate form.

4. Results

To present an analysis of the factors facilitating cooperation between businesses and academic research centres in the region under study, Table 1 first presents aggregated data for all surveyed businesses. The factor rated highest by the surveyed businesses was the high level of competence and expertise among university staff (73.2% - the sum of “high importance” and “very high importance” responses). Equally important was the opportunity for employee training and development (71.4%). Next, the companies identified factors such as: access to research infrastructure (66.3%) and access to funding and grants for research and development (65.9%). The factors of least importance according to the respondents included the university’s image and prestige (54%) as well as location and geographical proximity (56.4%).

Table 1: Factors facilitating cooperation between businesses and research centres (Total N=433)

Factors	Importance for cooperation between businesses and research institutions (facilitating importance) [scale used: 0 – not important; 1 – very low importance; 2 – low importance; 3 – moderate importance; 4 – high importance; 5 – very high importance]					
	0	1	2	3	4	5
access to funding and grants for research and development	11.3%	2.5%	9.2%	11.1%	17.6%	48.3%
access to research infrastructure	11.8%	1.2%	5.1%	15.7%	24.5%	41.8%
access to innovative ideas and research	12.7%	2.1%	6.7%	16.4%	23.6%	38.6%
access to modern technologies	12.2%	1.4%	5.5%	15.7%	17.8%	47.3%
the university’s flexibility and openness to business needs	12.2%	1.4%	5.3%	15.5%	25.2%	40.4%
location and geographical proximity	12.9%	1.4%	7.9%	21.5%	29.1%	27.3%
opportunity to carry out joint research and development projects	12.5%	1.4%	6.9%	14.5%	24.2%	40.4%
opportunities for employee training and development	11.5%	0.7%	4.2%	12.2%	26.6%	44.8%
networking and cooperation within clusters through university contacts	14.3%	1.6%	9.9%	15.5%	20.8%	37.9%

Factors	Importance for cooperation between businesses and research institutions (facilitating importance) [scale used: 0 – not important; 1 – very low importance; 2 – low importance; 3 – moderate importance; 4 – high importance; 5 – very high importance]					
	0	1	2	3	4	5
facilitations in recruiting highly qualified employees	12.5%	0.7%	7.4%	15.2%	26.6%	37.6%
university support in market analysis and product development	12.5%	1.8%	8.1%	14.8%	26.3%	36.5%
support from government and public policy	11.8%	1.6%	5.1%	17.3%	25.9%	38.3%
high level of competence and expertise among university staff	11.1%	1.4%	3.9%	10.4%	25.6%	47.6%
enhanced image and prestige through cooperation with renowned universities in the region	15.2%	1.4%	12.0%	17.3%	24.2%	29.8%

Source: Own work.

The TTCs survey found that access to modern technologies is the factor that most strongly encourages companies to cooperate with the TTCs surveyed (99.0% - the sum of "high importance" and "very high importance" responses). Also significant for establishing such cooperation were: access to funding and grants for research and development (91.0%), access to research infrastructure (90.0%), and support for companies in market analysis and product development (89.0%). The results are presented in Table 2.

Table 2: Factors facilitating cooperation between enterprises and the surveyed TTCs (Total N=100)

Factors	Importance for cooperation between businesses and research institutions (facilitating importance) [scale used: 0 – not important; 1 – very low importance; 2 – low importance; 3 – moderate importance; 4 – high importance; 5 – very high importance]					
	0	1	2	3	4	5
access to funding and grants for research and development	0.0%	0.0%	0.0%	9.0%	35.0%	56.0%
access to research infrastructure	0.0%	0.0%	0.0%	10.0%	66.0%	24.0%
access to innovative ideas and research	0.0%	0.0%	0.0%	21.0%	50.0%	29.0%
access to modern technologies	0.0%	0.0%	0.0%	1.0%	55.0%	44.0%
the university's flexibility and openness to business needs	0.0%	0.0%	3.0%	30.0%	38.0%	29.0%
location and geographical proximity	0.0%	0.0%	3.0%	33.0%	35.0%	29.0%
opportunity to carry out joint research and development projects	0.0%	0.0%	1.0%	20.0%	47.0%	32.0%
opportunities for employee training and development	0.0%	0.0%	1.0%	24.0%	42.0%	33.0%
networking and cooperation within clusters through university contacts	0.0%	0.0%	3.0%	11.0%	51.0%	35.0%
facilitations in recruiting highly qualified employees	0.0%	0.0%	4.0%	28.0%	38.0%	30.0%
university support in market analysis and product development	0.0%	0.0%	0.0%	11.0%	57.0%	32.0%
support from government and public policy	0.0%	0.0%	2.0%	35.0%	26.0%	37.0%
high level of competence and expertise among university staff	0.0%	0.0%	1.0%	14.0%	52.0%	33.0%
enhanced image and prestige through cooperation with renowned universities in the region	0.0%	0.0%	2.0%	31.0%	38.0%	29.0%

Source: Own work.

The data presented in Table 1 and Table 2 show that TTCs rated the factors surveyed as significantly more important in fostering cooperation. Additionally, it should be noted that among the TTCs surveyed, none of the respondents selected the "not important" option for any of the factors, which clearly distinguishes these assessments from those of businesses.

The study also examined factors limiting cooperation between enterprises and scientific research centres in the region. The most frequently cited limitations by enterprises were differences in goals and priorities between science and business (66.1% - sum of "high importance" and "very high importance" responses). Another significant obstacle was the lack of appropriate contacts and collaborative networks (60%). Other barriers included the low level of flexibility on the part of universities in adapting to business needs (58.4%) and differences in organizational culture (57.7%). Less importance was attributed to factors such as bureaucracy and formalities (51.3%), and risks related to intellectual property protection (52.4%). The results are presented in Table 3.

Table 3: Factors limiting cooperation between businesses and research centres in the region (Total N=433)

Factors	Importance for cooperation between businesses and research institutions (limiting importance) [scale used: 0 – not important; 1 – very low importance; 2 – low importance; 3 – moderate importance; 4 – high importance; 5 – very high importance]					
	0	1	2	3	4	5
lack of appropriate contacts and collaborative networks	18.0%	1.4%	6.2%	14.3%	21.5%	38.6%
differences in goals and priorities between academia and business	17.1%	0.5%	3.0%	13.4%	23.3%	42.7%
bureaucracy and red tape	17.3%	2.1%	7.9%	21.5%	28.4%	22.9%
high costs of cooperation with a university	16.6%	1.8%	10.9%	15.9%	25.9%	28.9%
low level of flexibility on the part of universities in adapting to business needs	16.9%	1.4%	5.3%	18.0%	24.2%	34.2%
differences in organizational culture	18.0%	0.5%	5.3%	18.5%	30.7%	27.0%
limited access to research results	17.6%	1.8%	9.2%	17.6%	26.6%	27.3%
lack of understanding and communication	17.3%	1.6%	9.7%	14.3%	18.9%	38.1%
lack of adequate human resources to undertake such cooperation	18.0%	1.6%	9.0%	15.7%	18.5%	37.2%
low support from administration and public policy	18.0%	2.8%	6.2%	18.0%	25.2%	29.8%
low awareness of the benefits of cooperation	17.6%	2.8%	8.1%	16.4%	26.3%	28.9%
risks related to intellectual property protection	19.9%	4.4%	10.2%	13.2%	20.8%	31.6%

Source: Own work.

In turn, the surveyed TTCs indicated that cooperation was primarily limited by: a lack of appropriate contacts and collaborative networks (89.0% - sum of "high importance" and "very high importance" responses), a lack of understanding and communication (88.0%), high costs of cooperation (87.0%), and bureaucracy and formalities (86.0%). The results are presented in Table 4.

Table 4: Factors limiting business cooperation with the surveyed TTCs (Total N=100)

Factors	Importance for cooperation between businesses and research institutions (limiting importance) [scale used: 0 – not important; 1 – very low importance; 2 – low importance; 3 – moderate importance; 4 – high importance; 5 – very high importance]					
	0	1	2	3	4	5
lack of appropriate contacts and collaborative networks	0.0%	0.0%	0.0%	11.0%	56.0%	33.0%
differences in goals and priorities between academia and business	0.0%	0.0%	2.0%	10.0%	56.0%	32.0%
bureaucracy and red tape	0.0%	0.0%	3.0%	10.0%	20.0%	67.0%
high costs of cooperation with a university	0.0%	0.0%	2.0%	12.0%	22.0%	64.0%
low level of flexibility on the part of universities in adapting to business needs	0.0%	0.0%	3.0%	17.0%	49.0%	31.0%
differences in organizational culture	0.0%	0.0%	1.0%	26.0%	39.0%	34.0%
limited access to research results	0.0%	0.0%	3.0%	27.0%	42.0%	28.0%
lack of understanding and communication	0.0%	0.0%	0.0%	31.0%	46.0%	23.0%
lack of adequate human resources to undertake such cooperation	0.0%	0.0%	1.0%	33.0%	39.0%	27.0%
low support from administration and public policy	0.0%	0.0%	3.0%	32.0%	39.0%	26.0%
low awareness of the benefits of cooperation	0.0%	0.0%	1.0%	35.0%	33.0%	31.0%
risks related to intellectual property protection	0.0%	0.0%	3.0%	33.0%	35.0%	29.0%

Source: Own work.

The data presented in Table 3 and Table 4 show that TTCs rated the factors surveyed as significantly more important in limiting cooperation. Additionally, it should be noted that among the TTCs surveyed, none of the respondents selected the “not important” option for any of the factors, which clearly distinguishes these assessments from those of businesses.

5. Conclusions

The study identified factors that facilitate and limit cooperation between businesses and research institutions in the region under study in Poland. The results reveal a consistent difference in perception between the two groups of respondents. TTCs rated both the factors facilitating and those limiting cooperation significantly higher (as being of greater importance) than business representatives. The vast majority of surveyed TTCs rated most of the analysed factors as being of high or very high importance, and none of the respondents representing TTCs indicated that any of the examined factors was irrelevant to cooperation. Businesses, on the other hand, were more reserved in their assessment of the importance of individual factors (both those facilitating and those limiting cooperation), and among the surveyed companies were entities that considered certain factors to be completely irrelevant to establishing cooperation with scientific research centres.

When it came to factors facilitating cooperation, the surveyed companies placed the highest importance on the high level of competence and expertise among university staff, as well as the opportunity to train their own personnel. Significantly, for the business sector, the ‘soft’ factor of academic staff expertise (73.2%) proved more important than the ‘hard’ factor of access to equipment and laboratories (66.3%). TTCs, on the other hand, identified access to modern technologies and access to R&D funding and grants as key factors facilitating cooperation. Both groups of respondents rated the image and prestige resulting from cooperation with renowned universities, as well as the partner’s location and geographical proximity, relatively lowest.

Among the factors limiting cooperation, the surveyed companies identified differences in goals and priorities, as well as difficulties in establishing contacts with representatives of the academic community, as the most significant barriers. TTCs, on the other hand, identified the lack of appropriate collaboration networks, a lack of understanding and communication, and the high costs of cooperation as the most serious obstacles. A particularly interesting finding is the discrepancy in the assessment of bureaucracy and complex procedures.

This factor was perceived as a significant barrier by 86% of TTC respondents, while among companies, this percentage was only 51.3%.

6. Discussion

The perspective of companies that place the highest importance on the competencies of research staff and the ability to train their own personnel confirms theoretical arguments emphasizing the importance of knowledge and skills for companies' ability to cooperate with the research sector and for their innovative activity (Drejer and Østergaard, 2017). These findings also align with the concept of absorptive capacity, according to which the ability to identify, assimilate, and utilize external knowledge forms the foundation of effective cooperation (Dell'Anno and Del Giudice, 2015; Muscio, 2007). Similar findings are presented by Fernández-Esquinas et al. (2016), who demonstrated that the most common forms of cooperate between firms and universities involve training, human resource exchange, and consulting services.

A more in-depth analysis may suggest that these discrepancies reflect differing understandings of the very value of science-business cooperation, which ties into the broader debate on the multidimensional nature of the motivations of participants in university-industry relationships (Perkmann et al., 2013). Companies demonstrate an orientation consistent with the principles of absorptive capacity and engage in relationships with academia not so much to acquire ready-made technological solutions, but to enhance their own ability to identify and assimilate external knowledge in the future. TTCs, on the other hand, exhibit an orientation characteristic of the institutional role of a technology intermediary (Siegel et al., 2003; Bergman, 2010). This duality of perspectives reveals significant differences. TTCs design cooperation offers centred on technological resources and financial instruments, while the surveyed companies primarily seek access to expert knowledge and opportunities to learn from academic partners. TTCs thus risk playing the role of an intermediary whose offerings remain structurally mismatched to the actual needs of the local business sector.

With regard to the factor of geographical proximity, the results obtained differ from the findings presented in the literature, where many authors emphasize that spatial proximity significantly fosters cooperation and the flow of knowledge (DellAnno and Del Giudice, 2015; OECD, 2019). However, the results are partially consistent with the research by Nilsen and Lauvås (2018), who demonstrated that social proximity combined with high organizational proximity allows for overcoming barriers resulting from short geographical distances. It can therefore be assumed that in the region under study, a partner's competencies and quality are more important than its location. This may be related both to the growing role of cross-regional cooperation and to the digitization of communication processes, which are gradually reducing the significance of the distance barrier.

The findings regarding barriers confirm that differences in goals and priorities constitute one of the most persistent obstacles to science-business cooperation (Howaniec and Okrzesik, 2015). What is surprising, however, is the reversal in the perception of the bureaucratic barrier. The fact that TTCs rate it significantly higher than businesses may suggest that it is the intermediary institutions that pay the most attention to complex procedures and safeguarding measures, rather than businesses. This result clearly diverges from earlier studies, which showed that bureaucracy is perceived as a serious barrier primarily by enterprises (Cyran, 2015), and requires further verification in subsequent research.

The findings have significant implications for the design of regional policies aimed at fostering science-business cooperation. Effective support instruments should take into account the dual nature of participants' motivations. Further analysis of the collected research data will include more advanced comparative and exploratory analyses, taking into account the differences between SMEs and large enterprises, in order to identify broader patterns regarding perceived factors of cooperation, which will help to a greater extent to fill the identified research gap.

Acknowledgements

This article was produced as part of a project carried out by the Bydgoszcz University of Technology entitled: Improving the transfer and commercialization of innovative solutions between science and the economy, "Science for Society II" - a publication co-financed from the state budget under the Ministry of Education and Science program titled "Science for Society II," project no. NdS-II/SP/0235/2024/01; co-financing amount: 1139.00 GBP; total project value: 626,941.33 PLN.

Ethics Declaration: No ethical clearance was needed for the research referred to in this paper.

AI Declaration: In preparing this article, the Consensus artificial intelligence tool was used to search for scientific articles addressing research on knowledge sharing and cooperation between businesses and academic research centres. The sources generated by the AI were verified by the authors. The authors bear full responsibility for the integrity and scientific credibility of the work.

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From Unstructured Procedural Text to Knowledge Graphs: Comparing LLM-based Extraction Strategies

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Abstract: As experienced workers retire across industrialized economies, organizations risk losing procedural expertise that often remains tacit, undocumented or scattered across unstructured documents. Translating this knowledge into structured, machine-readable representations is difficult to scale, labor-intensive, and prone to inconsistency when done manually. This paper addresses the automated construction of knowledge graphs from natural language procedural descriptions, developing a generic approach for transforming unstructured expert knowledge into structured knowledge graphs that support downstream retrieval and question-answering applications. Three text-to-knowledge-graph approaches were designed, implemented, and systematically evaluated. The first employed a large general-purpose language model (Qwen3-32B) with a single-stage zero-shot extraction prompt, the second applied the same strategy using a smaller base model (Llama2-13B), and the third combined supervised fine-tuning of the smaller model on synthetic extraction data with a decomposed extraction architecture targeting one to two ontology elements per phase. All approaches were evaluated across six procedural descriptions spanning multiple technical domains, with chunk size, model temperature, and ontology detail as configuration parameters. Results were assessed for intrinsic quality and extrinsic fitness for use, measured by question-answering accuracy in a Graph-RAG application. The results demonstrate that extraction strategy is a more decisive factor than model capacity. The fine-tuned model achieved a Question Answering (QA) pass rate of 55.3%, compared to 46.8% for the large model and 33% for the small base model, outperforming the general-purpose model on both intrinsic quality metrics and downstream performance. Average node degree, duplication rate, and ontology simplicity emerge as the strongest predictors of retrieval performance. Shorter ontologies consistently outperformed richer ones, suggesting that ontology design should be driven by the intended downstream application rather than semantic completeness. Over-extraction of procedural steps did not degrade performance but instead improved retrieval robustness by providing additional entry points for graph traversal. The findings offer practical guidance for designing scalable, locally deployable knowledge graph construction pipelines for procedural texts under computational and confidentiality constraints.

Keywords: Knowledge graphs, Large language models, Ontology, Procedural knowledge

1. Introduction

Demographic shifts are accelerating the loss of experienced workers across industrialized economies. In Germany alone, nearly 20 million baby boomers will retire by 2036, while only 12.5 million younger workers enter the workforce to replace them (Deschermeier and Schäfer, 2024). With each departure, organizations risk losing the operational expertise these workers have accumulated over years of practice, including established procedures, problem-solving strategies and process understanding that constitute much of an organization's institutional memory. A large part of this expertise is procedural knowledge, meaning knowledge of how to carry out defined tasks such as maintenance, assembly, or repair processes. This knowledge frequently remains tacit or scattered across unstructured natural language documents, making it inaccessible to automated systems and difficult to transfer reliably to non-experts. Consequently, there is a growing need for automated approaches that can transform unstructured procedural knowledge into structured, machine-readable representations. Knowledge graphs, structured networks of entities and their relationships, have become a pivotal technology for information retrieval, biomedical research and education, because they make the connections between concepts explicit and traversable (Hogan *et al.*, 2022). This property makes them particularly well-suited for encoding procedural knowledge, for which preserving the sequential and dependency relations between steps, tools, and conditions is essential. Unlike vector-based retrieval systems, which capture semantic similarity but discard relational structure, knowledge graphs retain these connections in queryable form. However, constructing knowledge graphs from procedural text remains often a manual process that is difficult to scale and prone to inconsistency. Recent advances in large language models have opened new possibilities for automating knowledge graph construction from text, as their zero-shot and few-shot capabilities allow information extraction without extensive domain-specific training data (Pan *et al.*, 2023). However, existing approaches have largely focused on general-purpose knowledge

extraction, while the systematic transformation of procedural text into ontology-conformant knowledge graphs remains underexplored. In particular, it is unclear how model capacity, extraction strategy, and ontology design interact to determine the quality of automatically generated procedural knowledge graphs. Further, most existing quality assessments rely on intrinsic structural metrics such as ontology conformance, connectivity, or completeness (Issa *et al.*, 2021; Seo *et al.*, 2022; R. Zhu *et al.*, 2023). Whether a knowledge graph that scores well on these metrics provides actual value in downstream applications, such as question answering for non-expert users, is rarely assessed (Zhu *et al.*, 2019). The disparity between structural quality and practical utility hinders the development of actionable design guidelines for automated knowledge graph construction pipelines. This paper addresses both gaps by designing, implementing and evaluating three LLM-based approaches for transforming unstructured procedural text into knowledge graphs conformant with the Procedural Knowledge Ontology. The approaches range from a single-stage zero-shot extraction using a large general-purpose model to a decomposed multi-stage pipeline built on a smaller model adapted through supervised fine-tuning on synthetic data. The most capable models are typically only available through cloud-based APIs, yet procedural knowledge in industrial settings is often confidential, favoring smaller models that can be deployed locally. Whether such models, when combined with task decomposition and fine-tuning, can match or exceed the extraction quality of larger cloud-hosted models is a central question of this work. All approaches are evaluated across six procedural descriptions from multiple domains, both through intrinsic quality metrics and through downstream question-answering accuracy in a Graph-RAG pipeline. The results show that extraction strategy is a more decisive factor than model capacity. The fine-tuned model outperforms the general-purpose model nearly three times its size on both evaluation dimensions. Average node degree, duplication rate, and ontology simplicity emerge as the strongest predictors of downstream retrieval performance. The rest of the paper is structured as follows: First, a general overview of related work that shapes the foundation of our research. Second, an overview of the methodology followed to reach the results. Third, results of implemented methodology. Fourth, a discussion on the relevance of the results. Finally, a summary, conclusion and directions for future work on this topic.

2. Related Work

2.1 Procedural Knowledge

(Sternberg, 2013) states that all knowledge can be divided into two categories: declarative knowledge, which is knowledge of facts, and procedural knowledge, which is knowledge of skill. (Surif, Ibrahim and Mokhtar, 2012; Curry *et al.*, 2025) describe procedural knowledge as ”how-to” knowledge or knowledge covering how to perform a certain task. (Eiriksdottir and Catrambone, 2011) add that procedural knowledge details the precise steps and methods required to complete a task, including the system states and the actions that change them. (Celino *et al.*, 2025) frame this in an industry context, defining procedural knowledge as the procedures employees must comply with to correctly perform tasks, with the aim of reducing risks and human errors. (Georgeff and Lansky, 1986) characterize procedural knowledge as sequences of actions for achieving goals, noting that representing this knowledge explicitly offers computational efficiency over reconstructing plans repeatedly from knowledge of atomic actions. (Carriero *et al.*, 2025; Sörqvist *et al.*, 2025) emphasize that procedural knowledge, frequently implicit or tacit, models a procedure as an ordered sequence of actions executed to achieve an outcome.

2.2 Procedural Knowledge Ontology

The ontology used to structure a knowledge graph determines how reliably machines can interpret and reason over the represented knowledge. (Carriero *et al.*, 2025) developed the Procedural Knowledge Ontology (PKO), a modular schema designed to represent procedural workflows in a structured, machine-readable format, following the Linked Open Terms (LOT) methodology (Poveda-Villalón *et al.*, 2022) for industry-domain ontologies. By expressing procedural knowledge in a formal semantic format, PKO ensures interoperability, enables reasoning and supports knowledge reuse, improving both compliance and employee training. A key innovation of PKO is its distinction between procedure definition and execution, an aspect not addressed by standards such as BPMN (Kurz, 2016). The ontology is modular and organized into a core section and industry sections. The PKO Core defines a procedure as a sequence of actions intended to achieve a specific outcome and models its execution using the ProcedureExecution and StepExecution classes, both of which are subclasses of the Activity class. It also captures unforeseen events using the IssueOccurrence class to model errors, causes, and solutions, and the UserQuestionOccurrence class to track questions encountered by the executing agent. As an extension of the PKO Core, PKO Industry was developed to address requirements that extend into the broader industrial domain. It primarily represents the physical and operational context of a

procedure by modeling entities such as machines, devices, energy sources, and equipment. This makes it especially effective for safety-related tasks and procedures.

2.3 Graph Generation Approaches

(Ren *et al*. 2023) propose a method for automatically constructing procedural graphs that captures not only sequential but also non-sequential dependency relations between steps, using syntactic and discourse features for node classification and edge prediction. While their approach relies on supervised classification over an annotated dataset, the approaches presented in this work use LLM-based extraction with ontology constraints, requiring no task-specific annotations. (Pan *et al.*, 2023) show that LLMs simplify key tasks in knowledge engineering, enabling knowledge graph construction at scale and with improved quality. A key advantage is that LLMs enable information extraction without extensive domain-specific training data through their zero-shot and few-shot capabilities (Y. Zhu *et al.*, 2023). This allows core subtasks of the text-to-knowledge-graph pipeline, such as entity recognition and relation extraction, to be streamlined through prompting rather than task-specific models. With LLM-based approaches, the quality of information extraction and graph creation is claimed to predominantly be a matter of model selection and prompt-engineering. Recent studies have begun to empirically compare these LLM-based extraction strategies. For example, Mo et al. (2025) proposed KGGen, a multi-stage pipeline that separates entity and relation extraction, cross-source aggregation, and entity clustering into distinct LLM-driven phases, demonstrating improved graph quality over single-pass extraction methods such as GraphRAG. While these works advance general-purpose knowledge extraction, they do not address ontology-conformant extraction from procedural text.

2.4 Research gap

The research community has made substantial progress in both defining procedural knowledge through ontological frameworks and automating knowledge graph construction using LLMs (Pan *et al.*, 2023). However, the intersection of these two fields, specifically the automated construction of ontology-conformant knowledge graphs from procedural text, remains underexplored. This work addresses this gap by comparing three LLM-based extraction approaches across six procedural texts, evaluating both intrinsic graph quality and downstream QA performance.

3. Methodology

Based on the findings of the literature review, this study aims to systematically evaluate the impact of model size, out-of-the-box vs. fine-tuned LLMs, and ontology distillation on knowledge graph quality. The overall methodology for assessing these parameters can be seen in Figure 1.

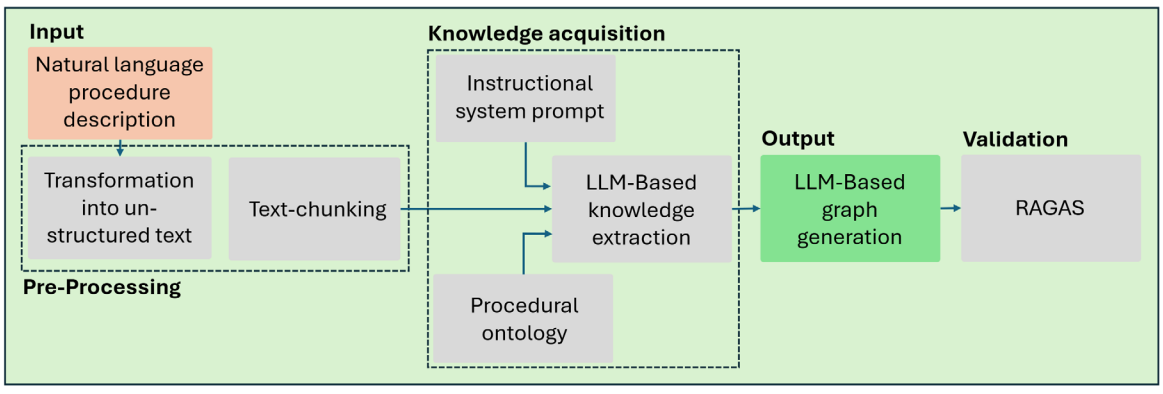


Figure 1: General pipeline for the three approaches addressed in this work.

It covers the entire systematic pipeline, from natural language procedure inputs and preprocessing to information extraction or knowledge acquisition, LLM-based graph generation, and validation. Following the text-to-graph workflow described by (Zhong *et al.*, 2023), the pipeline is structured into the subtasks of data preprocessing, knowledge acquisition, and knowledge refinement. Each subtask is implemented as a modular component, facilitating the transition from natural language instructions into a machine-readable network of entities and relationships.

3.1 Pre-processing: Transformation Into Unstructured Text and Text Chunking

To ensure the focus on semantic structure during Knowledge Acquisition instead of formatting cues, the decision was made to transform the originally structured texts of the procedures into unstructured texts by removing the step marker heading, such as ”Step 1:”. This also better approximates the characteristics of spoken instructions. Furthermore, chunk sizes of 5, 8, and 12 sentences were used to systematically examine the balance between local precision and contextual completeness in triplet extraction. This balance is especially important in procedural texts, where meaningful relationships can extend over varying lengths, sometimes even across longer paragraphs. By evaluating multiple levels of context granularity, we can observe how chunk size affects whether these semantically complete procedural relationships remain intact or become fragmented.

3.2 Knowledge Acquisition

3.2.1 Extraction approaches

To investigate the relative influence of model capacity and extraction strategy on Knowledge Graph quality, three approaches were designed that vary along these two dimensions. A *Large-Single-Stage* approach used Qwen3-32B to extract all ontology elements in a single pass per text chunk. A *Small-Single-Stage* approach applied the same strategy with the smaller Llama2-13B to isolate the effect of model size. A *Small-Multi-Stage* approach decomposed the extraction into separate phases, each targeting a subset of the ontology, using a fine-tuned Llama2-13B to test whether a carefully designed extraction pipeline can compensate for reduced model capacity. The *Large-Single-Stage* approach accessed Qwen3-32B via the Groq cloud inference API, with a context length of 32,768 tokens. The *Small-Single-Stage* approach loaded Llama2-13B-chat locally in 4-bit quantization, with a context length of 4,096 tokens. The *Small-Multi-Stage* approach used the same small base model but split the extraction into two phases using three separately fine-tuned models, each trained on a separate training subset with a different expected output so that it learned only the narrow extraction scope of its respective phase. In the first phase, one model extracted the central Procedure node and initial Step nodes with hasStep and nextStep relationships from the first text chunk, while a second model extracted further Step nodes with the same relationship types from all subsequent chunks. In the second phase, a third model received each text chunk together with the Steps previously extracted from it and generated Execution Instruction nodes that capture detailed guidance for each step.

3.2.2 Supervised fine-tuning

To move beyond general-purpose prompting and produce a model specialized in mapping procedural descriptions onto a formal ontology, supervised fine-tuning was applied to the Llama2-13B model. The training data was generated synthetically by prompting Qwen3-32B to produce 59 short, unstructured procedural descriptions spanning diverse tasks. For each description, the model also generated the expected extraction output, including Procedure, Step and Execution Instruction nodes with their corresponding relationships (hasStep, nextStep, advises). These outputs were formatted as JSONL and normalized into the prompt-response format required by Llama2. The data was then split into three subsets, all containing the same 59 procedural descriptions but with different expected outputs. The outputs in the first subset contain only the extracted Procedure and Step nodes, the second only the Step nodes, and the third contains the Step nodes as part of the system prompt and Execution Instruction nodes as part of the expected answer. For training, parameter-efficient fine-tuning (PEFT) with BitsAndBytes 4-bit quantization was used. The model was loaded in 4-bit precision with float32 compute dtype and gradient checkpointing enabled to reduce VRAM usage. Low-rank adapters were applied with rank r=16, alpha=32, and a dropout of 0.05. Training ran for 16 epochs with a batch size of one, gradient accumulation over eight steps, a learning rate of 5e-5 and fp16 mixed precision.

3.2.3 Prompting strategy

Each extraction pass was guided by a system prompt consisting of two components: an instructional part defining the extraction task and output format, and the target ontology specifying the entity classes and relationship types to extract. All prompts instructed the model to take on the role of an expert in Knowledge Graph construction for procedural tasks while discouraging it from using any prior knowledge. Output-format constraints required the model to respond only in JSON format without surrounding commentary, and imperative language was used to increase compliance for all critical constraints. Across all approaches, two prompt variants were used to handle multi-chunk documents. A first-chunk prompt instructed the model to identify the central Procedure node and connect it to the first extracted Step. For all subsequent chunks, an

after-chunk prompt provided the name of the previously extracted Procedure and the last Step node as carry-over context, with the explicit instruction to connect the first step of the current chunk to the last step of the previous chunk and not to create additional Procedure nodes. The key difference between the *single-stage* and *multi-stage* approaches lay in the scope of each prompt. In the *large* and *small-single-stage* approaches, each prompt contained the full or distilled ontology and instructed the model to extract all entity types and relationship types in a single pass. In the *Small-Multi-Stage* approach, each prompt targeted only a narrow subset of the ontology. The first-phase prompts were restricted to Procedure and Step nodes with hasStep and nextStep relationships. The second-phase prompt received the previously extracted Step nodes as part of the input and was instructed to extract only Execution Instruction nodes and their advised relationships.

3.2.4 Procedural ontology variants

To evaluate the trade-off between task-specific efficiency and level of detail, two distinct versions of the PKO by (Carriero et al., 2025) were used across the large and small-single-stage approaches. The full PKO included both the Core and Industry modules. The Core module modeled the specification and execution of a procedure, capturing complex relations such as action and tool requirements, step verifications, issue occurrences, and user questions. The industry module extended this with entities representing the physical and operational context, such as machines, energy sources, safety equipment and lockout-tagout procedures, broadening applicability to industrial domains. The goal of using the full ontology was to enable complex reasoning and interoperability across different industrial systems. The distilled variant focused on the core entities and relationships essential for procedural flows, reducing the input context length, and allowing the model to concentrate on the most retrieval-relevant subset of the ontology. The *Small-Multi-Stage* approach was not tested with different ontology variants, as its decomposed extraction architecture already targeted a minimal subset of the ontology in each phase.

3.3 LLM-based Knowledge Graph Generation

In the final step, we used the Neo4j Graph Builder module to automatically generate knowledge graphs from the JSON format triplets generated in the previous step.

3.4 Evaluation Strategy

The evaluation strategy consisted of intrinsic and extrinsic quality metrics evaluated using a set of natural language procedural knowledge texts.

3.4.1 Validation data

The source for validation was six publicly available "how-to" or DIY (do-it-yourself) procedural descriptions, which can be seen in Table 1. These procedures were chosen because they cover different domains, enabling the pipeline to be evaluated against various linguistic and structural challenges.

Table 1: Set of texts used as inputs for evaluation.

ID	Manual	Character	Word	Sentences
1	How to replace a laptop Battery	1964	255	21
2	How to replace a mobile phone Battery	14254	2623	164
3	How to replace a 3d printer nozzle	3122	512	34
4	How to change filament during printing	1661	335	11
5	How to build and assemble a Cat Treat Timer	2689	457	32
6	How to build a Pan-Tilt Head for DIY Motion Control	6793	1208	55

3.4.2 Intrinsic quality measures

Ontology conformance was evaluated using metrics that focus on correctness and graph structure rather than instantiation ratios. Specifically, the assessment considered class violations (when generated object classes are not part of the ontology), relationship violations (when generated relationships are not defined in the ontology), the number of disconnected subgraphs (which hinder graph traversal), and edge duplicates (redundant connections). Unlike instantiation ratios, where high values don't guarantee superior extraction, these metrics directly address the accuracy and coherence of the extracted knowledge, accounting for cases

where low instantiation may result from either the model's limitations or the absence of ontology concepts in the source text.

3.4.3 Extrinsic quality measures

To evaluate the extrinsic quality, or the "fitness for use" of the generated knowledge graphs we employed a Graph-RAG approach. The quality of any RAG-based application depends on the truthfulness of the generated response to the user's query. Evaluating RAG quality is challenging, as it involves multiple dimensions including retrieval quality, the LLM's ability to exploit retrieved information, and overall generation accuracy (Es *et al.*, 2023). To address this, (Es *et al.*, 2023) developed RAGAS (Retrieval Augmented Generation Assessment), a framework for evaluating RAG-based QA applications without requiring human ground-truth annotations. RAGAS assesses three quality dimensions: faithfulness, measuring whether the answer is grounded in the retrieved context; context relevance, measuring the absence of irrelevant information in the retrieved context; and answer relevance, measuring whether the answer addresses the posed question. For each of the six procedural source texts, 12 question-answer pairs were constructed as ground truth. Each generated knowledge graph was then used in a Graph-RAG pipeline to answer all questions, and an LLM-as-a-judge evaluated whether the generated answers matched the ground truth using a binary pass/fail judgment.

> Consider the response correct if it:
>
> (1.) Contains the key information from the expected answer
>
> (2.) Is factually accurate based on the provided context
>
> (3.) Adequately addresses the question asked.
>
> Return 'pass' if the response is correct, 'fail' if it's incorrect.

This evaluation process was systematically applied to all three approaches across our different parameters, *Chunk Size, Temperature*, and *Ontology Type*. The temperature was varied between 0.2 and 0.6 to test whether introducing moderate stochasticity during the generation process would improve extraction diversity without compromising compliance with the output format. Higher values were excluded to avoid parsing errors in tasks requiring strict JSON formatting.

4. Results

In total, 180 knowledge graphs were generated across the three approaches, six source texts and the full configuration space of chunk size, temperature, and ontology detail. Graph size, measured in nodes and edges, was strongly influenced by source text complexity, with longer procedural descriptions consistently producing larger graphs across all approaches. The *Large-Single-Stage* approach, based on Qwen3-32B, tended to produce the largest graphs in most configurations, while the *Small-Single-Stage* approach, using the base Llama2-13B model, generated the sparsest graphs with the highest rate of parsing errors. The *Small-Multi-Stage* approach, which combined fine-tuning with a decomposed extraction strategy, consistently achieved the highest average node degree while producing fewer unique nodes, suggesting that it captures relational structure more effectively rather than simply listing more entities.

4.1 Intrinsic Quality

Table 2 provides a comparative evaluation of ontology conformance approaches, focusing on three key intrinsic metrics: class violations, relationship violations, and edge duplicates. The *Large-Single-Stage* approach demonstrated a low level of hallucination, with only five class violations and one relationship violation, producing an average of 7.69 edge duplicates. These results suggest a high level of accuracy and coherence in the extracted knowledge, with minimal errors in class and relationship adherence. In contrast, the *Small-Single-Stage* (Llama-13B-4Q) approach exhibited significantly more violations: 179 class, and 60 relationships. However, its 7.31 edge duplicate rate is comparable to that of the *Large-Single-Stage* approach. This indicates a struggle in maintaining ontology conformance, which is likely due to limitations in accurately recognizing or extracting ontology elements. Finally, the *Small-Multi-Stage* approach (fine-tuned Llama-13B-4Q) performed almost as well as the *Large-Single-Stage* approach on class violations, producing 13 relationship violations, which is significantly more than the *Large-Single-Stage* approach but significantly less than the *Small-Single-Stage* approach. In terms of edge duplicates, this approach performed best with an average of 4.72.

Table 2: Intrinsic metrics across the three approaches.

Approach (distilled ontology)	Class violations	Relationship violations	Edge duplicates
Large-Single-Stage ***Qwen3-32B***	**5**	**1**	7.69
Small-Single-Stage ***Llama-13B-4Q***	179	60	7.31
SFT- Small-muti-stage ***Fine-tuned Llama-13B-4Q***	8	13	**4.72**

4.1.1 Extrinsic quality

Figure 2 shows the average performance across the six different guides presented in Table 1. The fine-tuned *SFT-Small-Multi-Stage* approach achieved the highest overall QA accuracy with an average pass rate of 48.4% and a peak pass rate of 55.3% when employing a chunk size of 5 and 0.2 temperature setting. The *Large-Single-Stage* approach averaged 40.3% and peaked at 46.8% with the same settings. The *Small-Single-Stage* approach performed the worst, with an average of 26.4% and a peak of 33%, using the same chunk and temperature settings. Chunk size had a notable influence on performance, while temperature showed a slight but inconsistent tendency toward better results at lower values.

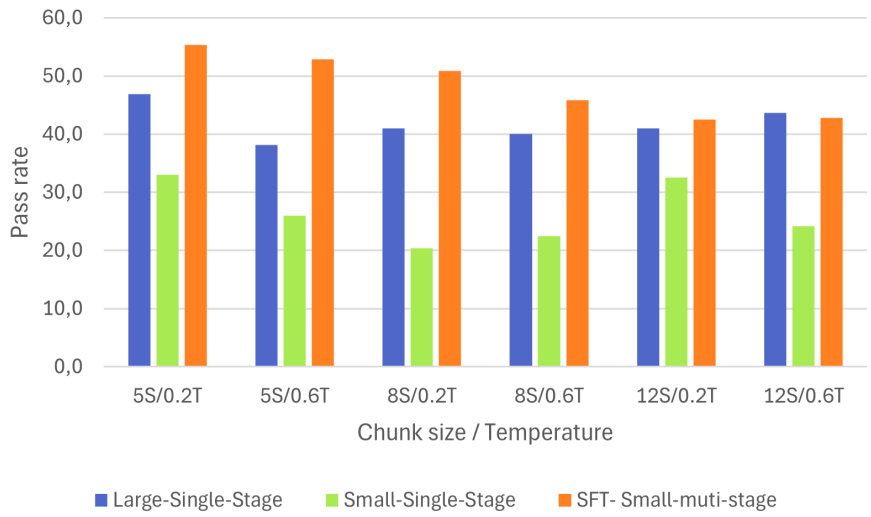


Figure 2: The three approaches showing average pass rate across 6 different chunk size+temperature extraction conditions

5. Discussion

The most notable finding is that a fine-tuned 13-billion parameter model scored higher than the 32-billion parameter general-purpose model on both intrinsic quality metrics and downstream QA accuracy. This pattern held across six procedural texts spanning device repair, 3D printing, and DIY assembly. For practitioners with limited computational resources or API budgets, this means comparable results at a fraction of the cost. This result can be attributed to two factors: supervised fine-tuning on synthetic extraction data and a decomposed extraction strategy that targeted only one or two ontology elements per phase. The decomposed extraction strategy reduced the complexity of each individual phase, allowing a smaller model to outperform a larger one that had to extract all ontology elements in a single pass. Among the intrinsic quality metrics, average node degree and duplication rate showed the strongest correlation with QA accuracy. Graphs with a higher average node degree provided a richer context during retrieval, since each seed node connected to more neighboring information. Duplicate triples had the opposite effect, filling the retrieval context with redundant information, leaving less room for relevant facts. Raw graph size, by contrast, did not predict QA performance. More triples did not uniformly translate to more useful information. Structural connectivity and ontological conformance acted as minimum thresholds rather than performance predictors. Graphs that violated them showed

degraded QA accuracy, but among graphs that satisfied both, these metrics did not account for performance differences. Over-extraction of step nodes did not degrade retrieval quality. Instead, the additional nodes provided more seed entities for Graph-RAG traversal. These findings favor recall-oriented extraction over precision. Missing a step hurts retrieval more than extracting too many. Similarly, a richer ontology did not guarantee better results. Ontology design should be driven by the intended downstream use. In this evaluation, test questions focused on step-level information, and the distilled ontology that prioritized steps outperformed the full PKO. Including ontology elements that the evaluation does not query adds extraction overhead without measurable benefit. Of the configuration parameters tested, chunk size affected extraction quality while model temperature showed a slight but inconsistent tendency toward better results at lower values. The experimental design has several limitations. Fine-tuning and the decomposed extraction strategy were introduced together, so their individual contributions cannot be separated. A sample of just six procedural texts from technical domains is small. The fine-tuned, decomposed approach performed best across all six, suggesting that the finding is not domain specific. However, it is unclear whether this would also apply to medical protocols or legal procedures. Finally, QA accuracy depends on the retrieval implementation used, and different strategies may interact differently with graph structure.

6. Conclusion and Future Work

This study shows that a fine-tuned 13-billion parameter model with a decomposed extraction strategy can outperform a much bigger general-purpose model for automated KG construction from procedural text. For practitioners, this means effective pipelines are feasible without large-scale compute infrastructure. Future work could address four directions. First, testing multi-stage extraction with base models would separate the contributions of fine-tuning from extraction strategy, clarifying whether performance gains require synthetic training data or can be achieved via prompt engineering. Beyond this, exploring even smaller models and agentic architectures, where multiple specialized sub-models collaborate on different extraction phases, could further reduce computational requirements while maintaining extraction quality. Second, expanded evaluation frameworks including semantic consistency checks and structural redundancy measures would more fully assess intrinsic KG quality, potentially using LLMs as automated judges. Additionally, constructing gold-standard reference graphs for each source text would enable triple-level completeness evaluation, which the current proxy metrics cannot provide. Third, broader datasets covering varied domains, modalities, and formality levels, including audio-transcribed and written instructions, would test the generalizability of the findings. Fourth, extension beyond procedural text to user manuals, narratives, technical specifications, and scientific abstracts would explore domain-independent KG generation.

Acknowledgement

This research and development project is funded by the German Federal Ministry of Research, Technology and Space (BMFTR). The author is / The authors are responsible for the content of this publication.

Ethical Declaration: A self-evaluation document consisting of 13 questions, provided by the Ethics Committee at the Technical University of Berlin, was completed to assess the conducted research. If any of the questions had been answered with “yes,” a full ethics approval application would have been required. In this case, all 13 questions were answered with “no,” and therefore no further ethical approval was necessary. Questionnaire link: https://www.tu.berlin/en/ipa/ueber-uns/ipa/representatives-and-committees/ethics-committee

AI Declaration: AI tools were used for proofreading the entire text.

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Comparative Analysis of the Efficiency Indicators of the Formation of Intellectual Capital in the Field of Humanities and Arts Sciences

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Abstract: In the present situation, a comparative analysis of the efficiency of the formation of intellectual capital (IC) in the humanities and arts sciences at scientific institutions (SIs) in Latvia is an actual research topic. The object of the research is the formation of IC of humanities and art sciences at SIs, while the subject of the research is the comparative analysis of the efficiency of the formation of IC of humanities and art sciences at SIs of Latvia. The objective of the research is to compare various efficiency indicators of the formation of IC of humanities and art sciences at SIs in Latvia in the period from 2013 to 2018. The following tasks were determined to reach the objective: to study the formation of IC of humanities and art sciences at SIs; to identify various efficiency indicators of the formation of IC of humanities and art sciences; to calculate various indicators thereof; and to carry out the comparative analysis of various efficiency indicators that characterise the formation of IC of humanities and art sciences at SIs in Latvia. Research methods used in the paper are content analysis, economic analysis, financial analysis, and economic experiment.

Keywords: Intellectual capital, Humanities sciences, Art sciences, Efficiency indicators, Latvia

1. Introduction

Every six years, the Ministry of Education and Science of the Republic of Latvia (MoES) organises an international eva-luation of SIs registered in Latvia. The first International Evaluation of Scientific Institutions' Activity (IESIA) in Latvia covered the period from 2006 to 2011. The second IESIA refers to the period from 2013 to 2018. In order to establish the dynamics of the efficiency indicators of academic staff involved in the formation of IC in humanities and art sciences at SIs of Latvia (MoES, 2021), the authors used the output data of findings across the set of evaluations of SIs of humanities and art sciences for the period from 2013 to 2018 offered by "Technopolis Group" (TG).

TG developed the above IESIA for the periods from 2006 to 2011 and from 2013 to 2018 using a similar methodology. It enables the authors to calculate the IC indicators in humanities and art sciences at SIs of Latvia and to compare their dynamics during the period from 2013 to 2018.

The comparative analysis of efficiency indicators of involvement of academic staff of humanities and art sciences at SIs of Latvia in the IC formation and its financial efficiency indicators will let them establish whether and how the ma-nagement of SIs affects them. Data from the comparative analysis will help to develop support programmes to increase the efficiency of involvement of the academic staff in the IC formation and its financial efficiency. In addition, the comparative analysis will reveal whether the score of humanities and art sciences at SIs of Latvia in the IESIA of TG coincides with the place of SIs of Latvia in the ratings of IC indicators, and whether the overall score of SIs of Latvia also reflects the efficiency of the involvement of academic staff of SIs of Latvia in the IC formation and its financial efficiency.

> *Hypothesis: The overall score of SIs shows the efficiency of the IC formation at SIs of Latvia and its financial efficiency.*

2. Theoretical Background

The authors rely on the research on understanding, adapting, and applying intellectual capital (IC) in universities (Mercado-Salgado et al., 2016); and on the research on the role of human capital in the educational and training process at a university (Contu, 2017), which presented different aspects of IC.

Spica et al. (2017a) state that IC is an economic category, a spiritual value created by human potential, and it can be accumulated and converted into the value of other capitals. By investigating certain information about educational management, we can increase the capacity and significance of the country's total economic capital movement.

Rondeau et al. (2022) remind us that peer-reviewed publications remain a traditional form of academic productivity. Spica et al. (2017a; 2017b) have elaborated four indicators of the efficiency of the IC formation in a higher education establishment (HEE): (1) the efficiency of the involvement of academic staff in the IC formation per year in percentage (AIK); (2) the efficiency of the involvement of academic staff with a Doctorate degree in the IC formation per year in percentage (DIK); (3) the efficiency of the involvement of students in the IC formation per year in percentage (SIK).

The authors unsuccessfully searched databases SCOPUS and Web of Science (WoS) for scientific literature on indicators of financial efficiency of the involvement of academic staff of SIs' in IC formation as part of the content analysis.

Therefore, on basis of the recognition that financial indicators are explains of financial relationships based on the company's financial information and aim at ensuring comparisons between companies in the financial field, the authors decided, as part of the economic experiment, to develop a number of new financial efficiency indicators and to check them in practice.

3. Methodology

In order to calculate the AIK, DIK, and SIK of a HEE, Spica et al. (2017a; 2017b) have developed three formulas: (1) AIK = (ZPS : AS) × 100; (2) DIK = (ZPS : DS) × 100; (3) SIK = (ZPS : SS) × 100.

Where: ZPS represents the number of scientific publications of the HEE per year; AS represents the number of academic staff in full-time jobs per year; DS represents the number of academic staff with Doctorate degrees holding full-time jobs per year; SS represents the number of students per year.

For the purposes of the study, the authors modified these formulas. Namely, they calculated IC efficiency indicators for total numbers of full-time equivalent (FTE) academic and research personnel (KIK), for FTE academic personnel (AIK), for FTE academic and research personnel (PIK), and for PhDs obtained at SIs (ZIK). In addition, all the said IC efficiency indicators were calculated for different forms of IC, such as the total number of self-reported outputs of IC (GS), articles in peer-reviewed scientific edited journals and conference proceedings included in WoS or SCOPUS (WS), articles in peer-reviewed edited journals and conference proceedings not included in WoS or SCOPUS (RS), monographs (MS), and Latvian patents (LPS).

The authors have elaborated new indicators for the purpose of the study of the financial efficiency of the IC formation at the SIs: (1) the financial efficiency of the involvement of academic personnel in the IC formation per year in percentage (AIKF); (2) the financial efficiency of the involvement of academic and research personnel in the IC formation per year in percentage (PIKF); (3) the financial efficiency of the involvement of total numbers of academic and research personnel in the IC formation per year in percentage (KIKF); (4) the financial efficiency of the involvement of PhDs obtained in the IC formation per year in percentage (ZIKF).

In the present research, the authors used the following data from the IESIA: output data on the number of FTE academic personnel (AS), the number of FTE academic and research personnel (PS), the total number of FTE academic and research personnel (KS), the number of PhDs obtained (ZS), the number of articles in peer-reviewed scientific edited journals and conference proceedings included in WoS or SCOPUS (WS), the number of articles in peer-reviewed scientific edited journals and conference proceedings not included in WoS or SCOPUS (RS), the number of monographs (MS), the number of Latvian patents (LPS), the total number of self-reported outputs (GS), the amount of total funding (TF), and the amount of total funding per researcher (RF) in the period from 2013 to 2018 per SI of humanities and art sciences in Latvia. The authors revised the above WS, RS, MS, LPS, KS, and TF figures for one year.

The number of scientific publications and patents represents the main results of the IC formation at SIs of humanities and art sciences. TG analysed 11 SIs of humanities and art sciences in Latvia. Within the IESIA, output data on 10 public SIs and one private SI in Latvia were collected.

During the period analysed in the IESIA, there were only 11 such SIs in Latvia: Faculty of Architecture and Design and Faculty of Media and Creative Technologies of RISEBA University of Applied Sciences (RISEBA/H); National Library of Latvia (NLL); Latvian Academy of Culture (LAC); Faculty of Architecture of Riga Technical University (RTU/H); Faculty of Translation Studies of Ventspils University of Applied Sciences (VeU/H); Faculty of Humanities and Arts of Liepaja University (LU/H); Daugavpils University Research Programme "Regional Studies, Literature and Arts" (DU/H); Art Academy of Latvia (AAL); Institute of Literature, Folklore and Art of the University of Latvia (UL/LFA); Jāzeps Vītols Latvian Academy of Music (JVLAM); and Cluster of Humanities and Arts of the University of Latvia (UL/CHA).

In this study, one scientific publication or one patent is accepted as one unit of IC. Further, KIK, AIK, PIK, and ZIK were calculated using the modified formulas 1, 2, and 3, while KIKF, AIKF, PIKF, and ZIKF were calculated using the four new formulas. Next, according to the results obtained through the authors' calculations, a corresponding rating place was assigned to each SI of Latvia per year and for each of the new indicators KIKF, AIKF, PIKF, and ZIKF.

Each place in the rating was then assessed with an appropriate score, where the lowest score is 1 point, while the highest score is 5 points. Thus, the SI that took first or second place in KIKF, AIKF, PIKF, and ZIKF received 5 points in the ranking; third or fourth place received 4 points; fifth or sixth place received 3 points; seventh or eighth place received 2 points; and ninth to eleventh place received 1 point.

The above-mentioned assessment system allows the comparison of the quantitative efficiency indicators of SIs of humanities and art sciences in Latvia calculated by the authors with the IESIA overall assessment criterion—the quality of the SI research performance. The relevant TG Panel assessed the research performance of each SI using a scale where score 5 means an outstanding level of research, score 4 means a very good level of research, score 3 means a good level of research, score 2 means an adequate level of research, and score 1 means a poor level of research (MoES, 2021).

The score assigned to the overall assessment by the relevant TG Panel was based on the assessment of five sub-elements from A to E, where element A characterises the quality of the research, element B the impact on the development of the specific field of science, element C the economic and social impact of the research, element D the research environment and infrastructure of the institution, and element E the institution's development potential. The Panel was provided with scores for each sub-element and the overall score and was also provided with narrative descriptions of their scores, the overall score, and the sub-elements (MoES, 2021).

The authors subsequently compared the results of their own estimates of the SIs' quantitative indicators with the qua-litative indicators of the relevant TG Panel and calculated the differences between the indicators and the changes. For this purpose, the authors calculated the average score of indicators for each SI recording the financial efficiency of the IC formation and compared these scores with the scores for the research quality of each SI and the overall score developed by the TG Panel.

4. Results

According to Spica et al. (2023) estimates, the IESIA data show that the total number of self-reported outputs of SIs of humanities and art sciences in Latvia is represented in the largest proportion by RS—70,16%, followed by WS—16,22%, MS—13,55%, and LPS—0,07%.

To calculate the efficiency of the involvement of academic and research staff in the WS formation, the authors used formulas that had been developed and applied previously and have now been modified.

AIK = (WS : AS) x 100 (1)
PIK = (WS : PS) x 100 (2)
KIK = (WS : KS) x 100 (3)
SIK = (WS : ZS) x 100 (4)

To calculate the financial efficiency of the involvement of academic and research staff in the WS formation, the authors have now elaborated four new formulas.

AIKF= (TF : AS) / (TF : WS) x 100 (5)
PIKF = (TF : PS) / (TF : WS) x 100 (6)
KIKF = (TF : KS) / (TF : WS) x 100 (7)
SIKF = (TF : ZS) / (TF : WS) x 100 (8)

The summarized indicators show that, in general, as presented in Table 1, the figures range from 3.53% to 450.00% with respect to a SI in Latvia. The highest indicators are ZIK and ZIKF in the NLL, while the lowest indicators are KIK and KIKF in the AAL. Comparing the figures presented in Table 1, the authors conclude that the highest AIK and AIKF indicators belong to the DU/H, while the lowest AIK and AIKF indicators belong to the AAL; the highest KIK and KIKF indicators belong to the NLL, while the lowest KIK and KIKF indicators belong to the AAL; the highest ZIK and ZIKF indicators belong to the NLL, while the lowest ZIK and ZIKF indicators belong to the JVLAM.

Table 1: Comparative Analysis of the Financial Efficiency Indicators of the Involvement of Academic Staff in the WS Formation and the Efficiency Indicators of the Involvement of Academic Staff in the WS Formation at SIs of Humanities and Art Sciences in Latvia per Year in the Period from 2013 to 2018

SI	AIK (%)	AIKF (%)	PIK (%)	PIKF (%)	KIK (%)	KIKF (%)	ZIK (%)	ZIKF (%)
RISEBA/H	38,60	38,60	41,50	41,50	20,00	20,00	-	-
NLL	-	-	52,94	52,94	52,94	52,94	450,00	450,00
LAC	8,70	8,70	72,88	72,88	7,77	7,77	48,58	48,58
RTU/H	23,07	23,07	120,73	120,72	19,37	19,37	58,25	58,25
VeU/H	9,76	9,76	44,11	44,11	7,99	7,99	36,17	36,17
LU/H	19,20	19,21	51,89	51,89	14,02	14,02	42,45	42,45
DU/H	53,65	53,64	353,90	353,90	46,58	46,58	130,00	130,00
AAL	3,53	3,53	40,78	40,78	3,25	3,25	24,47	24,47
UL/LFA	-	-	28,40	28,40	28,40	28,40	344,33	344,33
JVLAM	5,23	5,23	35,28	35,28	4,55	4,55	12,76	12,77
UL/CHA	49,34	49,34	22,15	22,15	15,29	15,29	34,21	34,21
Average	22,74	18,85	39,25	91,77	14,40	24,26	51,20	143,36

In Table 2, the authors have calculated the efficiency of the involvement of academic and research staff in the RS formation using formulas 9, 10, 11, and 12.

AIK = (RS : AS) x 100 (9)
PIK = (RS : PS) x 100 (10)
KIK = (RS : KS) x 100 (11)
SIK = (RS : ZS) x 100 (12)

To calculate the financial efficiency of the involvement of academic and research staff in the RS formation, the authors used formulas that had been developed and applied previously and have now been modified.

AIKF= (TF : AS) / (TF : RS) x 100 (13)
PIKF = (TF : PS) / (TF : RS) x 100 (14)
KIKF = (TF : KS) / (TF : RS) x 100 (15)
SIKF = (TF : ZS) / (TF : RS) x 100 (16)

In Table 2, with respect to SIs of humanities and art sciences in Latvia, the figures range from 4.13% to 1683.01%. The highest indicators are ZIK and ZIKF in the NLL, while the lowest indicators are AIK, AIKF, KIK, and KIKF in the AAL.

Table 2: Comparative Analysis of the Financial Efficiency Indicators of the Involvement of Academic Staff in the RS Formation and the Efficiency Indicators of the Involvement of Academic Staff in the RS Formation at SIs of Humanities and Art Sciences in Latvia per Year in the Period from 2013 to 2018

SI	AIK (%)	AIKF (%)	PIK (%)	PIKF (%)	KIK (%)	KIKF (%)	ZIK (%)	ZIKF (%)
RISEBA/H	526,98	526,93	566,50	566,45	273,01	272,99	-	-
NLL	-	-	198,00	198,00	198,00	198,00	1683,00	1683,01
LAC	19,66	19,66	164,63	164,62	17,56	17,56	109,75	109,75
RTU/H	308,61	308,56	1615,03	1614,76	259,10	259,05	779,25	779,14
VeU/H	143,18	143,18	646,95	646,92	117,24	117,23	530,50	530,47
LU/H	54,83	54,83	148,11	148,11	40,02	40,02	121,18	121,18
DU/H	186,16	186,16	1228,13	1228,14	161,66	161,66	451,13	451,14
AAL	4,49	4,49	51,89	51,89	4,13	4,13	31,13	31,13
UL/LFA	-	-	96,23	96,23	96,23	96,23	1166,67	1166,69
JVLAM	56,61	56,61	382,11	382,15	49,31	49,30	138,24	138,25
UL/CHA	201,46	201,46	90,47	90,47	62,43	62,43	139,70	139,70
Average	98,41	65,48	169,86	318,83	62,31	84,27	221,58	498,07

Comparing the figures presented in Table 2, the authors conclude that the highest AIK indicator of 526.98% and the highest AIKF indicator of 526.93% belong to the RISEBA/H, while the lowest AIK and AIKF indicators of 4.49% belong to the AAL; the highest PIK indicator of 1615.03% and the highest PIKF indicator of 1614.76% belong to the RTU/H, while the lowest PIK and PIKF indicators of 51.89% belong to the AAL; the highest ZIKF indicator of 1683.01% and the highest ZIK indicator of 1683.00% belong to the NLL, while the lowest ZIK and ZIKF indicators of 31.13% belong to the AAL.

In Table 3, the authors have calculated the efficiency of the involvement of academic and research staff in the MS formation using formulas 17, 18, 19, and 20.

AIK = (MS : AS) x 100 (17)
PIK = (MS : PS) x 100 (18)
KIK = (MS : KS) x 100 (19)
SIK = (MS : ZS) x 100 (20)

To calculate the financial efficiency of the involvement of academic and research staff in the MS formation, the authors used formulas that had been developed and applied previously and have now been modified.

AIKF= (TF : AS) / (TF : MS) x 100 (21)
PIKF = (TF : PS) / (TF : MS) x 100 (22)
KIKF = (TF : KS) / (TF : MS) x 100 (23)
SIKF = (TF : ZS) / (TF : MS) x 100 (24)

In Table 3, according to the AIK, AIKF, PIK, PIKF, KIK, KIKF, ZIK, and ZIKF indicators, the first place and highest score is taken by the LU/H.

Table 3: Comparative Analysis of the Financial Efficiency Indicators of the Involvement of Academic Staff in the MS Formation and the Efficiency Indicators of the Involvement of Academic Staff in the MS Formation at SIs of Humanities and Art Sciences in Latvia per Year in the Period from 2013 to 2018

SI	AIK (%)	AIKF (%)	PIK (%)	PIKF (%)	KIK (%)	KIKF (%)	ZIK (%)	ZIKF (%)
RISEBA/H	54,42	54,42	58,50	58,50	28,19	28,19	-	-
NLL	-	-	3,88	3,88	3,88	3,88	33,00	33,00
LAC	23,63	23,63	197,88	197,88	21,11	21,11	131,92	131,92
RTU/H	21,49	21,48	112,44	112,43	18,04	18,04	54,25	54,25
VeU/H	6,75	6,75	30,49	30,49	5,52	5,53	25,00	25,00
LU/H	124,11	124,11	335,22	335,21	90,57	90,57	274,27	274,27
DU/H	10,10	10,10	66,61	66,61	8,77	8,77	24,47	24,47
AAL	2,24	2,24	25,89	25,89	2,06	2,06	15,53	15,53
UL/LFA	-	-	14,65	14,65	14,65	14,65	177,67	177,67
JVLAM	2,41	2,41	16,26	16,26	2,10	2,10	5,88	5,88
UL/CHA	43,64	43,64	19,60	19,60	13,52	13,52	30,26	30,26
Average	23,99	5,03	41,41	24,50	15,19	6,48	54,02	38,27

Table 4: Comparative Analysis of the Financial Efficiency Indicators of the Involvement of Academic Staff in the LPS Formation and the Efficiency Indicators of the Involvement of Academic Staff in the LPS Formation at SIs of Humanities and Art Sciences in Latvia per Year in the Period from 2013 to 2018

SI	AIK (%)	AIKF (%)	PIK (%)	PIKF (%)	KIK (%)	KIKF (%)	ZIK (%)	ZIKF (%)
RISEBA/H	93,02	93,02	100,00	100,00	48,19	48,19	-	-
Average	0,55	629,14	0,95	3063,22	0,35	809,67	-	-

In Table 4, the authors have calculated the efficiency of the involvement of academic and research staff in the LPS formation using formulas 25, 26, 27, and 28.

AIK = (LPS : AS) x 100 (25)
PIK = (LPS : PS) x 100 (26)
KIK = (LPS : KS) x 100 (27)
SIK = (LPS : ZS) x 100 (28)

To calculate the financial efficiency of the involvement of academic and research staff in the LPS formation, the authors used formulas that had been developed and applied previously and have now been modified.

AIKF= (TF : AS) / (TF : LPS) x 100 (29)
PIKF = (TF : PS) / (TF : LPS) x 100 (30)
KIKF = (TF : KS) / (TF : LPS) x 100 (31)
SIKF = (TF : ZS) / (TF : LPS) x 100 (32)

In Table 4, according to the AIK, AIKF, PIK, PIKF, and KIK, KIKF indicators, the first and only place is taken by the RISEBA/H.

From the results summarised in Tables 1, 2, and 3, the authors conclude that the average ZIK and ZIKF indicators are the highest for all IC forms.

Table 5: Comparison of the results of qualitative and quantitative evaluation of Latvian SIs in the field of humanities and art sciences using the IC form and financial efficiency indicators of IC formation for the period from 2013 to 2018

SI	Quality score by TG (QTG)	Overall score by TG (OTG)	Total average score of AIKF & PIKF by IC form (TAAPF)	Difference of score (QTG-TAAPF)	Difference of score (OTG-TAAPF)	Total average score of AIKF & PIKF & ZIKF by IC form (TAAPZF)	Difference of score (QTG-TAAPZF)	Difference of score (OTG-TAAPZF)
RISEBA/H	2	1	3,3	-1,3	-2,3	2,2	-0,2	-1,2
NLL	4	4	0,8	3,2	3,2	1,4	2,6	2,6
LAC	4	4	1,9	2,1	2,1	1,8	2,2	2,2
RTU/H	3	3	2,6	0,4	0,4	2,5	0,5	0,5
VeU/H	2	2	1,8	0,2	0,2	1,3	0,7	0,7
LU/H	3	3	2,0	1,0	1,0	2,0	1,0	1,0
DU/H	4	4	2,6	1,4	1,4	2,3	1,7	1,7
AAL	4	4	0,8	3,2	3,2	0,7	3,3	3,3
UL/LFA	4	5	0,3	3,7	4,7	1,2	2,8	3,8
JVLAM	3	3	1,2	1,8	1,8	1,1	1,9	1,9
UL/CHA	3	3	1,7	1,3	1,3	1,7	1,3	1,3

From the data summarised in Tables 1, 2, 3, and 4, the follow-up authors created the rating and score of SIs in Latvia based on the AIKF, PIKF, KIKF, and ZIKF indicators of academic research personnel and PhD involvement in the IC formation. After that, the authors calculated the total average score of the AIKF and PIKF by IC form TAAPF, and the total average score of the AIKF, PIKF, and ZIKF by IC form TAAPZF. Then, the authors calculated the differences between the quality and overall scores by TG and TAAPF, and TAAPZF calculated by the authors (see Table 5).

In Table 6, the authors summarised the results of the calculation of the total average score of the KIKF by IC overall TAKOF and the total average score of the KIKF and ZIKF by IC overall TAKOZF, and its differences between the quality score and overall score by TG.

Table 6: Comparison of the results of qualitative and quantitative evaluation of Latvian SIs in the field of humanities and art sciences using the overall IC and financial efficiency indicators of IC formation for the period from 2013 to 2018

SI	Quality score by TG (QTG)	Overall score by TG (OTG)	Total average score of KIKF by IC overall (TAKOF)	Difference of score (QTGTAKOF)	Difference of score (OTG-TAKOF)	Total average score of KIKF & ZIKF by IC overall (TAKOZF)	Difference of score (QTG—TAKOZF)	Difference of score (OTG-TAKOZF)
RISEBA/H	2	1	3,8	-1,8	-2,8	1,9	0,1	-0,9
NLL	4	4	2,0	2,0	2,0	2,3	1,7	1,7
LAC	4	4	1,2	2,8	2,8	1,4	2,6	2,6
RTU/H	3	3	2,4	0,6	0,6	2,4	0,6	0,6
VeU/H	2	2	1,4	0,6	0,6	1,5	0,5	0,5
LU/H	3	3	1,6	1,4	1,4	1,8	1,2	1,2
DU/H	4	4	2,2	1,8	1,8	2,0	2,0	2,0
AAL	4	4	0,6	3,4	3,4	0,6	3,4	3,4
UL/LFA	4	5	2,0	2,0	3,0	2,5	1,5	2,5
JVLAM	3	3	0,8	2,2	2,2	0,8	2,2	2,2
UL/CHA	3	3	1,6	1,4	1,4	1,6	1,4	1,4

5. Discussion

The four mathematical formulae recreated by the authors to calculate the financial efficiency of the academic staff involved in the formation of the IC were developed in practice.

For this purpose, each of the four newly created mathematical formulae included the respective volume indicators of each SI and the total financing indicators from the IESIA of the Latvian humanities and arts sciences for the period 2008-2013, which the authors recalculated to annual indicators before inserting them in mathematical formulae. In addition, the corresponding figures for the total number of academic staff were inserted in each of the formulae. The financial efficiency indicators of the academic staff involved in the IC formation of each scientific institution, AIKF, PIKF, KIKF and SIKF, were then calculated.

Similarly, the authors to check the four mathematical formulae previously developed to calculate the efficiency of academic staff involved in formation the IC for the AIK, PIK, KIK and ZIK. For this reason, in each of the four mathematical formulae previously established, the relevant volume indicators of the IC were inserted from the IESIA in the Latvian humanities and arts sciences for the period 2008-2013, which the authors recalculated to annual indicators before inserting them in mathematical formulae. Each of the formulae also included relevant figures for the total number of academic staff. As a result, the efficiency indicators of the academic staff involved in the IC formation of each scientific institution, AIK, PIK, KIK and ZIK, were calculated.

In the course of the economic experiment, the authors compared the results of the calculations obtained using the four newly created mathematical formulae for calculating AIKF, PIKF, KIKF, and ZIKF indices with the results of the calculations obtained using the four previously developed mathematical formulae for calculating the AIK,

PIK, KIK, and ZIK indices. It was thus concluded that the calculated results coincided with the accuracy of two decimal places. It follows that AIKF = AIK, PIKF = PIK, KIKF = KIK and ZIKF = ZIK.

Over the course of the economic experiment, the authors were also able to arrive at the above conclusions by mathematically converting the four newly created mathematical formulae for calculating AIKF, PIKF, KIKF, and ZIKF scores and getting that AIKF = AIK, PIKF = PIK, KIKF = KIK, and ZIKF = ZIK. However, this would undermine the reliability of the data generated by the economic experiment.

The results of the authors' study led to the conclusion that the efficiency of the involvement of academic staff in the formation of IC also shows the financial efficiency of the involvement of academic staff in the formation of IC and vice versa. In practice, this may be useful if data on the funding of SIs are not available, but data on the amount of IC generated by the SI and the number of academic staff are available.

6. Conclusions

The study of the authors did not result in confirmation of their hypothesis. When comparing the qualitative ratings of the TG group to the quantitative assessments performed by the authors, it can be concluded that they differ from minus 2.8 to plus 4.7 points in total. The hypothesis is accepted pro tem for other branches of SIs in Latvia.

The study evidences that the KIKF, AIKF, PIKF, and ZIKF of SIs of humanities and art sciences in Latvia were lower than the results compiled by the relevant TG Panel, except for one SI of humanities and art sciences.

The authors' four mathematical formulae, designed to clarify the financial efficiency of the involvement of SIs in IC formation, allow the calculation of AIKF, PIKF, KIKF and ZIKF indicators. It is further clarified that AIKF = AIK, PIKF = PIK, KIKF = KIK and ZIKF = ZIK. Consequently, the efficiency of the involvement of SIs in the formation of IC also shows the financial efficiency of the involvement of SIs in the formation of IC and vice versa.

The various efficiency indicators provide an opportunity to identify more efficient SIs in the field of humanities and art sciences and to distribute public funding to SIs representing science more efficiently in accordance with these results. Of course, to distribute public funding for SIs should also take into account the results of the qualitative evaluation of SIs from the IESIA. An appropriate methodology for granting public funding to SIs could be developed for this purpose, taking into account the results of their qualitative and quantitative evaluation. Efficiency indicators can serve as a basis for management and future improvement of SIs' performance.

Ethical Declaration: The authors declare that there are no ethical issues related to the research presented in this paper.

AI Declaration: The authors declare that no significant AI tools or technologies were used in the conduct of the research for this paper.

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Deliberating Sustainability Transitions: Citizen Assemblies as Knowledge Intermediaries

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Abstract: Municipalities play a critical role in driving sustainability transitions, but they often face significant challenges when considering complex and contested technologies such as waste-to-energy with carbon capture and storage (WtE-CCS). This paper examines the use of a citizen assembly as a deliberative democratic method for exploring sustainability transitions. The study pays particular attention to how knowledge is generated, deliberated, and managed throughout this participatory process. Drawing on deliberative democratic theory, the research conceptualises the citizen assembly not only as a participatory governance mechanism but also as a temporary knowledge intermediary that bridges expert, experiential, and institutional forms of knowledge. Empirically, the study is based on close, participatory observation of an actual citizen assembly process, and in-depth interviews with participants after the assembly. The findings indicate that citizen assemblies can strengthen the reflexive capacity of municipal governance. Through the process, participants and organisers developed shared framings of the problem, and the assembly helped legitimise a diversity of knowledge claims. However, the study also notes tensions that emerged, such as questions pertaining to the mandate, the uncertainty inherent in new technologies, and the limited time available for deliberation. Overall, the paper contributes to the literature on sustainability transitions by highlighting the role of deliberative democratic innovations, such as citizen assemblies, in local knowledge management. It argues that well-designed citizen assemblies, which explicitly focus on the processes by which knowledge is generated and exchanged, can support more inclusive transition pathways at the local level.

Keywords: Citizen assembly, Knowledge intermediary, Sustainability transitions, Deliberation, Democratic innovation, CCS

1. Introduction

Cities and municipalities now occupy a pivotal position in sustainability transitions. National and supranational climate targets increasingly depend on local implementation, yet many of the technologies implicated in decarbonisation are politically contested, socially uneven in their effects, and perceived as difficult for non-specialists to assess (Fritz et al, 2024; Geels, 2002). Carbon capture and storage (CCS) is a particularly illustrative case. While often framed as an essential component of decarbonisation pathways, CCS remains controversial because of its costs, infrastructure requirements, uncertain long-term effects, and association with existing industrial and energy systems (Bellamy and Lezaun, 2017; Fritz et al, 2024). These tensions become especially acute when CCS is linked to waste incineration in urban settings, where decisions intersect with questions of justice, local environmental burden, consumption, district heating and public trust.

In this context, deliberative democratic innovations such as citizen assemblies have gained visibility as mechanisms through which public authorities can involve residents in difficult policy choices. Literature suggests that mini-publics, an umbrella term for citizen engagement methods such as citizen assemblies, can improve the quality of public reasoning, generate considered judgements, and strengthen legitimacy when conventional representative channels are strained (Smith, 2009; Warren and Gastil, 2015; Curato and Farrell, 2021). Yet there remains a need for more empirically grounded research on how such publics work in sustainability transitions where knowledge is uncertain, distributed and contested. Little attention has been paid to how they organise the movement of knowledge between experts, organisers, institutions and lay participants, and how this process shapes both understanding and social acceptance.

This paper addresses that gap through a study of a municipal citizen assembly in Trondheim, Norway, convened to deliberate on waste-to-energy with CCS at the city's residual waste incineration facility. The assembly was explicitly asked to consider how carbon capture could be implemented in a way that was sustainable and perceived as fair by residents. This question did not merely require participants to register preferences. It required them to interpret technical information, weigh uncertain consequences, connect local and national scales of responsibility, and translate abstract climate commitments into practical and distributive criteria. In that sense, the assembly functioned not only as a participatory forum but also as a temporary site of knowledge intermediation.

The study therefore asks: 1) how did the citizen assembly mediate between expert, experiential and institutional forms of knowledge? 2) what kinds of shared understandings did this process enable? and 3) what tensions limited its effectiveness as a knowledge intermediary? The central argument is that the assembly helped create a more reflexive local governance process by broadening the range of recognised knowledge claims and

generating collectively articulated criteria for fairness, transparency and risk. However, the case also demonstrates that the knowledge intermediary role of a citizen assembly is fragile. It depends on careful design, clear political positioning, adequate time, and explicit treatment of uncertainty.

2. Deliberative Democracy, Knowledge Intermediation and Sustainability Transitions

2.1 Citizen Assemblies and Deliberative Mini-publics

Citizen assemblies belong to the wider family of deliberative mini-publics which are often small groups of citizens, typically selected through random stratified sampling, convened to learn about and deliberate on public issues before producing recommendations or judgements (Smith, 2009; Curato and Farrell, 2021; Curato et al, 2025). They are usually valued for combining representativeness, structured learning and reason-giving. Unlike conventional consultation, mini-publics seek to move participants beyond immediate opinion by exposing them to information, disagreement and collective reflection (Dryzek, 2000; Bächtiger et al, 2018).

The normative appeal of mini-publics rests on several claims. First, they can improve the epistemic quality of democratic judgement by creating settings in which citizens are better informed and more reflective than under everyday conditions of mass politics (Warren and Gastil, 2015). Second, they may enhance legitimacy by demonstrating that policy recommendations emerge from considered public reasoning rather than lobbying or partisan competition alone (Smith 2009). Third, they can enlarge democratic inclusion by enabling participation from citizens who are not organised into advocacy groups or political parties (Curato and Farrell, 2021).

At the same time, deliberative scholars have cautioned against treating mini-publics as democratic solutions in themselves. Their influence depends on how they are connected to wider deliberative systems and institutional decision-making (Dryzek, 2009; Farrell et al, 2019). Questions of agenda-setting, mandate clarity, facilitation, participant support, and post-assembly uptake shape whether a mini-public becomes meaningful or symbolic. Mini-publics can also generate frustration when their outputs are weakly connected to decision authority or when participants feel that the central question has already been settled (Setälä, 2017; Parry, 2025). Thus, the analytical challenge is not only whether assemblies deliberate well, but what kind of institutional work they actually perform.

2.2 Sustainability Transitions and the Role of Publics

Sustainability transitions scholarship has long shown that decarbonisation is not simply a matter of deploying superior technologies. Transitions involve reconfiguring socio-technical systems, infrastructures, markets, institutions and everyday practices (Geels, 2002; Markard, Raven and Truffer, 2012). Because transitions redistribute costs, risks and benefits, they are inherently political. Questions of justice, legitimacy and acceptance are therefore constitutive rather than secondary (Sovacool, 2016; Newell and Mulvaney, 2013; Heffron, 2022).

Recent research has moved beyond seeing publics as passive recipients of innovation and instead conceptualises participation as integral to transition dynamics (Chilvers and Longhurst, 2016; Chilvers et al, 2018). Public engagement shapes the meanings attached to technologies, the concerns considered relevant, and the institutional pathways through which change proceeds. This is especially significant for controversial climate technologies such as CCS, where both awareness and perceptions differ (Pietzner et al, 2011), and where public support cannot be reduced to a simple knowledge deficit-model. Citizens often evaluate such technologies through broader concerns about fairness, trust, responsibility and moral hazard (Bellamy, Chilvers and Vaughan, 2016; Fritz et al, 2024).

From this perspective, citizen assemblies can matter not only because they produce recommendations but because they stage encounters between competing framings of transition problems. They can make visible the tensions between emissions reduction and social equity, between local burdens and national goals, and between technological optimism and precaution. In doing so, they may contribute to what Dryzek (2009) calls deliberative capacity, which is the ability of governance systems to process contested claims in reflective and inclusive ways.

2.3 Knowledge, Expertise and Intermediation

A key issue in sustainability governance concerns the status of expertise. Technical controversies are rarely settled by numbers and data alone because evidence is uncertain, values are implicated, and the consequences of action are distributed unevenly. Fischer (2000) contends that expertise in environmental governance cannot be understood as separate from citizen judgement, as practical, local and experiential knowledges also shape policy-relevant understanding.

The concept of intermediation is useful here. In transition studies, intermediaries are actors or platforms that connect different domains, translate between constituencies, and help coordinate systemic change (Kivimaa et al, 2019; Kanda et al, 2018). Intermediaries do not merely transmit information neutrally. They frame issues, broker relationships, define relevance and sometimes stabilise new pathways. Municipalities themselves can operate as transition intermediaries, but so can temporary participatory spaces when they connect institutions, experts and publics around a concrete transition problem (Masuda et al, 2022).

This study extends that insight by treating the citizen assembly as a temporary knowledge intermediary. During the assembly, knowledge did not flow in one direction from experts to lay citizens. Rather, expert information was translated, questioned, reformulated and combined with lived concerns about affordability, logistics, environmental risk, democratic accountability and local place attachment. The assembly thus became a site of co-production in which knowledge and legitimacy were generated together (Wyborn 2015; Vincent et al, 2018).

3. Methodology

3.1 Case Selection

The case examined here is a municipal citizen assembly organised over four days in Trondheim, Norway, in June 2025 to deliberate on the possible introduction of CCS at the city's residual waste incineration facility. The assembly was tasked with considering how such a project could be realised in a manner that was sustainable and perceived as fair by residents. The case is analytically relevant for three reasons. First, it concerns a technology that is both climate-relevant and publicly contested. Second, it takes place at the municipal scale, where ambitious climate goals meet concrete infrastructure decisions. Third, the assembly was explicitly organised around fairness, responsibility and participation, making it especially suitable for exploring the relationship between deliberation and knowledge management.

The final assembly summary shows that the process was organised over four sessions and that participants were recruited through random invitation with stratification criteria relating to demographic composition. The final set of recommendations covered economy and cost allocation, democracy and decision basis, responsibility and ethics, risk, local impact, and waste and consumption (Trondheim kommune, 2025). These recommendations provide an important output against which to interpret the more process-oriented empirical material.

3.2 Data

The study draws on four qualitative sources: close participatory observation across three of the four assembly days, recorded group deliberations, post-assembly interviews and transcripts, and the final citizen assembly summary and recommendation document. Observation notes captured presentations, group interactions, disagreements, procedural dynamics, and the development of themes across sessions. All personal data were anonymised before analysis, and participant names were removed from transcripts.

All 19 citizen assembly participants were invited for post-assembly interviews, and 13 accepted. These hour-long semi-structured interviews explored participants' motivations, learning experiences, challenges, views on the recommendations, and assessments of the municipality's role. Because the assembly was conducted in Norwegian, transcripts and translated excerpts were checked for meaning as well as literal equivalence. Interviewees are anonymised using participant codes I1–I13. The interviews are especially valuable because they reveal participants' retrospective interpretations, including concerns about technological uncertainty, responsibility, facilitation, and the compressed timeframe.

3.3 Analytical Approach

The study employs a qualitative, inductive approach informed by reflexive thematic analysis (Braun and Clarke, 2021). The coding process moved iteratively between empirical material and conceptual categories from deliberative democracy, transitions and intermediation research. Initial coding identified recurring issues such as fairness, cost, expertise, uncertainty, mandate, facilitation, responsibility and local impact. These codes were then grouped into broader interpretive themes concerning knowledge intermediation, shared problem framing, legitimacy, and design tensions.

The author coded the material in MAXQDA using an iterative reflexive thematic analysis approach across observations, interview transcriptions, and the final recommendations. The author's role as a participatory observer was managed reflexively by distinguishing descriptive fieldnotes from analytic impressions and by treating the researcher's proximity to the process as part of the interpretation. The analysis examined how participants experienced the assembly as a knowledge process, focusing on repeated meanings, reported

experiences and links between design and understanding, while cross-checking themes against the final recommendations.

4. Findings

4.1 The Assembly as a Temporary Knowledge Intermediary

Participants consistently described the assembly as more than a consultation exercise, but worried it could be a "mock" process or mandate. Many entered the process with little prior knowledge of CCS, and several said that the invitation initially seemed surprising because the issue felt technically complex. Yet the assembly created a space in which participants could learn enough to engage meaningfully with the problem. Several interviewees emphasised that hearing multiple presentations and meeting people with different backgrounds helped them take the issue seriously. As one interviewee explained, "Information was provided from both the positive and negative sides. Critics and enthusiasts were involved, and it was understandable. I could understand quite quickly what it was about and what type of technology this was. I experienced that those who became involved were very serious, and people worked hard" (I1). The process consequently worked as a temporary knowledge infrastructure as it assembled technical presentations, procedural prompts, group discussion and institutional framing into a setting where an otherwise remote technology became publicly discussable.

This intermediation was not linear. Participants did not simply receive expert information and convert it into fixed opinions. Instead, they translated expert claims through everyday concerns. Technical information about CCS repeatedly became entangled with questions about local traffic, district heating, household costs, national responsibility, waste reduction and the future of the fjord. In that respect, the assembly broadened the relevant knowledge base. It legitimised the view that lived experience and just transition were not secondary to technical expertise but part of what a sustainable decision required.

At the same time, participants often understood the assembly as a complement to, not a substitute for, expert assessment. Some explicitly said that the process functioned as an informed opinion exercise rather than a professional evaluation. This distinction is important. Participants accepted the value of lay deliberation, but many also insisted that final decisions on a project of this complexity required further technical review. The assembly's intermediary role was therefore twofold: it translated expert material into public reasoning, and it translated public concerns into criteria that could inform subsequent expert and political work.

4.2 Shared Framings: Fairness, Responsibility and Local Burden

Although participants disagreed on many points, the assembly generated several shared framings that were later visible in the final recommendations. One of the strongest concerned fairness in cost allocation. Participants repeatedly returned to the question of who should pay. But this was not merely a narrow consumer issue. Through deliberation, cost concerns expanded into broader criteria for distributive justice. The final recommendations reflected this shift by arguing that costs should be shared among the state, municipality, businesses and citizens according to responsibility and carbon footprint, while protecting low-income groups and avoiding the reinforcement of inequality.

Another shared framing concerned multilevel responsibility. Participants found it difficult to discuss a municipal assembly topic when responsibility appeared to be dispersed across private owners, municipal authorities and the national state. Rather than resolving this tension, deliberation made it more explicit. The assembly recommendations therefore did not simply address the municipality, they repeatedly invoked the need for national anchoring, broader decision bases and involvement of other affected municipalities.

A third shared framing concerned local burden and affected communities. Participants did not discuss CCS solely in terms of emissions reduction. They foregrounded concrete questions of logistics, noise, traffic, infrastructure, ecological risk and the experience of living near the facility. This concern with the local did not amount to rejection. Rather, it reflected a demand that decarbonisation should not be pursued through burdens placed on particular neighbourhoods. The recommendations on logistics, infrastructure, emission-free transport chains and special consideration for those most affected emerged directly from this framing.

4.3 Learning, but With Caution: From Scepticism to Conditional Acceptance

A pattern emerging in the interviews was that participants often moved from initial scepticism or unfamiliarity toward more conditional and qualified acceptance. Exposure to multiple presentations helped many understand why CCS was being considered and why municipalities regarded it as climate relevant. Some interviewees said

that the technology appeared less alien by the end of the process than at the beginning. Deliberation thus had a clear learning effect.

However, increased understanding did not produce unconditional support. What emerged instead was cautious conditionality. Participants became more willing to accept the possibility of CCS if certain criteria were met, such as transparent information, robust financial planning, clear risk assessment, fair cost distribution, and stronger attention to alternatives such as waste reduction and reuse. In other words, deliberation shifted the question from whether the technology is simply good or bad, to under what conditions and with what safeguards, it could be justified. This is a classic intermediary effect, where the assembly did not erase controversy but transformed it into a more structured public judgement.

The final recommendations demonstrate this pattern clearly. They did not endorse CCS in an enthusiastic or unqualified manner. Instead, they placed the project under conditions of transparency, assessment, fairness and caution. The assembly thereby contributed not to social acceptance in a simplistic sense, but to a more articulate social conditionality around acceptance.

4.4 Frictions in Knowledge Management: Uncertainty, Mandate and Ownership

The assembly's intermediary role was constrained by how uncertainty was handled. Participants frequently distinguished between moral or justice-oriented questions, which they felt more capable of discussing, and technical questions. One interviewee explained, "I do not think the technology itself was the biggest topic. We had very different knowledge about technology, so it was not really a big discussion in our group. It was much more about society, socio-economics, costs for Trondheim's residents, and the overall environmental perspective" (I5). Some worried that discussion about uncertainty remained too abstract, yet noted that the topic at hand, namely WtE-CCS, was fitting for a citizen assembly exactly because it is complex with elements of uncertainty.

Although the official question centred on how CCS could be implemented fairly and sustainably, some participants interpreted the process as if they were also being asked whether CCS should happen at all. Others noted that the municipality did not fully control the facility and that ownership changes during the planning process made the institutional context harder to understand. As a result, participants sometimes felt caught between a narrow implementation mandate and a wider political debate they could not avoid. For some, this raised concerns that the assembly risked becoming a form of "rubber stamping" or symbolic validation, even though others noted the organisers acted in good faith and presented information objectively.

These tensions reveal a core challenge of deliberative design. A citizen assembly can act as a knowledge intermediary only when participants know what kind of judgement they are being asked to produce and where that judgement sits in the policy process. If the mandate is under-specified or politically ambiguous, the assembly becomes burdened with interpretive work that should have been done institutionally before deliberation begins.

4.5 Facilitation and Time as Conditions of Intermediation

Interviewees repeatedly underlined the importance of facilitation. In stronger groups, discussion appears to have connected diverse experiences and produced constructive movement toward shared understanding. As one participant put it, "It was open to everyone, and both I and others had a-ha experiences constantly from seeing what other people came up with. Everyone contributed at different levels and brought a slightly different focus, and that is the whole point, because then you have to think a little outside the box" (I7). In weaker groups, participants reported circular discussion, repeated returns to personal cost concerns, and insufficient steering toward the actual mandate. This mattered because the assembly involved substantial information in a compressed period. Without active facilitation, some participants experienced that group conversations lost focus or remained trapped in already rehearsed positions.

Time pressure was the other major limitation. Participants described the process as intense and cognitively demanding. Others suggested that a longer timeline, or more space between sessions, would have allowed them to absorb information and return with more mature reflections.

From the perspective of knowledge intermediation, these observations are significant. Intermediation requires translation, reflection and iteration. When time is too limited, participants may receive information without adequately processing it, or they may formulate recommendations before collective understanding has stabilised. The result is not necessarily negative for the final result; indeed, the assembly still produced a

coherent recommendation set. But the process becomes more fragile and dependent on the sound facilitation, prior knowledge differences and ad hoc group dynamics.

5. Discussion

The Trondheim case suggests that citizen assemblies can play a meaningful role in sustainability transitions when understood as temporary knowledge intermediaries. This argument adds nuance to both deliberative democracy and transitions research.

The findings support deliberative scholarship showing that mini-publics can enhance considered judgement rather than merely collect raw opinion (Warren and Gastil 2015; Curato and Farrell, 2021). Participants entered with uneven knowledge and in some cases strong reservations, but deliberation enabled them to articulate more structured criteria for decision-making. Importantly, this did not require consensus on the intrinsic merits of CCS. What emerged instead was a collectively usable framing of the conditions under which implementation might be legitimate. This suggests that the democratic value of assemblies may lie less in generating agreement than in clarifying public conditionalities and relevant evaluative criteria.

Further, the paper contributes to transitions scholarship by showing that participatory forums can mediate the socio-technical politics of decarbonisation. Much research on transition intermediaries focuses on organisations, networks or support structures operating across markets and policy domains (Kivimaa et al, 2019; Masuda et al, 2022). This case shows that a citizen assembly can perform similar intermediary functions temporarily. It translated expert discourse into public reasoning and shared understanding, surfaced neglected local concerns, and generated outputs that linked to municipal climate ambitions. Figure 1 presents a conceptual model of the citizen assembly as a knowledge intermediary.

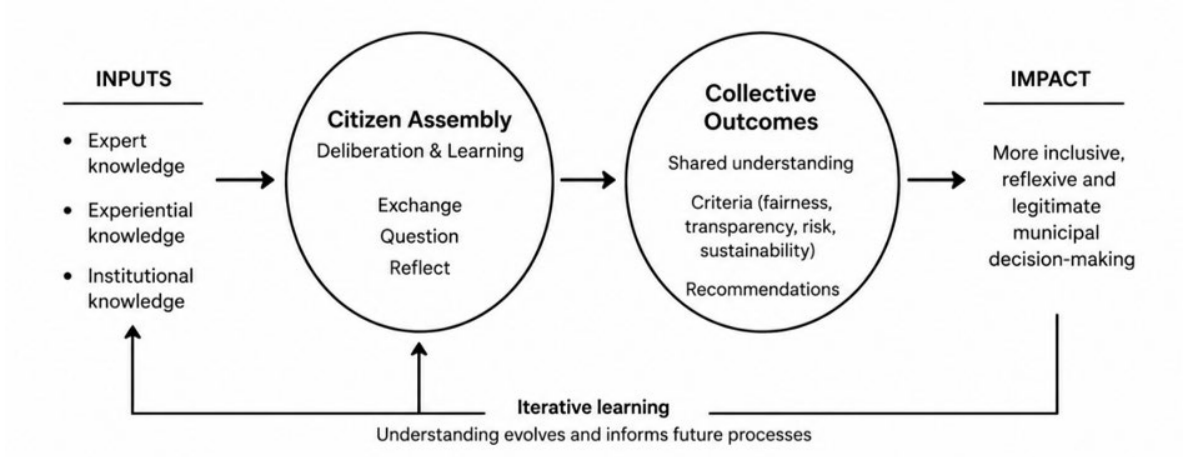


Figure 1: Conceptual model of the citizen assembly as a knowledge intermediary

The findings reinforce arguments that governance under uncertainty requires co-production rather than one-way communication (Jasanoff, 2003; Fischer, 2000; Wyborn, 2015). Participants did not resist expert knowledge as such. Rather, they wanted clearer acknowledgement of what remained uncertain and more opportunity to interrogate the implications of those uncertainties for fairness and local impact. The case therefore challenges deficit-model assumptions that more information automatically produces support. Information mattered, but so did the framing of uncertainty and the institutional transparency of the process.

6. Conclusions, Limitations, and Future Research

This study demonstrates that citizen assemblies can play an important role in managing knowledge within local sustainability transitions. By convening members of the public around the WtE-CCS question, the assembly in Trondheim enabled the co-generation of knowledge that was both technically informed and socially grounded. Participants developed shared understanding and legitimised multiple perspectives, enhancing the reflexivity of municipal governance in transition (Gutmann and Thompson, 2004). The process gave voice to community values and concerns, potentially easing the path for technically complex policies.

However, the analysis also highlights constraints. The efficacy of assemblies depends on design and context where mandate ambiguity, unresolved uncertainties, and time pressure all limit the extent to which citizens can fully arbitrate complex issues. These findings underscore that deliberative innovation is no panacea, it must be

matched with institutional will and supportive structures to translate knowledge into action (Moseley et al, 2025).

Furthermore, this research is based on a single case, so generalisation is limited. The insights come from one municipality and one technology, and different contexts (e.g. more polarized issues or larger assemblies) might yield other dynamics. Finally, since the focus was on knowledge processes, long-term impacts of the assembly on policy outcomes or participant attitudes were not measured.

Future research should focus on comparative studies of multiple assemblies, and longitudinal tracking of participants would help assess lasting impacts on governance and social acceptance. Moreover, experimental variations in assembly design, e.g. longer duration, digital tools for information processing, could be tested to see how they affect knowledge integration.

In closing, this study finds that citizens' assemblies, when well-crafted, can indeed serve as effective knowledge intermediaries in sustainability transitions. By explicitly designing for knowledge exchange, treating experts and citizens as co-producers, local governments can glean from the rich resource of public insight and values. Such deliberative mechanisms do not automatically simplify policymaking hence but offer more inclusivity in sustainability transition processes.

Acknowledgements

The author is grateful to Trondheim municipality, EU project members, the interview subjects, and all participants in the citizen assembly. The author would also like to thank Dr. Bård Haugland for contributing to the collection of interview data. This research is funded by the European Research Council under grant no. G130280.

Ethics declaration: Ethical approval for the study was obtained through Sikt – the Norwegian Agency for Shared Services in Education and Research – prior to the commencement of data collection.

AI declaration: No AI tools were used the creation of this paper.

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Unpacking KM Challenges for Building Resilient Destinations: A Qualitative Study from Poland

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Abstract: Purpose: The tourism industry is fundamentally defined by volatility and exposure to diverse shocks. Considering its vulnerability, tourism requires a robust understanding of resilience to accelerate post-crisis recovery. With knowledge management established in the literature as a vital element in navigating crises and fostering long-term resilience, this study aims to explore KM challenges as emerging difficulties during crises on the pathway toward organisational resilience. Methodology: This study employs a qualitative in-depth analysis of data gathered from Polish destination management organisations (DMOs). The research involved semi-structured interviews with 13 key representatives. Following the analysis, identified KM challenges were mapped against a resilience framework, consisting of absorptive, adaptive, and transformative capacities. Findings: The results indicate that absorptive capacity of the organisations was primarily undermined by informational chaos, disrupted information flows, and inconsistencies, which complicated knowledge management in the face of high volatility. Regarding adaptive capacity, KM challenges pertained to the necessity of unlearning standard operating procedures, managing emergent knowledge, and generating novel ideas under crisis conditions. Finally, KM-related challenges for transformative capacity stemmed from a lack of codified post-crisis knowledge (lessons learned) and a deficiency in translating crisis experiences into strategic organisational protocols. Research limitations: As this is a qualitative study based on the analysis of a limited number of organisations, its findings cannot be generalised and do not represent the sector as a whole. Furthermore, the research was conducted within a single country and in the context of two specific crises, which limits its broader applicability. Practical implications: This study offers valuable insights for practitioners into the challenges arising during a crisis, serving as a baseline for proactive preparation and building the organisational resilience before a new crisis emerges. Originality/value: By integrating KM challenges with the resilience framework, it offers a more nuanced understanding of the role of knowledge management within the tourism crisis context and provides a food for thought for researchers focusing on KM and resilience.

Keywords: Knowledge management, Tourism crisis, DMO, Resilience

1. Introduction

The tourism industry is fundamentally defined by volatility and exposure to diverse shocks (Borazon et al., 2023; Pappas et al., 2023). The rise of emerging disruptions has intensified the need to analyse and fortify organisational resilience, making it a paramount objective for contemporary research and practice (Haider & Cleaver, 2023). Given its systemic vulnerability, the tourism industry requires a robust understanding of resilience to accelerate post-crisis recovery and ensure its enduring sustainability (Ramos Jesus et al., 2026). With knowledge management established in the literature as a vital element in navigating crises and fostering long-term resilience (Bhati et al., 2016; Paraskevas et al., 2013; Yanuarni et al., 2024), this study aims to explore KM challenges as emerging difficulties during crises on the pathway toward organisational resilience.

Despite the significant role of KM in the tourism sector, literature on this topic remains limited (Anand et al., 2023), and existing studies are often narrow and primarily descriptive (Hallin & Marnburg, 2008). A similar situation occurs regarding the study of knowledge management in the context of organisational resilience. Current research addresses public institutions, industrial enterprises, micro-enterprises, rural communities, travel agencies, and tour operators (Aunchistha, 2025; Chen et al., 2025; Fani, 2015; Ghaka et al., 2026; Mafabi et al., 2012; Morong et al., 2025; Umoh & Amah, 2013). However, to the best of the author's knowledge, there is a lack of research focusing on KM in the context of destination resilience in the face of crisis. Applying a resilience-based perspective to KM challenges, specifically through the three-fold capability model, provides insights into the mechanisms of knowledge gathering and utilisation, as well as the forgetting under crisis conditions. The author of this study contends that a deeper understanding of this phenomenon will enable DMOs to develop methods and practices, that will serve as countermeasures positively influencing the cultivation of organisational resilience within the sector.

This article develops as follows. First, it discusses the theoretical background of KM challenges and resilience, followed by the methodology. Subsequently, the results and discussion are presented. The paper concludes with conclusions and directions for future research.

2. Theoretical Framework

2.1 Knowledge Management Challenges

Knowledge management entails the strategic oversight of organisational knowledge (Uit Beijerse, 2000). In the face of crisis situations, it plays a pivotal role in supporting tourism organisations, serving as a fundamental instrument for their managerial strategies (Stolarek-Muszyńska & Zieba, 2025). Yet, in the process of managing knowledge, organisations struggle with multiple difficulties. Notably, the literature lacks a universal conceptualisation of KM challenges. Therefore, for the purposes of this study, the author defines the knowledge management challenge from a process-oriented perspective as *the difficulty an organisation encounters in identifying, acquiring, developing, sharing, and applying knowledge within both internal and external environments*.

The literature offers extensive deliberations on knowledge management challenges across various domains, including the public sector, new business development, the construction industry, consulting firms, and NGOs (Asoh et al., 2002; Berends et al., 2007; Carrillo et al., 2004; Dunford, 2000; Siami-Namini, 2018; Smith & Lumba, 2008; Yusof et al., 2019). Of these, the following KM-related challenges can be highlighted:

- managing tacit knowledge and the integration of information technology in capturing such knowledge;
- cultural adaptation which requires from organisations the transition toward a knowledge-oriented culture;
- human resources management that facilitates the seamless flow and exchange of employee expertise;
- regular update of internal knowledge repositories alongside the systematic monitoring of industry trends;
- preservation of expertise amidst high employee turnover, where the lack of formal codification processes leads to the erosion of organisational memory;
- managing collaborations with external experts;
- navigating intensifying competition which requires the adoption of agile response frameworks (Bolisani et al., 2023; Denizhan Kalkan, 2008; Gupta et al., 2000).

However, to the best of the author's knowledge, there is a notable absence of research focusing on KM challenges specifically within the context of tourism crises. While certain KM difficulties may be universal across different contexts, the unique nature of a crisis situation acts as a differentiating factor, often rendering standard solutions no longer applicable.

2.2 Resilience

As defined by Béné et al. (2012), resilience is the ability to maintain functional continuity while effectively mitigating the adverse effects of the unforeseen disruptions. It constitutes a vital crisis management mechanism for organisational stability, enabling companies to navigate and adapt to various risks (Sharma et al., 2021). Organisational resilience describes the proficiency of the companies in restoring standard functions following a disruption (Borazon et al., 2023).

According to Béné et al. (2012) resilience emerges from three distinct functional capacities: absorptive capacity, which enables persistence; adaptive capacity, which facilitates incremental adjustments; and transformative capacity, which drives fundamental systemic change. The resilience framework by Béné et al. (2012) serves for operationalising and understanding the process of "strengthening resilience", and was used within this study as a contextual framework for the analysis.

Absorptive capacity is essentially the measure of a system's ability to withstand and neutralise sudden external shocks (Haider & Cleaver, 2023). According to Cohen & Levinthal (1990), a firm's absorptive capacity is built on its existing knowledge base, which allows it to identify the worth of new data, integrate it into current operations, and leverage it for competitive advantage. Zahra & George (2002) conceptualise absorptive capacity as a series of interconnected organisational workflows, consisting of four distinct capabilities: acquisition (finding information), assimilation (understanding it), transformation (integrating it), and exploitation (using it). Similarly, Tu et al. (2006) state that absorptive capacity refers to the internal processes that allow an organisation to recognise valuable knowledge, circulate it through the right channels, and successfully assimilate it into the business.

Widely regarded as a driver of resilience, adaptive capacity allows an organisation to remain functional while adjusting to diverse external pressures (Haider & Cleaver, 2023). Adaptability is the power to learn and integrate diverse forms of knowledge and experience into a cohesive response (Folke et al., 2010). Through adaptive management, organisations can proactively navigate volatility by testing new practices on a limited scale; and this systematic approach uses real-time monitoring of shock-responsive elements to turn every disruption into a learning opportunity for future policy adjustments (Holladay, 2018). According to Walker et al. (2004), adaptability denotes the ability of individuals within a system to impact its resilience, and it represents the collective human capacity to manage and maintain systemic stability.

When a system's ability to adapt is finally overwhelmed by the scale of required change, incremental adjustments are no longer enough; this triggers a complete transformation (Béné et al., 2012). Transformation is a conscious move toward a new systemic reality (Haider & Cleaver, 2023). It drives multi-level change that breaks from the status quo. As stated by Walker et al. (2004), transformability refers to the capacity to architect a completely new system when the current ecological, economic, or social frameworks become unsustainable and can no longer be maintained.

3. Methodology

This study employs a qualitative in-depth analysis of data gathered from Polish tourism organisations which operate within a destination management organisations (DMOs) framework. These institutions are responsible for the oversight and promotion of tourism destinations. As noted by the UNWTO (2007), they serve as vital coordinators for a diverse network of industry stakeholders. Their unique position as a central communication link within the industry makes them essential for maintaining stability during a crisis.

This study aims to identify the knowledge management challenges encountered by these organisations during crisis situations and to understand the role they play on the pathway toward achieving organisational resilience. This leads to the following primary research question, namely: what is the role of KM-related challenges in the pursuit of the organisational resilience among tourism organisations navigating crises?

To facilitate a detailed exploration of the phenomenon, this study applied a multiple case study framework (Yin, 2018). The research involved semi-structured interviews with 13 key representatives from seven local and regional tourism organisations at two organisational positions, i.e., decision-makers and staff employees. In their responses, the interviewees referred to specific crisis contexts experienced during their tenure in the DMO sector. Of the thirteen participants, twelve identified COVID-19 as their primary reference point, while one respondent focused on the war in Ukraine. Consequently, the following conclusions are situated within the context of these two specific crises.

Data were collected between November 2023 and January 2024. Selection criteria for the informants included both their functional role within the organisation and a professional tenure commencing no later than 2020. All interviews were recorded and transcribed verbatim in Polish (Poland, 1995), followed by a translation into English. Data were analysed through the thematic analysis (TA) approach as conceptualised by Braun & Clarke (2006, 2012). The analytical process was guided by their six-step framework, facilitating a comprehensive identification and refinement of themes. MAXQDA software was employed for data coding. Following the analysis, identified KM challenges were mapped against a resilience framework, consisting of absorptive, adaptive, and transformative capacities.

4. Findings and Discussion

This section presents the findings based on mapping the knowledge management challenges encountered by tourism organisations during crises against the three resilient capacities.

The results indicate that KM challenges at the absorptive capacity level pertained to both the operations of the organisations and their employees, while also impacting external stakeholders. Based on the data, it can be concluded that the primary threats included information chaos, manifested by a lack of access to critical information during the initial phase of the crisis. This was followed by information overload and disrupted communication flows as presented in Table 2.

Table 2: Knowledge-related absorptive capacity challenges

Aspect	Quotation
Absence of information	"Primarily, it was access to information, in many places it turned out that the information is difficult to access or not available at all." – Organisation F, CEO
Constant changes and informational chaos	"there was uncertainty and a lot of informational chaos at times. Everything was changing like in a kaleidoscope." – Organisation F, Tourism Specialist
Disrupted information flow	"So I have the impression that the transmission of information failed somewhat at the [place]-us and government-[place] level, because this information was already reaching the Internet and people already knew […]" – Organisation A, Product Specialist
Verification of information	"A big problem was certainly the selection and verification of what is real, what is actually available for our entities, and what is, […], sector-dependent." – Organisation C, CEO
Lack of broader perspective	"[…] it seems to me that it was only fragments that we looked at and what was missing was a broader perspective." – Organisation E, Vice-Director

From the organisational perspective, securing access to critical information proved problematic, especially during the incipient phase of the crisis when such data was often unavailable or if they appeared, they remained difficult to interpret. This presents a critical barrier to the development of absorptive capacity. As Murovec & Prodan (2008) posit, this capacity relies on the exploitation of external information and resources for problem-solving. In the absence of access to relevant knowledge resources, absorptive capacity remains constrained.

Disrupted communication and information flow between the government and the organisation was indicated by respondent from Organisation A as another challenge. The participant noted a breakdown in the rhythm of information circulation, where the public received news ahead of the tourism organisation. Furthermore, the absence of informational alignment across local and central government authorities introduced significant ambiguity.

Fragmented and inconsistent reporting across diverse channels resulted in widespread informational turbulence, necessitating careful selection of reliable information (Representative of Organisation C). Fani (2015) in his research proved a positive relationship between knowledge acquisition and organisational resilience. Consequently, it may be argued that a compromised acquisition process may influence on the entity's systemic resilience.

Knowledge transfer to collaborative partners presented a further challenge. Despite preliminary verification by the organisation, stakeholders were inundated with such a vast volume of information that it hindered their ability to navigate it effectively.

The absence of a comprehensive overview of the crisis constituted another significant challenge. As noted by the Vice-Director from Organisation E, the institution received only fragmented data, which impeded a holistic understanding of the situation. The literature provides a "sensemaking" concept which entails constructing a rational framework to understand and communicate complex realities (Duchek, 2020). As Duchek (2020) notes, in crisis situations, this process is critical, as situational awareness and comprehension are the essential precursors to any meaningful organisational action.

Regarding adaptive capacity, KM challenges pertained to the necessity of unlearning standard operating procedures, managing emergent knowledge, and generating novel ideas under crisis conditions which presents Table 3.

Table 3: Knowledge-related adaptive capacity challenges

Aspect	Quotation
Unlearning standard ways of acting	"It was somewhat new knowledge that had to be managed, right? On one hand, we were accustomed to certain actions, somewhat standard you could say" – Organisation A, CEO
Transition to remote work	"It was complicated because you had to catch the other person outside working hours […] someone had to stay with the kids in the morning, someone worked more in the evening" – Organisation F, Tourism Specialist
Managing personal challenges	"knowledge management […] also became management of knowledge about the team, meaning who has what challenges, also how they deal with such […] personal challenges in this crisis" – Organisation A, CEO

Aspect	Quotation
Establishing own guidelines	"based on those general guidelines we created our own guidelines." – Organisation C, Tourist Office Employee
Creating new ideas	"A challenge was somewhat also in creating new ideas. " – Organisation G, CEO

A significant challenge involved the departure from established standard practices, as the crisis necessitated the management of entirely new, emergent knowledge. In this context, the transition to a remote work model constituted a significant difficulty, as it was previously unfamiliar to the study participants. Numerous barriers emerged, including a lack of infrastructural support, as well as difficulties in maintaining communication, the speed of information transmission, and effective knowledge sharing among employees (Representative from Organisation F). As Wang et al. (2021) affirm, these issues were systemic rather than isolated. Most workers possessed minimal remote work experience before COVID-19, and organisations were largely ill-equipped to facilitate or sustain this transition (Wang et al., 2021).

From a managerial perspective, it was crucial to identify and address the specific challenges faced by individual staff members, as certain employees required heightened attention during the crisis, which was highlighted by CEO from Organisation A. Additionally, the interpersonal dynamics presented a significant challenge, as individuals exhibited diverse behavioural responses to the crisis. This necessitated a process of mutual learning to align disparate perspectives and coping mechanisms. As the literature indicates, the adaptability of an entire organisation is predicated upon the individual capabilities of its employees; thus, safeguarding human capacity becomes pivotal to the overall resilience of the organisation (Vogus & Sutcliffe, 2007; Walker et al., 2004).

As indicated by Representative from Organisation C, due to the insufficient clarity of central instructions, the organisation found it necessary to establish independent operational protocols. This represents proactive measures at the intersection of adaptation and transformation, moving beyond a mere attempt to comply with general guidelines. The conceptualisation of new initiatives and ideas presented another challenge for organisations, as they sought to align their strategies with the shifting realities of the crisis environment as depicted by CEO from Organisation G.

Finally, KM-related challenges for transformative capacity stemmed from a lack of codified post-crisis knowledge (lessons learned) and a deficiency in translating crisis experiences into strategic organisational protocols as depicted in Table 4.

Table 4: Knowledge-related transformative capacity challenges

Aspect	Quotation
Loss of valuable lessons learned	"So, from that perspective, it seems to me that Covid hasn't taught us anything and I speak very broadly here" – Organisation A, CEO
Lack of codified lessons learned	"there is nothing formal, it is informally established. We try to adhere to this to prevent another crisis" – Organisation D, Tourism Specialist

According to CEO of Organisation A, the crisis did not serve as a transformative catalyst for the tourism sector at large, and the potential lessons from this period remained largely unlearned. This so-called "organisational amnesia" was also observed in another evidence indicating that no formal procedures were integrated into the organisation post-crisis; instead, only certain informal operational patterns persisted.

This absence of lessons learned implemented at a strategic level was recurring aspect across data. These findings can be examined from two perspectives. On one hand, the organisation generated knowledge based on its crisis experience, however it failed to transfer this knowledge effectively enough to permanently alter behaviours and operational procedures in the post-crisis context, a phenomenon frequently documented in the literature (Duchek, 2020). Furthermore, the failure to codify acquired knowledge within the internal knowledge base prevented it from being preserved in institutional memory. Given that resilience is contingent on the existing stock of organisational knowledge, developing a broad knowledge base is necessary for the proactive anticipation of both internal and external shifts (Cohen & Levinthal, 1990; Duchek, 2020). Fani (2015) demonstrated that the knowledge storage process is correlated with organisational resilience. Thus, it can be concluded that any disruption to this process adversely affects the organisation's overall resilience.

On the other hand, the establishment of certain informal activities within the organisation may indicate the presence of reflective practices that can facilitate experiential learning (Daudelin, 1996).

5. Conclusion

In addressing the primary research question regarding the role of KM challenges in the path toward achieving organisational resilience, it is necessary to focus on several key issues. These challenges arising at various stages of a crisis influenced the resilience capabilities of tourism organisations to varying degrees. Regarding absorptive capacity, the most significant challenge was the lack of adequate information resources, particularly during the initial phases of the crisis. Despite active environmental scanning (Duchek, 2020) and efforts to acquire knowledge, organisations faced difficulties to leverage external information for real-time crisis resolution. As research by Umoh & Amah (2013) indicates, while the knowledge acquisition process is vital for building resilience, it may be concluded that a scarcity of knowledge resources effectively constrains an organisation's capabilities in that matter.

Regarding adaptive capabilities, examining KM challenges sheds light on the mechanisms impeding an organisation's ability to adapt to changing circumstances. Central to this process is the unlearning of old operational methods and protocols that are no longer viable. Crises demand managing new knowledge and implementing new responsive actions, which often necessitates moving away from established practices. From a management perspective, focusing on individual-level challenges is vital, given that organisational adaptability is built upon the adaptive potential of its personnel (Walker et al., 2004). Therefore, securing the well-being of staff during a crisis and proactively developing their adaptive skills beforehand is of critical importance.

The challenge of codifying lessons learned and updating internal knowledge with crisis experience may constrain the organisations transformative capabilities. Without transferring this knowledge into operating procedures, crisis experience remains limited to the tacit knowledge (Nonaka & Takeuchi, 1995) of individuals, which could hinder the company's response to future crises. This also refers to the phenomenon of organisational amnesia (Othman & Azuan Hashim, 2004), whereby the organisation loses valuable lessons in its haste to return to a state of "normal" activity.

Future studies could employ quantitative methods to examine these preliminary findings on a larger scale. Additionally, comparing DMOs across various cultural contexts remains a compelling area for research. As this is a qualitative study based on the analysis of a limited number of organisations, its findings cannot be generalised and do not represent the sector as a whole. Furthermore, the research was conducted within a single country and in the context of two specific crises, which limits its broader applicability. This study offers valuable insights for practitioners into the challenges arising during a crisis, serving as a baseline for proactive preparation and building the organisational resilience before a new crisis emerges. By integrating KM challenges with the resilience framework, it offers a more nuanced understanding of the role of knowledge management within the tourism crisis context and provides a food for thought for researchers focusing on KM and resilience.

Acknowledgements

The author greatly acknowledges the financial support from the National Science Centre, Poland, within the grant no. UMO-2022/45/B/HS4/02631, entitled "Knowledge management in tourism organisations in crisis.".

Ethics Declaration: The author reports there are no competing interests to declare, and ethical clearance was not required for the research.

AI Declaration: The author reports that AI tools assisted in the translation process to improve readability. The output has been critically evaluated and revised.

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Retaining Tacit Knowledge Through Dialogue: The AI Moderator in Work Processes

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Abstract: Tacit knowledge is regarded as a central difficult-to-access resource for organizational learning. Drawing on Michael Polanyi (1985), this kind of knowledge is closely tied to individual action, experience, and contexts, and largely resists documentation capture. In complex work settings, tacit knowledge constitutes a basis for performance and quality assurance. Against the backdrop of demographic change and skills shortages, the challenge of securing, transferring, and making this knowledge usable for subsequent generations is intensifying: around one quarter of the workforce in Germany will reach retirement age within the next ten to fifteen years (Statistisches Bundesamt, 2025). This paper presents an AI-based assistance approach developed at the Fraunhofer Institute for Factory Operation and Automation IFF to support workers when additional guidance is needed, particularly during complex or non-routine tasks. The assistance enables hands-free interaction and goes beyond AI-driven dialogue management by addressing upstream and downstream processes, including preparing existing knowledge for AI use, structured content modelling, and linguistic adaptations. At its core, KIMO (short for AI Moderator) is a dialogue-based AI system that supports employees within their work processes. KIMO facilitates reflection on one's actions and fosters the articulation of experiential knowledge that remains implicit in everyday practice. The approach builds on narrative methods that prompt reflection and the telling of experience-based stories, making implicitly applied heuristics and decision logics more visible (Erlach & Thier, 2004). These methods are complemented by an instructional dialogue design aligned with Bloom's taxonomy of learning objectives (2004). Unlike conventional knowledge management systems, which focus on retrospective documentation and explicit knowledge repositories, KIMO emphasizes AI-based interaction at the moment when knowledge emerges. Through its dialogic mode, person-bound experiential knowledge is externalized, structured, and transformed into organizationally usable knowledge structures. The paper discusses the potential of dialogue-based AI systems for sustainable knowledge transfer and the long-term preservation of organizational memory. It concludes by outlining implications for the design of AI-enabled knowledge management systems, including required information and content infrastructures (e.g., a structured knowledge base).

Keywords: Knowledge transfer, Tacit knowledge, AI-assisted knowledge management, Dialogue-based AI systems, Experiential knowledge

1. Introduction

In the context of an environment characterised by volatility, uncertainty, complexity and ambiguity (VUCA), the management of knowledge is gaining increasing strategic importance, as organisational capability to act depends significantly on the availability and transfer of experience-based decision-making foundations (Weick, 2005). In this regard, the transfer of tacit knowledge represents a central challenge for organisational learning. This implicit form of knowledge—drawing on Michael Polanyi (1985)—is closely tied to individual action and situational contexts and largely resists comprehensive documentation. In complex work environments, it constitutes a key basis for performance and quality assurance.

With increasing automation, tasks are shifting towards monitoring and supervisory activities, while a high level of action competence remains essential in the event of disruptions. At the same time, opportunities for gaining experience within the work process are diminishing. This creates a need to systematically capture implicit knowledge and make it accessible in critical situations. This challenge is further exacerbated by demographic developments: a significant proportion of the workforce will retire in the coming years (Statistisches Bundesamt, 2025). As experiential knowledge is largely developed through practical action, it is particularly at risk of being lost. Without appropriate transfer mechanisms, organisation-specific problem-solving strategies may disappear, thereby impairing organisational performance (Polanyi, 1985). A key issue is the transition from tacit to explicit knowledge. Skilled workers possess extensive experience, yet often lack the means to convey it in a structured manner. Consequently, approaches that not only externalise experiential knowledge but also systematically prepare and integrate it into organisational knowledge bases are gaining importance.

Digital assistance systems already support work processes; however, they are often associated with considerable manual effort in knowledge preparation. Advances in artificial intelligence open up new possibilities to design knowledge transfer in a process-integrated and context-sensitive manner (Stürzebecher et al., 2025). In

particular, the combination of work science methods with Industry 4.0 technologies offers potential for the integrated capture, structuring and utilisation of experiential knowledge. Against this background, this paper presents an AI-based assistance approach developed at the Fraunhofer IFF. The focus lies on how experiential knowledge can be systematically elicited, preserved and made usable for organisational learning processes with the help of AI. Following a classification of the state of research, Section 3 introduces the KIMO system, followed by a discussion of dialogue-based AI systems for sustainable knowledge transfer and implications for research and practice.

2. Theoretical Foundations

This section examines the challenges of explicating tacit knowledge as well as the socio-technical embedding of knowledge processes. Against this background, existing methods and emerging technological developments for supporting the transfer of experiential knowledge are brought into focus in the following section.

2.1 Tacit Knowledge

A central theoretical foundation of knowledge transfer is the distinction between tacit and explicit knowledge. While explicit knowledge is formalised and documented, tacit knowledge—drawing on Michael Polanyi (1985)—is closely tied to individual action, experience and situational contexts, and is hardly articulable. This gives rise to a key challenge for organisational learning: action-relevant experiential knowledge emerges and is applied situationally, yet is rarely transferred into explicit knowledge bases. As a result, a fundamental structural gap arises between knowledge holders and knowledge recipients. Experts possess contextualised experience and implicit decision logics, whereas novices are often not (yet) able to fully reconstruct these relationships. Consequently, the transfer of experiential knowledge should not be understood as a mere transmission of information, but rather as a process of meaning-making in which context, application situations and decision-making processes are conveyed.

Against this background, clear limitations of existing knowledge management systems become apparent: they are primarily designed for the storage and provision of explicit knowledge, enabling structured documentation and efficient access to information. However, in practical application, the embedding in concrete action contexts is often lacking. Documented content rarely includes the underlying decision-making processes or situational problem-solving strategies required for application in complex work settings. Technical documentation and manuals are particularly suited to standardised and repetitive processes, but reach their limits when dealing with variable and non-routine tasks (Kothes, 2010). In such cases, the most relevant portion of knowledge remains tacit and is not accessible to others.

2.2 Socio-technical Perspective

The sustainable design and use of digital knowledge platforms require an understanding of work as a socio-technical system. Work systems can be differentiated into a social and a technical subsystem, which may be analysed separately but must be designed jointly in their interaction (Ulich, 2011). Against this background, knowledge and experiential transfer cannot be understood as a purely technical function, but rather as the result of the interplay between human, organisational and technological factors.

For the analysis of socio-technical systems, the integrative human–technology–organisation approach developed by Sydow (1985) has become established. This approach encompasses design levels ranging from the individual to the organisation and addresses the coordinated design of work systems in the context of technological innovation. The effectiveness of digital tools depends significantly on their alignment with human capabilities, experiential knowledge and organisational conditions (Vuong et al., 2025). A key focus of the socio-technical approach lies in the design of interfaces between subsystems. For the transfer of experiential knowledge, three interfaces are particularly relevant, the design of which substantially influences the effectiveness of digital knowledge systems (Keller et al., 2021):

- the human–technology interface, which describes interaction with digital systems,
- the human–organisation interface, which encompasses the integration of knowledge transfer into roles and organisational structures, and
- the technology–organisation interface, which addresses the integration of digital systems into existing work processes and communication structures.

Effective knowledge transfer can only be achieved through an integrated design approach. Approaches that fail to address all three dimensions are therefore often insufficient.

2.3 Methods for the Explication of Experiential Knowledge

The elicitation of tacit knowledge is particularly supported by the use of narrative methods aimed at externalising experiential knowledge. Approaches such as storytelling enable knowledge to be articulated in the form of narratives, thereby making contextual information and implicit heuristics visible (Erlach & Thier, 2004). The think-aloud method provides a complementary approach to capturing cognitive processes by verbalising actions during their execution (Van Someren et al., 1994). While narration can make tacit knowledge accessible beyond the individual, it is subject to methodological limitations. In particular, narrative methods require targeted facilitation, are time-consuming, and can only be integrated to a limited extent into existing work processes. Their scalability is therefore constrained, especially in dynamic and time-critical work environments.

Furthermore, the usability of experiential knowledge depends significantly on its structured preparation. Didactic models provide suitable reference frameworks in this regard. Bloom's taxonomy (2004) enables a systematic structuring of knowledge across different cognitive levels of employees and thus supports target group-oriented preparation for various usage contexts. Clearly structured and reduced information presentation can support learning processes by taking into account the limited cognitive processing capacity of humans (Wood et al., 1976; Sweller et al., 2011). Overall, it becomes evident that the effectiveness of knowledge provision largely depends on how content is didactically prepared and adapted to the cognitive prerequisites of users. At the same time, such concepts have so far been insufficiently integrated into technical systems and have therefore not yet fully realised their potential for organisational knowledge transfer.

2.4 Artificial Intelligence Approaches for Experiential Knowledge Transfer

With the increasing use of artificial intelligence in assistance systems, new potential for experiential knowledge transfer is emerging. However, current applications primarily focus on the processing and provision of explicit knowledge, for example through document-based knowledge management systems. In this context, Retrieval Augmented Generation (RAG) is frequently applied, whereby large language models generate responses based on previously retrieved information from documents or web sources. While such systems enable efficient access to explicit knowledge, they do not adequately address the elicitation of experiential knowledge (Böhm & Durst, 2025). The focus remains on information retrieval, whereas the generation and structuring of tacit knowledge within the work process are still underrepresented.

Recent approaches therefore emphasise process-integrated and context-sensitive knowledge integration. In particular, combining continuous documentation with feedback mechanisms shows potential to gradually externalise tacit knowledge and transform it into structured knowledge bases (Stürzebecher et al., 2025). However, the challenge remains to design these processes so that they are integrated into everyday work, scalable, and didactically sound.

Overall, existing approaches to the elicitation, structuring and provision of knowledge are often considered in isolation. Knowledge management systems focus on explicit knowledge, narrative methods enable the externalisation of tacit knowledge, and didactic models support the structuring of learning content. AI-based systems offer new potential but are mainly used to access existing knowledge. This highlights the need for a holistic perspective that integrates these approaches within the work process while considering socio-technical requirements. Section 3 therefore introduces a dialogue-based AI-based assistance system that enables context-sensitive elicitation, didactic preparation and broader organisational use of experiential knowledge.

3. The AI-based Moderator KIMO

The following section introduces KIMO (named after the German term KI-Moderator, which translates to AI moderator in English), developed at the Fraunhofer Institute for Factory Operation and Automation IFF in Magdeburg. KIMO is a dialogue-based, AI-based assistance system designed to support knowledge retention by:

- providing situational guidance to employees during work processes,
- capturing tacit knowledge not retrospectively but directly within the work process,
- structuring and preparing this knowledge, and
- making it available for organisational learning processes.

KIMO addresses the challenges identified in Section 2 by integrating the elicitation, structuring and provision of experiential knowledge into a unified, process-oriented system. The development of KIMO was guided by Design Science Research principles, with the aim of designing, implementing and exploratively evaluating an AI-based artefact for tacit knowledge retention. Following an agile and iterative development process, early prototypes

were progressively refined through technical testing and feedback from potential users. The crane commissioning use case served as the primary application context in which successive cycles of problem identification, artefact development and evaluation informed the evolution of the system. KIMO is used by crane commissioning personnel during commissioning activities to provide hands-free procedural guidance and to capture expert knowledge for future reuse. While novice workers benefit from step-by-step support and access to expert knowledge, experienced workers can use the system to document and transfer their experiential knowledge.

The system was developed in the context of crane commissioning, a safety-critical industrial application characterised by complex procedures and a high dependence on experiential knowledge (Figure 1). In this use case, the knowledge base is particularly diverse, as key processes are often highly dependent on the specific situation of the crane installation. The knowledge base was initially derived from existing crane commissioning documentation and procedural instructions. To complement these formal sources, tacit knowledge was elicited from domain experts through semi-structured interviews and translated into structured process descriptions and action sequences. The resulting knowledge structures were reviewed and validated by experts to ensure their technical correctness and practical applicability. This scenario serves as a reference framework for the subsequent discussion of the system. Within this context, KIMO is used directly by crane commissioning personnel during the execution of commissioning tasks. Its purpose is to provide process guidance, support decision-making in complex situations, and preserve experiential knowledge that would otherwise remain undocumented. A further particularity arises at the human–technology interface: operators require both hands to control the crane, meaning that only hands-free assistance systems can be employed. Within this application context, KIMO functions as a rule-based support system designed to ensure safe and transparent assistance for actions performed during the work process. In contrast to generative dialogue systems, the approach is based on a clearly structured dialogue design with a limited knowledge base in the sense of a closed-world assumption (Jurafsky & Martin, 2026). This enables controlled and robust interaction, which is of particular importance in safety-critical environments.

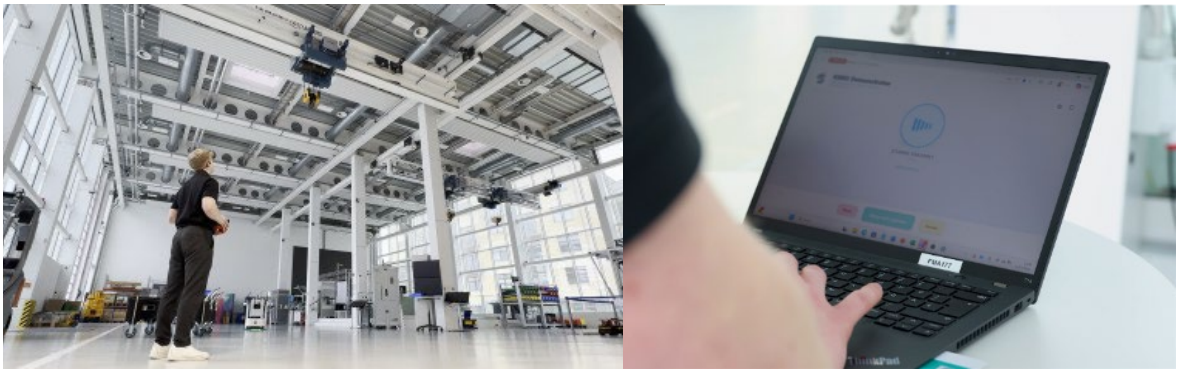


Figure 1: Use case “crane commissioning”

From a socio-technical perspective (section 2.2), KIMO assumes a structuring function at the interface between humans, technology and organisation. It supports the interaction between operators and technical systems, integrates into existing work processes, and enables the systematic transfer of experiential knowledge into organisational knowledge structures. Through this approach, KIMO addresses the shortcomings of isolated approaches identified in Section 2 by pursuing an integrated design of knowledge transfer in line with the human–technology–organisation approach. It not only considers the socio-technical integration outlined in Section 2.2 at a conceptual level, but also implements it concretely within the system architecture and usage context.

From a technical perspective, KIMO is realised as a dialogue-based, AI-based assistance system (Colabianchi et al., 2023) that enables interaction with users via natural language. The underlying system process is illustrated schematically in Figure 2. Spoken input is automatically converted into text by a speech-to-text system and processed by a central dialogue manager. This dialogue manager takes the current request as well as the previous course of the interaction into account and determines which information or functions are needed to provide an appropriate response. The system is built upon a knowledge base containing validated, domain-specific information such as work instructions and process descriptions. This knowledge is organised into structured sequences of work steps that represent the logical flow of a task. When a user asks a question or requests support, KIMO searches the knowledge base for relevant information and provides the most suitable

content for the situation. In this way, the system can access existing organisational knowledge and make it available to users directly within their work process.

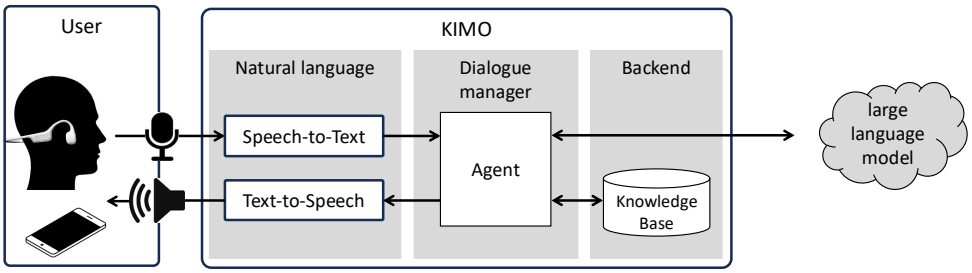


Figure 2: The technical architecture of the AI-based moderator

For response generation, an external large language model is used which formulates a comprehensible and context-specific answer on the basis of a structured prompt consisting of the user query and the previously identified content. The determination of the current processing state as well as the next appropriate action steps is not based on an explicit system-controlled state model; instead, it is implicitly handled by the language model on the basis of the dialogue context. Thereby, the model does not independently access unverified knowledge sources but operates exclusively within the provided information base. The response is initially generated in text form and subsequently converted into spoken output via a text-to-speech system, thereby enabling hands-free use within the work process.

The interaction with the AI-based moderator can be described as a multidimensional state model. At a fundamental level, KIMO distinguishes between listening and non-listening states. In the non-listening state, the system may either be completely inactive or passively await an activation keyword (“KIMO”), thereby enabling event-based reactivation. In the listening state, user speech input is continuously transmitted to the back end and processed accordingly. A distinction is made between situations in which no speech input is detected and those in which user activity is recognised, the latter typically triggering a system response. Independently of these states, KIMO operates along three functional dimensions: listening, thinking and speaking. During the “thinking” phase, the underlying language model generates a response, which is subsequently transformed into an auditory output (“speaking”). These processes can, in principle, occur in parallel, thereby enabling smooth and context-adaptive interaction. At the same time, the system is designed to immediately interrupt its output processes as soon as new speech input is detected, ensuring that interaction remains user-centred at all times.

3.1 Conceptual Development of the AI-based Moderator

KIMO fulfils two closely interrelated core functions: (1) assistance within the work process and (2) knowledge capture.

Within its *assistance function*, KIMO supports both inexperienced users in carrying out work processes and experts in performing infrequent or less routinised tasks. This goes beyond dialogue management and includes the preparation of existing knowledge for AI use, structured content modelling, and linguistic adaptation. Interaction takes place hands-free via an ergonomic headset (bone conduction headphones) using natural language, enabling flexible use across work contexts. The design follows the principle of instructional scaffolding (Wood et al., 1976): the system provides sequential action steps and proceeds only after user confirmation. This enables context-adaptive, step-by-step support, reduces cognitive load, and ensures the safe execution of complex tasks. In this way, KIMO assumes a tutorial role and supports learning within the work process by making contextualised decision-making foundations accessible, thereby helping to bridge the gap between experts and novices described in Section 2.

In addition, KIMO enables process-integrated *capture of experiential knowledge* directly within the work process. Experienced employees are encouraged to verbalise their actions and decision-making processes in line with the think-aloud method (Van Someren et al., 1994). These verbal inputs are recorded continuously without interrupting task execution. Knowledge capture and structuring take place in a subsequent processing step, in which dialogue data are analysed and transformed into structured knowledge units, such as revised or newly created instructions. Based on a predefined knowledge categorisation, KIMO evaluates whether relevant information should be added or outdated or incorrect content removed. This includes not only procedural knowledge but also underlying reasoning (conditional knowledge), ensuring deeper understanding and transferability. By capturing these reasoning processes, the system makes the “why” behind actions visible—an

aspect often missing in conventional documentation (Section 2.1). In this way, KIMO supports the development of continuously evolving instructions and addresses the challenge of explicating tacit knowledge (Polanyi, 1985).

The subsequent processing step is implemented as a separate review process to ensure quality assurance and continuous development of the knowledge base (Figure 3). During this phase, interaction is paused and no speech processing or output occurs. KIMO analyses the recorded dialogue data and generates proposals for updating knowledge content. These results are presented to users, distinguishing between unchanged and revised instructions. In both cases, users are informed visually (via a pop-up window) and can confirm or reject the proposed changes.

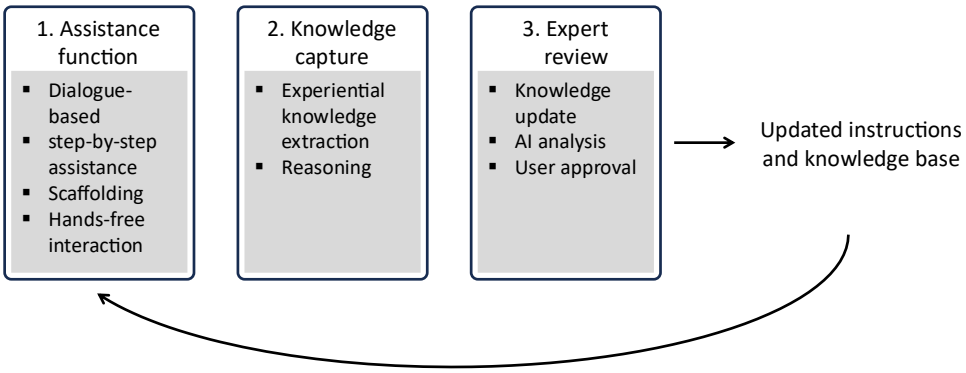


Figure 3: Knowledge capture with KIMO

3.2 Methodological Design of the Dialogue

The dialogue design of the AI-based moderator combines didactic and narrative approaches to support the explication of tacit knowledge. The content structure follows Bloom's taxonomy (2004), with targeted follow-up questions encouraging experts to articulate not only procedural knowledge in the form of action steps, but also underlying reasoning and experience-based narratives. Initial dialogue sequences and prompts were derived from crane commissioning procedures and expert interviews and were iteratively refined through technical testing, user interactions and feedback from the exploratory evaluation. Particular attention was given to eliciting both procedural and conditional knowledge while ensuring clarity, brevity and suitability for industrial practice. Guided by the concept of action competence (Erpenbeck & Heyse, 2015), the dialogue structure supports users in carrying out work processes while preserving their autonomy and systematically capturing knowledge in terms of both application and rationale.

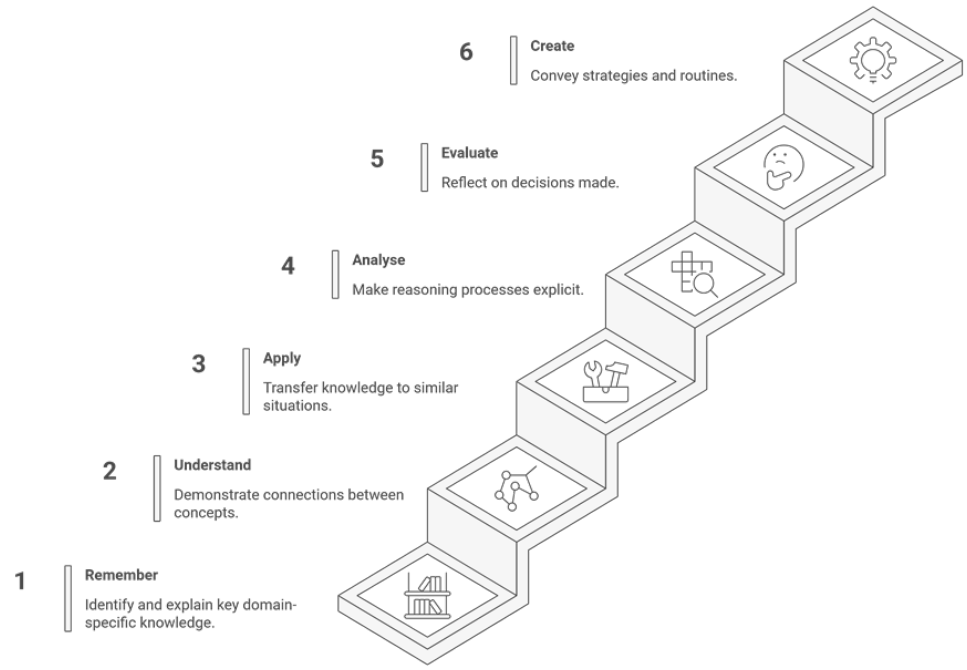


Figure 4: Bloom's taxonomy of learning objectives (2004)

To reduce cognitive load, the interaction follows the principles of Cognitive Load Theory as proposed by John Sweller et al. (2011): by focusing on individual action steps and providing clearly structured and reduced information, cognitive demands are minimised. This is particularly important in complex and safety-critical work environments in order to prevent errors caused by overload.

Through the open prompts used during knowledge capture, which encourage users to describe new knowledge in their own words, reflection on individual actions is stimulated while also supporting the articulation of experiential knowledge that would otherwise remain implicit in everyday work (Erlach & Thier, 2004). In line with the think-aloud method, experts describe their actions during task execution, while the AI-based moderator structures these descriptions through targeted follow-up questions and prepares them for subsequent use (Van Someren et al., 1994). In contrast to traditional narrative elicitation methods, which are often time-consuming and only limited in scalability (Section 2.3), KIMO enables continuous knowledge capture that is directly integrated into the work process.

3.3 Exploratory Evaluation

To obtain initial insights into the usability and practical applicability of the AI-based moderator, an exploratory evaluation was conducted. The evaluation pursued two objectives: to assess the usability of the dialogue-based assistance system and investigate its suitability for knowledge transfer in an industrial context. The evaluation was carried out in two phases involving different participant groups. In the first phase, nine students interacted with the demonstrator to assess fundamental interaction patterns and general usability. In the second phase, two crane commissioning experts representing the intended target group evaluated the system from a domain-specific perspective. Participants were introduced to the demonstrator and its role within the crane commissioning process before interacting with KIMO in a demonstration setting. Participants first completed a questionnaire created using LIME that collected socio-demographic data, expectations regarding the system, and prior experience with artificial intelligence. Subsequently, the crane commissioning procedure was carried out in pairs using KIMO. One participant performed the tasks while the second documented observations and issues. Following the practical testing phase, participants took part in a guided group discussion addressing perceived effectiveness, user satisfaction, and Responsible AI aspects. This qualitative exchange provided additional insights into user experiences and recommendations for future improvements. The evaluation provided initial evidence regarding the practical applicability of the approach. Participants reported a positive sense of safety and perceived the dialogue-based guidance as supportive during the execution of complex tasks. Particularly noteworthy was the reported feeling of remaining “in command” throughout the interaction. This perception of control is especially relevant in safety-critical industrial environments, where users must remain responsible for operational decisions despite receiving AI-based assistance. Furthermore, participants reported a high level of trust in the system. The guidance provided by KIMO was perceived as reliable, and the suggested process flow was evaluated as logical and comprehensible. The dialogue structure, which was designed on the basis of instructional scaffolding and informed by Bloom’s taxonomy (Bloom, 2004), was perceived as beneficial for supporting users during task execution.

The evaluation also indicated a high level of acceptance of KIMO for training-on-the-job scenarios. Participants highlighted the potential of the system to support inexperienced employees by providing contextual guidance directly within the work process while simultaneously facilitating the transfer of experiential knowledge. One participant described the system as “very practical for inexperienced users” and particularly valuable “for the new generation” of employees. The evaluation also revealed several limitations of the current approach. Industrial noise environments remain challenging for speech recognition, as standard microphone solutions quickly reach their limits. In addition, participants highlighted a fundamental limitation of the system architecture. As one expert noted, “KIMO listens, but does not see.” The system relies on verbal user input and cannot independently verify whether actions are performed correctly. Future versions could therefore benefit from the integration of complementary visual sensing technologies. Another challenge concerns the maintenance of the knowledge base. While KIMO can capture new insights from user interactions, knowledge updates derived from dialogue data still require expert validation before integration to ensure correctness and relevance.

Furthermore, the findings should be interpreted with caution due to the exploratory nature of the study and the limited number of participants. Since the evaluation was conducted exclusively in the context of crane commissioning, the transferability of the results to other industrial domains remains to be investigated in future research.

4. Implications for Research and Practice

Dialogue-based AI systems should be conceptualised more explicitly as socio-technical systems (Ulich, 2011; Sydow, 1985). Rather than deriving value from isolated components such as speech processing, their effectiveness emerges from the interaction of human–AI communication, knowledge structuring, and organisational integration. Future research should therefore examine how these dimensions can be jointly designed and aligned (Keller et al., 2021). A central challenge concerns the representation of procedural and conditional knowledge, which is often tacit and context-dependent (Erlach & Thier, 2004). This highlights the potential of hybrid approaches that combine data-driven methods with structured knowledge models. At the same time, continuously evolving knowledge bases require mechanisms for versioning, updating, and contextual adaptation. Closely related are issues of quality assurance: transforming dialogue data into organisational knowledge structures demands processes that ensure reliability, traceability, and transparency while balancing automated suggestions with human validation (Böhm & Durst, 2025). Beyond technical considerations, the increasing use of AI-based assistance systems raises questions about their long-term effects on learning and competence development (Dehnbostel, 2021). Future studies should investigate under which conditions such systems foster learning, which competences users require, and how AI can support rather than replace expertise development. Several limitations of this study should be acknowledged. The evaluation was exploratory and involved a small number of participants, providing initial insights rather than generalisable findings. Furthermore, the study focused exclusively on crane commissioning, leaving the transferability of the approach to other industrial contexts open. The current system relies solely on speech-based interaction and therefore depends entirely on verbal user input. Integrating complementary sensing technologies could improve contextual awareness and robustness. In addition, the evaluation focused on user perceptions and practical applicability; objective measures such as task completion time, error rates, cognitive load, knowledge retention, and learning outcomes were not assessed.

From a practical perspective, the successful implementation of dialogue-based AI systems requires a holistic organisational approach. User acceptance is critical, as interaction with a speech-based and largely invisible system depends on trust, familiarisation, and training. Equally important is the integration of knowledge capture into existing work processes. Although knowledge can be captured during task execution, organisations must establish structures for reviewing and validating content without impairing operational performance. Maintaining the knowledge base also remains a key challenge, as experiential knowledge evolves through technological change, new workflows, and personnel turnover (Stürzebecher et al., 2025). Finally, organisations must address the risk of de-qualification. While AI-based assistance can facilitate complex tasks, excessive reliance on automated support may reduce opportunities for developing problem-solving competences. Complementary learning and reflection activities therefore remain essential.

5. Conclusion and Outlook

This paper demonstrates that AI systems represent a promising approach to addressing the gap between explicit and tacit knowledge in organisational contexts. At the core of this approach is the shift from retrospective documentation towards a process-integrated, interactive elicitation and utilisation of experiential knowledge. By combining narrative methods with didactically structured dialogue design and AI-based processing, it becomes possible to systematically access and utilise even those elements of knowledge that are difficult to articulate. A key contribution of the approach lies in the integration of perspectives that have previously been considered in isolation: while traditional knowledge management systems primarily focus on explicit content and narrative methods are often applied only selectively, KIMO brings both approaches together within a single system—thereby conceptualising knowledge provision as situational support within the context of action. At the same time, the approach highlights the importance of a didactically grounded design of human–AI interaction, using dialogue specifically to structure, reflect upon and further develop knowledge bases.

The findings indicate that the effectiveness of such systems does not depend solely on technological progress, but is significantly shaped by the interplay between knowledge structures, interaction design and organisational embedding. In this sense, KIMO can be understood as a prototype for a new generation of knowledge systems that are more strongly oriented towards context sensitivity, interaction and continuous learning. Several directions for future development emerge: these include adaptive systems that are more closely tailored to individual users and specific work situations, as well as integration into broader digital infrastructures, for example in the context of digital twins. Furthermore, ongoing advances in AI create opportunities to support reflection and learning processes more explicitly by making underlying rationales and alternative courses of action visible. Overall, dialogue-based AI systems such as KIMO have the potential to make a significant

contribution to the sustainable retention and transfer of experiential knowledge by systematically transforming individual experience into explicit structures, thereby strengthening organisational capability to act.

Ethics Declaration: No ethical clearance was required for the research presented in this paper. Since the study did not involve human or animal subjects or the collection of sensitive or personal data, approval from an ethics committee was not needed.

AI Declaration: An AI tool (Fraunhofer Gesellschaft's FhGenie) was used during the development of this paper for minor tasks related to structure and translation. Specifically, the tool helped the author rephrase and organize certain sections more clearly and translate select passages from German to English. All content generated or revised with the help of the AI was carefully reviewed and edited by the author to ensure accuracy, coherence and academic integrity.

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Knowledge Management During Organizational Crisis: The Influence of Leadership

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Abstract: This qualitative case study investigates how leadership influences knowledge management (KM) and organizational learning (OL) within a Swedish manufacturing organization facing economic pressure. In an increasingly volatile environment, maintaining knowledge continuity is essential for being competitive and organizational resilient. Data were collected through 27 semi-structured interviews with 31 participants and then analyzed using thematic analysis. The study shows the importance of leadership styles and the leadership's ability to understand the organization from a holistic perspective as well as the digital maturity of the company. The results reveal a significant loss of knowledge resulting from downsizing in order to manage economic pressure, specifically regarding critical tacit knowledge described as "fingertip feeling". This personal, intuitive expertise is vital for navigating production variables and maintaining an old machine park that relies on specialized in-house competence. This means that even if workforce downsizing may be effective in the short-term for managing economic pressure, in the long-term it likely results in critical (tacit) knowledge loss and hence have a negative impact on effectiveness and competitiveness. The study finds that an authoritarian, top-down leadership style acts as a primary barrier to a healthy knowledge culture. Furthermore, it revealed that a lack of transparency regarding major leaderships decisions fosters a culture of silence. The study also revealed a digitalization maturity gap where leadership-driven tools are viewed as administrative burdens due to low digital maturity and a preference for analog methods suited to situated practice. Organizational learning is further hindered because employee improvement initiatives often run out in the sand due to a lack of systematic follow-up and structured feedback loops. The study confirms that leadership is the primary driver for building a culture of continuous learning. To maintain competitiveness and resilience during crises, leadership needs to adopt a holistic perspective that values tacit knowledge and organizational learning. Failing to integrate KM and OL into daily work processes directly compromises long-term organizational memory and the ability to adapt to adverse events.

Keywords: Leadership, Knowledge management, Organizational learning, Digital maturity, Tacit knowledge

1. Introduction

In a fast-changing world, organizations must have the ability to meet demands of both their internal and external environment (Yeo, 2005), to be competitive. Economic pressures often result in downsizing, restructuring, and increased managerial control. This may improve short-term financial performance, but today when the most valuable asset is knowledge (Marchegiani, 2021), organizations need to be aware that employee turnover results in an organization's inability to ensure continuity of knowledge and hence will have a negative effect on their competitiveness (Hana & Lucie, 2011). It will also have a negative impact on organizational resilience since organizational learning and organizational resilience are inherently interrelated (Evenseth et al, 2020).

Organizational resilience is about an organization's ability to anticipate potential threats, to cope effectively with adverse events, and to adapt to changing conditions (Duchek, 2019, p.220), i.e. to be a learning organization (LO). Evenseth et al (2020) argue that learning is connected to all three stages of resilience (anticipation, coping, and adaptation) that organizations need to develop. Organizations must learn how to learn and how to manage their knowledge resources, i.e. performing knowledge management (KM) (Aggestam, 2006a; Aggestam, 2006b). KM is about ensuring that knowledge from previous experiences can be utilised and applied in decision-making and organisational development (Jennex et al., 2007; Jennex, 2005).

Leadership is responsible for KM and has a crucial influence on the organizational culture, communication patterns, and the level of trust between employees and management. These factors are critical for creating an environment that supports knowledge sharing and collaboration (e.g. Lei, et al., 2019). Leadership styles

characterized by transparency, participation, and support for learning encourage employees to share knowledge and to contribute to continuous improvement (Jiang & Lou, 2018). In contrast, highly centralized and authoritarian leadership styles may discourage open communication and reduce employee engagement (Busse & Regenberg, 2019).

Despite extensive research on KM and organizational learning, relatively limited attention has been given to how leadership influences KM in organizations experiencing economic crisis (Buhagiar & Anand, 2023). Understanding this relationship is particularly important in manufacturing environments where tacit knowledge, as for example as "fingertip feeling", plays a critical role in maintaining production quality and operational performance. Research has increasingly emphasized the importance of leadership for knowledge management processes and organizational learning within organizations (Pellegrini, et al., (2020). Leadership is often seen as a key factor in creating conditions that support knowledge creation, sharing, and the development of learning practices. However, as noted by Pellegrini et al. (2020), the relationship between leadership and knowledge-related processes remains fragmented and requires further investigation in different organizational contexts. In particular, there is a need for a deeper understanding of how leadership shapes knowledge management and learning processes in organizations experiencing structural and economic pressures.

The purpose of this study is therefore to explore how leadership influences KM and organizational learning within a manufacturing company facing economic pressure. The study contributes to filling the knowledge gap concerning how leadership, in a manufacturing organization experiencing economic pressure, influences KM processes and practices, knowledge sharing, and organizational learning.

2. Theoretical Background

Being a learning organization (LO) positively affects work engagement and employee resilience (Malik & Grag, 2020). To build a culture of continuous learning within organizations, leadership is the key (Ahsan, 2025). There is also a strong relationship between LO and knowledge management (KM) and the process to become, or be, a LO must include KM (Aggestam, 2006a, Aggestam, 2006b). Figure 1 gives a conceptual description of LO and KM.

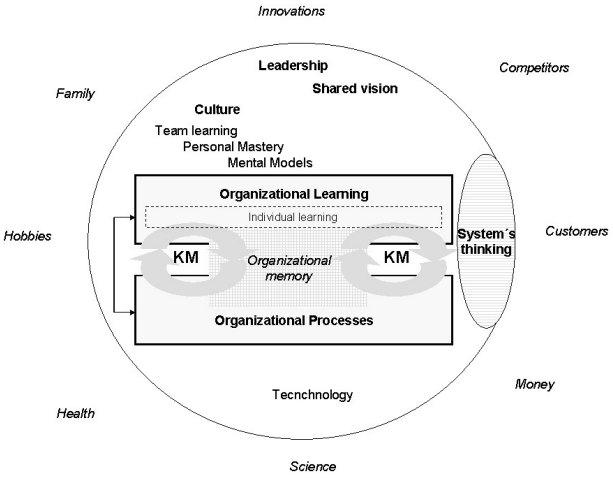


Figure 1: A conceptual model of LO and KM (Aggestam, 2006a)

2.1 Learning Organizations and Leadership

A learning organization (LO) is one that facilitates the learning of all the individuals in the organization (Pedler et al, 1989) and "continually expanding its capacity to create its future." (Senge, 1990, p. 14). A LO considers the needs of the individuals in it (Kline and Saunders, 1993) and has a culture that supports learning and innovations, both by individuals and by the organization itself (Wiig, 1993). Leadership has a key role in creating and shaping the culture (Krapfl & Kruja, 2015; Schein, 2004; Bertassini et al, 2021; Ashan, 2024).

In the beginning, the founders form the culture, and as long as the organization is successful this culture defines the leadership, but if the organization has problems and difficulties, the leadership must do something

(Schein, 2004), see Figure 2. It takes time to foster a new (learning) culture. Culture as a concept is abstract, but its consequences in, for example, behaviors are concrete (Schein, 2004).

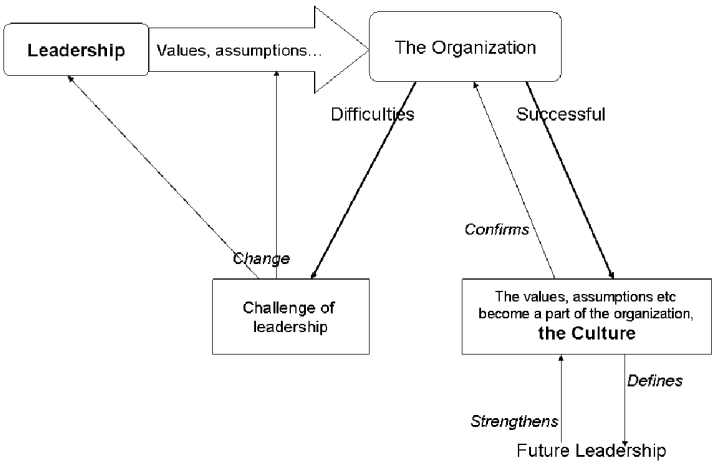


Figure 2: Leadership and culture (Based on Schein, 2004)

Leadership and a learning culture are also important for employee well-being. By fostering a learning culture, organizations can enhance employee engagement, creativity, innovation and adapt more effectively to a changing environment (Ahsan, 2024).

2.2 Learning Organizations (LO) and Knowledge Management (KM)

LO and KM are dependent on each other, and KM can be regarded as a subsystem of LO; changes in KM result in changes in the organization and vice versa (Aggestam, 2006a). A LO must facilitate communication and knowledge sharing, both within and across organizations and stakeholders (Evenseth et al, 2022). KM aims to create value by learning from past experiences and not repeat mistakes. It is about ensuring that the right knowledge is available for the right person at the right time, so that knowledge and previous experiences can be applied in decision-making and organizational development (Jennex et al., 2007; Jennex, 2005). This includes knowledge sharing, i.e. managing knowledge so that knowledge relevant to the organization can be easily captured, packaged, shared, and used. To be successful, there must be a knowledge sharing attitude (Call, 2005; Chua and Lam, 2005; Sun and Scot, 2005; Busch and Richards, 2004). Furthermore, while the management has the responsibility for the strategic level, all the members of the organization are responsible for the daily KM work.

There are different types of knowledge and different ways of describing and categorizing these (e.g. Nonaka & Takeuchi, 1995; Wiig, 1993; Svensson & Durst, 2021; Wang & Jacobson, 2023). A common distinction in the literature is between tacit and explicit knowledge (e.g. Gore & Gore 1999; Loermans, 1993; Nonaka & Takeuchi, 1995; Wiig, 1993). Tacit knowledge is difficult to identify and to express since it is highly personal and concerns insights and intuition (Nonaka & Takeuchi 1995; Blodgood & Salisbury, 2001). Explicit knowledge is easier to express and can, in contrast to tacit knowledge, also be processed by a computer (Blodgood & Salisbury 2001; Nonaka & Takeuchi, 1995). Different types of knowledge have different implications for KM work (e.g., Nonaka & Takeuchi, 1995). Knowledge develops from information (Wiig, 1993) and also has a function of contributing to new information (Schreiber et al., 2000). Activities aimed at creating knowledge occur within individuals or through interaction between people. (Davenport & Prusak, 1998), but the real transformation process, when information is transformed into knowledge, is individual. Learning is situated in practice (Mehrizi et al.,2022; Nicolini et al., 2003). This means that professional knowledge changes as practice develops and learning occurs through the change in practice (Hopwood, 2016).

There is also a difference between organizational knowledge and individual knowledge, where organizational knowledge is knowledge that remains in the organization even if an employee leave (Aggestam et al., 2010). Figure 3 visualizes KM and its different parts. Effective knowledge sharing with support from digital technology requires culture and work processes that enable both to contribute and to find the knowledge and information needed. For the knowledge to be used it must contribute to benefit, be of high quality and be relevant (Cheuk

et al., 2017; Sharma & Bock, 2005). Therefore, it is critical that a culture and working methods are established that ensure that knowledge is kept up to date and up to date over time (Aggestam et al., 2010). Leadership, as well as champions, have a key role in creating culture, structures and incentives for knowledge to become a strategic resource and to build a learning culture.

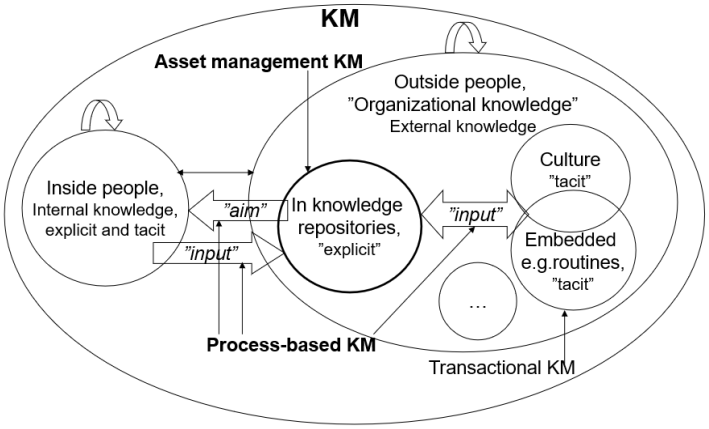


Figure 3: KM and its different parts (adapted from Aggestam et al, 2010)

3. Method and Analysis

3.1 Study Design

This study was conducted as a qualitative case study (Myers & Avison, 2002). The study is conducted in a Swedish family-owned manufacturing company experiencing economic pressure and workforce downsizing. A single case study can be justified if it is purposeful and provides a large amount of information (Gummesson, 2001). The company produces prefabricated concrete elements and related products used in building and infrastructure projects. Its operations combine industrial manufacturing with practical expertise to deliver durable building solutions for both private and public clients. The company has traditionally been characterized by an authoritarian leadership style. This has shaped how decisions are made, how responsibilities are distributed, and how employees relate to management, and is therefore still an important contextual factor for the company culture. A case study approach was considered appropriate because it allows for an in-depth exploration of complex processes, such as the interplay between leadership, knowledge management, and organizational learning, within their real-life organizational context.

The research design was guided by the principle of capturing multiple perspectives across the company. By involving nearly all employees in the study, the design enabled a comprehensive understanding, including different perspectives, of how leadership influences knowledge management and learning processes throughout the company. The study also incorporated iterative interactions with participants, including dialogue meetings on preliminary findings (Grundén, et al., 2020), to ensure that interpretations accurately reflected participants' experiences. This design provides a rich, contextually grounded data set that supports an in-depth analysis, while enhancing the credibility and trustworthiness of the findings.

3.2 Data Collection

The research process began with an introductory phase in which the study was discussed with the company's management. Two further initial meetings were held with the CEO to set up the study and discuss the purpose of the study, clarify the organizational context, and establish access to participants within the company.

Qualitative data were collected through semi-structured interviews (Silverman, 2017). In total, 27 interviews were conducted involving 31 participants from different parts of the company. Nearly all employees participated; only two were unable to take part due to absence at the time of the interviews. This high level of participation allowed the study to capture perspectives from across the company. Each interview lasted approximately 45–50 minutes. The interviews were recorded and transcribed for analysis.

After the initial analysis had been conducted, the preliminary findings were presented to the interview participants in a dialogue meeting (Grundén, et al 2020), where also the management participated. This session allowed participants to reflect on the interpretations, clarify statements, and contribute additional perspectives. Comments and reflections from this session were documented and incorporated into the

ongoing analysis. The findings were subsequently presented to the organization's management as part of the feedback process.

3.3 Analysis Method

The empirical material was analyzed using thematic analysis (Braun & Clarke, 2006). The analysis followed an iterative process in which the interview transcripts were read repeatedly to gain familiarity with the data. Initial codes were generated and subsequently grouped into broader themes. From this analysis central aspects of leadership, knowledge management, and organizational learning were captured and grouped into themes focusing on how leadership influences KM and organizational learning within the manufacturing company facing economic pressure. Throughout the analysis, attention was paid to identifying recurring patterns while also considering variations in perspectives among participants.

4. Results

Based on the empirical data collected and the analysis conducted, the following themes outline how leadership influences KM and organizational learning within a manufacturing organization facing economic

4.1 Leadership Styles: Impact on Trust, Knowledge Sharing, and Professional Culture

The historically authoritarian and top-down leadership style prevents effective knowledge sharing and a sense of connection among employees. A critical lack of transparency is evident, where decisions are made without explaining the underlying "why," leaving employees feeling excluded from the company's broader direction. Furthermore, for the intention to have open discussion is perceived by many employees as a manipulation rather than a genuine invitation for feedback. This perception fosters a culture of silence where workers stop offering insights to managers because they believe their input cannot influence actual outcomes.

Knowledge sharing within the company is strongly influenced by workload and managerial priorities. During less-pressured periods, employees are granted a relatively high degree of autonomy in organizing their own work, creating opportunities for informal learning. During periods of high work pressure, opportunities for knowledge sharing are limited, as employees must prioritize immediate production tasks over collaborative learning. As a result, knowledge exchange tends to be deprioritized in everyday practice. In addition, management does not appear to emphasize the importance of knowledge sharing, partly because employees are viewed as largely interchangeable. This perspective reduces the need to invest in the development and dissemination of individual or collective expertise.

This leadership style has damaged the organization's social ties and reduced professional pride among employees. Employees who previously felt a sense of ownership, citing examples like being proud of a specific wall they created, now report a shift toward indifference and stress following layoff notices. The "us and them" mentality is not only geographic, between different factory sites, but also functional, where a lack of communication between sales and production prevents the transfer of vital knowledge across organizational boundaries. Furthermore, management's focus on short-term cost control has led to increased physical strain, with reports of employees being expected to perform heavy lifting alone, tasks that safely require two people, due to reduced staffing levels.

4.2 The Erosion of Tacit Knowledge and "Fingertip Feeling"

A significant finding in this study is the gap between how management views the work and how complex the production process actually is. Employees report that mastering the manufacturing of precast concrete requires a specific "fingertip feeling", a deep form of tacit knowledge built over many years. This expertise involves navigating subtle variables such as different types of stone, fluctuating weather conditions, and precise temperatures. The study indicates that management underestimates the time and experience required to build this competence, often seeing employees as replaceable instead of recognizing their specialized knowledge. This perception is further reflected in organizational responses to economic downturns, where employees may be temporarily laid off, reinforcing the notion that individual knowledge and experience are not considered critical organizational assets.

This knowledge loss is critically exacerbated by the physical context of the factory, which relies on an old machine park, with some equipment dating back to the 1970s. Maintaining and troubleshooting these old machines requires highly specialized in-house competence that is not easily documented or transferred. As workforce downsizing is initiated to respond to economic pressure, the company loses the veteran staff who possess the tacit knowledge required to keep these machines running. Consequently, the layoffs create a state

of high vulnerability; newer staff face a steep learning curve and are often left without the mentorship or support needed to perform complex repairs, leading to extensive production downtime when old machines inevitably fail.

4.3 Barriers to Organizational Learning: Ideas "Running Out in the Sand"

The most significant barrier to OL is the lack of a structured process for transforming individual insights into organizational action. Employees frequently take the initiative to suggest improvements, but these ideas often "run out in the sand" because management fails to provide action plans or consistent follow-up. While deviations are recorded, they rarely result in actual changes to work methods, giving staff the feeling that their work does not matter.

The old machinery and the economic pressure serve as the ultimate bottleneck for improvement initiatives. Many employee suggestions require major interventions or investments that a reductionistic leadership, focused purely on cost-cutting, is unwilling to make. This lack of structure for capturing and implementing ideas kills motivation. If employees feel that even their most practical suggestions regarding the machines they operate daily are ignored, they eventually stop contributing to the KM process altogether. The study confirms that the historically rooted authoritarian leadership style, which fails to understand the holistic need for structured feedback and the integration of learning into daily work, actively compromises the company's long-term knowledge capital.

4.4 The Digitalization Gap and the "Maturity Trap"

There is a profound contrast between management's modernization strategy and the company's actual operational and KM maturity. While leadership pushes for digital tools like Teams and other digital tools, the workforce often lacks the technical proficiency to utilize them effectively, having trouble with basic things like logins and passwords. This indicates a low level of KM maturity, where digital tools are viewed as administrative burdens rather than integrated components of daily learning.

The limitations of the physical environment further widen this gap. In an old and spatially constrained factory where machines from the 1970s dominate the production landscape, employees often find digital interfaces cumbersome and instead prefer analogue methods, such as physical whiteboards for improvement suggestions. The digital strategy appears disconnected from the situated practice of the workers; for many, the constant stress of managing technical failures and repairs and service on aging machines makes digital adoption a secondary priority. Successful KM requires that technology, culture, and physical work processes interact seamlessly, but the current leadership fails to integrate these digital tools into the actual workflow of the production staff.

5. Discussion

Our study confirms that leadership is critical to build a culture of continuous learning (Ahsan, 2025; Bertassini et al., 2021) and fostering the connection between KM and OL (Aggestam, 2006a; Evenseth et al., 2022). It is evident that leadership shapes communication and collaboration, and that an authoritarian, top-down leadership style that lack transparency can undermine the trust needed for knowledge sharing (Busse & Regenberg, 2019). It is critical that leaders value knowledge and competence in practice, specifically through performing KM and encouraging a learning culture, as failing to do so directly compromises organizational sustainability (Hana & Lucie, 2011). This is particularly vital in manufacturing firms where old machine parks make tacit knowledge indispensable for effective production, highlighting the clear necessity for a holistic leadership understanding.

A key finding is that leadership often overlooks employees' personal, intuitive expertise, the "fingertip knowledge" (Mohanty, et al., 2024), and treats them as replaceable, which prevents the organization from fully using their skills. This creates strategic risks as downsizing and turnover prevent knowledge continuity (Hana & Lucie, 2011). Losing experienced staff means the organization also loses valuable knowledge. This study shows that a historically authoritarian leadership style is risking deterring a healthy knowledge culture. A lack of transparency regarding the "why" behind decisions causes employees to view open discussion as manipulation. Three levels of inquiry (why, what, how) as described by Van Gigch (1991) is an important part of a holistic perspective. While centralized leadership discourages engagement (Busse & Regenberg, 2019). When leadership is centralized, employees are less engaged and trust in management is decreasing (Figueiredo et al., 2025). This leadership style shapes social connections and fosters an "us and them" mindset, which hinders knowledge sharing across departments (Evenseth et al., 2022).

There is also a profound contrast between digitalization strategies and actual digital maturity. Leadership must understand this maturity to move beyond administrative burdens Effective KM requires that technology, culture, and processes interact seamlessly. In this study it is shown that analog methods often better suit the "situated practice" of workers, when digital adoption is deprioritized (Mehrizi et al., 2022). Since professional knowledge and learning develop through practice changes (Hopwood, 2016), failing to integrate tools into production workflows misses critical opportunities to support KM.

The study indicates that a significant barrier to organizational learning is that individual insights and tacit knowledge are not effectively used across the organization. In the studied company, employee initiatives frequently "run out in the sand" because management fails to provide action plans or consistent follow-up. Ultimately, organizational resilience is tied to learning, specifically the ability to anticipate, cope with, and adapt to adverse events (Duchek, 2020). A leadership that lacks a holistic understanding of how cost-cutting measures compromise long-term knowledge capital will struggle to maintain resilience in an increasingly complex and volatile environment. This study also adds knowledge to developing of organizational resilience, since there is a clear relation between learning and resilience (Malik & Grag, 2020; Evenseth et al., 2020).

6. Conclusions

The study revealed the importance of style of leadership and their capability of having a holistic perspective. To understand that workforce downsizing as a method to solve economic problems may be effective in the short-term, but in the long-term it likely results in critical (tacit) knowledge loss and hence has a negative impact on effectiveness and competitiveness which in turn lead to further economic problems. This is even worse in a company as our case with old machines that require highly specialized in-house competence that is not easily documented or transferred. It also highlights the importance of digitalization and the necessity for management to understand the digital maturity in the company whether digitalization should support KM and learning, and not the other way around.

This study has several limitations worth noting. As a single-case study of one Swedish manufacturing company, the findings cannot be straightforwardly generalized to other organizational or cultural contexts. Additionally, the largely tacit and situated nature of "fingertip feeling" makes it inherently difficult to fully capture through interviews alone, thus observational methods might have provided additional depth. Furthermore, the study captures knowledge management dynamics at a specific moment of economic pressure, meaning that how the situation develops over time falls outside the scope of the study.

Ethics Declaration: No formal ethical approval was required for this study, as it did not involve sensitive personal data. Nevertheless, the research was conducted in accordance with the principles of the Declaration of Helsinki. All participants were provided with information about the study and its purpose, and informed consent was obtained prior to participation. Participants were also assured of confidentiality and their right to withdraw from the study at any time.

AI Declaration: AI-assisted tools were used to improve grammar and readability and to support preliminary data analysis. Interpretation and conclusions remain the responsibility of the authors.

Acknowledgements

This research was funded by the Knowledge Foundation of Sweden, and by the GOOZO Team.

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Learning Through Experimentation: Growth Hacking in Organisational Development Strategy

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Abstract: This article attempts to explore the role of continuous learning through experimentation, considered within the context of the concept of growth hacking. The turbulence of the environment and the pace of change in this field mean that modern organisations are faced with the need to react quickly, including making immediate decisions and introducing innovations. In light of this, the first part of this article presents the theoretical foundations of growth hacking and the closely related practice of experimentation. A review of the literature led to the formulation of the following research question: Does an organisation's general approach to experimentation influence its level of experimentation in technical terms? In the practical section, an attempt was made to verify the cause-and-effect relationship between these areas. To this end, the results of a survey conducted among 250 large and medium-sized IT companies in Poland in the second half of 2024 were utilised. The analysis was carried out in R, within which structural equation modelling (SEM) was developed. On this basis, it was found that a higher level of experimentation in general terms determines the level of technical experimentation. The final section of the article also highlights the limitations and directions for further research.

Keywords: Growth hacking, Experimentation, Learning, Structural equation modelling (SEM)

1. Introduction

The pace of change taking place in the organisation's immediate and wider environment has a significant impact on its competitive position. The turbulence of the environment and the need to maintain a specific market position force companies to take specific actions, which are usually immediate in nature. The operating conditions of modern enterprises dictate specific responses, within which experimentation is becoming particularly important.

Experimentation has gained significant popularity in the operations of modern enterprises. This is evidenced, among other things, by the increasing number of studies in this area, which confirm the benefits of its application, including improvements in a company's profitability in the initial phase of its operations and during its further development. The need for change arising from environmental dynamics means that, in this regard, a special role is attributed to the concept of growth hacking (GH), understood as the undertaking of experimental initiatives. Its aim is to define methods for scaling a business (Sanasi et al., 2023), that allow for the initiation of new development activities whilst maintaining the current level of resource commitment (Sanasi, 2025).

It is worth noting that the widespread adoption of growth hacking within a company involves accepting certain principles, namely:

- decision-making processes are based on large data sets,
- the solutions implemented are characterised by innovation,
- experiments often also involve digital innovation,
- continuous learning takes place on the basis of the experiments carried out,
- dynamic skills play a key role.

Organisations characterised by a strong focus on development embrace change (Korombel & Ławińska, 2025) . Consequently, they face the need to implement experiments and learning, which are considered the foundation of growth hacking (Giordino et al., 2025).

It should be assumed that growth hacking, viewed as a form of data-driven experimentation, contributes significantly to the process of continuous learning, which ultimately impacts the organisation's development and growth. Furthermore, it is emphasised that, through experimentation, this approach helps to bridge the gap between planning, formulating and implementing growth strategies. The following section of the article outlines the theoretical foundations of growth hacking from a learning perspective.

2. Literature Review

The term 'growth hacking' was first introduced in the literature by Sean Ellis, who defined it as 'process of rapid experimentation across the funnel to learn the most effective way to scale sustainable customer adoption' (Ellis & Brown, 2017). The growing interest in this concept in practice has led to it being viewed as a key factor in

achieving rapid organisational growth. Although for a long time growth hacking was seen solely through the lens of start-up development, it has since come to be described as a 'data-driven approach to improving processes and activities through continuous experimentation'. It is assumed that growth hacking fosters product, process and organisational innovation (Schiavone et al., 2025).

GH is identified with taking rapid, experimental action (Rezazadeh et al., 2025). Creativity plays a key role in this area, as it determines the implementation of financially profitable initiatives – that is, those that generate profits without requiring the allocation of additional resources (Bargoni, Santoro, et al., 2024). It is worth noting that this approach has become particularly widespread among companies operating in the high-tech sector, which, due to their substantial digital resources, have significant potential for business scaling (Sanasi, 2025).

Organisations that promote the idea of experimentation as part of their activities must take into account the fact that not every experiment is successful. Nevertheless, even failure provides specific information that constitutes a valuable resource for the organisation (Migduła, 2026). Learning from mistakes is regarded as the foundation of a learning organisation, which improves through continuous learning processes and the practice of knowledge sharing. As Cristofaro et al. note, improving these processes is possible through regular meetings on the experiments being conducted. This approach ensures that activities remain aligned with business objectives, that the learning process is sustainable, and that the organisation develops progressively (Cristofaro et al., 2025).

An organisation's ability to learn enables it to adapt quickly to the current market situation. Furthermore, it involves deepening knowledge and transferring it within the company. It plays a significant role in growth hacking, which relies on rapid implementation and the ability to adapt to market changes. This is an essential prerequisite for gaining a competitive advantage (Foggetti et al., 2025).

As highlighted in the literature, an organisation's intellectual potential determines its development in the field of growth hacking, where learning processes are driven by experimentation. This, in turn, relies on large datasets, which form the foundation of knowledge management. Experimentation shapes learning processes and inspires organisations to innovate. Learning from mistakes and repeating actions aimed at optimising performance play a particular role in this context. The experience gained in this way is further reinforced by growth hacking, which ultimately intensifies learning processes and determines market outcomes (Schiavone et al., 2025).

In the context of the topic under discussion, it is worth noting that the concept of growth hacking involves transforming collected data into knowledge, which has a significant impact on learning processes (Bargoni, Santoro, et al., 2024a). Growth hacking is a way of embedding an approach to collecting and analysing large datasets within decision-making processes. It is argued that organisations should focus on acquiring and verifying data, and then transforming it into information and knowledge, as these activities significantly support learning processes and contribute to the development of innovation (Bargoni, Smrčka, et al., 2024; Troisi et al., 2020).

Santoro et al. suggest that growth hacking has not yet been sufficiently analysed in a management context, where it should be considered through the prism of innovation, growth strategy and entrepreneurship (Santoro et al., 2026). This raises the question: how do organisations understand and approach experimentation? It is worth noting that experimental methods such as growth hacking are often seen as the link between strategy development and its implementation (Sanasi, 2025).

As noted Bargoni et al. (Bargoni, Jabeen, et al., 2024; Bargoni, Smrčka, et al., 2024) growth hacking should be viewed as a data-driven decision-making process that enables the implementation of rapid, short-term experiments in the field of strategic management (Giordino et al., 2025). This integration of data analysis and the learning process enables decision-making that aligns with customers' expressed needs. In this context, growth hacking provides the conditions for an organisation to adapt quickly to a turbulent environment. It is worth emphasising here that growth hacking is also viewed through the prism of dynamic capabilities (Teece, 2010, 2018). The collection and analysis of big data plays a crucial role in this context, particularly in terms of fostering a data-driven mindset (Gerlich et al., 2025).

Growth hacking is a determinant of dynamic growth, achieved through the integration of continuous learning and ongoing experimentation. It enhances organisational potential, enables adaptation in a competitive environment, and boosts short-term performance metrics. It emphasises the importance of gathering information about users and the need to tailor the product to their expectations (Bargoni, Santoro, et al., 2024).

These measures have a significant impact on consumers' decision-making and their long-term loyalty (Amoozad Mahdiraji et al., 2025).

Joshi et al. following Bohsnack and Liesner (Bohnsack & Liesner, 2019) highlight the unconventional nature of growth hacking, particularly in terms of bridging the gap between the formulation and implementation of strategic objectives (Troisi et al., 2020). They point out that the development of dynamic capabilities to date, together with the widespread adoption of experiments based on data collection and analysis, has helped to enhance the organisation's capacity to implement modern technological solutions and business models (Joshi et al., 2025).

A common feature of the aforementioned approaches to the concept of growth hacking is the frequent integration of two processes: continuous learning and decision-making (based on large datasets) (Giordino et al., 2025). The literature on the subject emphasises that this approach allows strategic objectives to be adapted to the conditions of a constantly changing environment. The term 'growth hacking' is based on rapid experimentation, closely linked to the dynamic capabilities possessed by organisations, which are considered essential in the context of a company's development in the broadest sense. It is worth noting that these capabilities do not serve solely to streamline the decision-making process, but are aimed at introducing innovations and prototypes that meet reported market demand (Scuotto et al., 2025).

In light of the above, it can be concluded that the introduction of rapid, short-term experiments significantly contributes to continuous learning, which ultimately determines an organisation's potential. The uncertainty of the environment and the dynamics of the changes taking place within it mean that a key role is attributed to innovative solutions, which, in practice, facilitate the planning and implementation of strategic objectives.

In this regard, the following research question was posed: Does an organisation's general approach to experimentation influence its level of experimentation in technical terms?

3. Methodology and Results

The empirical section of the article attempts to verify the cause-and-effect relationships between selected variables. To this end, structural equation modelling (SEM) was applied, which enables the testing of relationships between observable and latent variables and allows for the estimation of unobservable variables (Sagan, 2003; Zasuwa, 2011).

The variables used to develop the SEM model were obtained from a survey conducted in the second half of 2024 among 250 companies in the IT sector. The questions in the survey questionnaire were rated on a Likert scale (1–5). They concerned the area of experimentation and were divided into two groups for the purposes of model construction. The first group of questions focused on experimentation in the technical dimension, highlighting the use of: social media, Artificial Intelligence, Design Thinking, Lean Startup, Agile, Agile Scrum and Kanban. The second group emphasised the respondents' general approach to experimentation. In this regard, aspects related to, amongst others, the direct involvement of employees and stakeholders in business processes, the development of multidisciplinary teams, the creation of product and process innovations, and continuous learning processes in the face of failure were taken into account. These variables were labelled respectively: EXPTech (E2:E8) and EXP (E9:E14). They are included in Table 1. The analysis was conducted in R. The results obtained in this regard are presented below.

Table 1: Variables used in the study

Experimentation in the technical dimension (EXPTech)	
E2	We experiment by using social media
E3	We experiment by using artificial intelligence (AI)
E4	We experiment by promoting a modern approach to management, which is: Design Thinking (careful understanding of customer needs, based, among other things, on empathy)
E5	We experiment by promoting a modern management approach, such as: Lean Startup (experimenting with the initial, simplest version of the product, which is then tested on customers)
E6	We experiment by promoting a modern approach to management, which is: Agile (dividing the project into stages, i.e. according to the priorities of individual tasks, which facilitates the introduction of modifications)

Experimentation in the technical dimension (EXPTech)	
E7	We experiment by promoting a modern management approach, which is: Agile Scrum (based on daily meetings during which progress and difficulties related to the implementation of a given task are discussed – these meetings are attended by the client and the Scrum Master)
E8	We experiment by promoting a modern approach to management, which is: Kanban (visualisation of workflow using a Kanban board)
General approach to experimentation (EXP)	
E9	We experiment by engaging employees to generate ideas
E10	We experiment by engaging stakeholders to understand their needs
E11	We experiment by developing multidisciplinary teams
E12	We experiment by creating product/service innovations
E13	We experiment by creating process innovations
E14	When the experiments we implement end in failure, we rely on the process of continuous learning and introduce further new experiments

Firstly, attention was paid to the model's fit to the data (Table 2). It is worth noting that initially 15 variables were used to build the model; however, in order to obtain the best possible fit indices, modifications were made, and ultimately two of them were rejected.

Table 2: Fit indicators

Name	**Value**
Comparative Fit Index (CFI)	0.943
Tucker-Lewis Index (TLI)	0.931
Root Mean Square Error of Approximation (RMSEA)	0.055
Standardized Root Mean Square Residual (SRMR)	0.048

The information in Table 2 indicates that the model fits the data very well. The CFI stood at 0.943, whilst the TLI was 0.931; in both cases, it was >0.9. The RMSEA value was 0.055, suggesting it lies on the borderline between satisfactory and good results. The SRMR index of 0.048, in turn, suggests an ideal fit. The fit assessment was conducted solely on the basis of the above indices. The table does not include the chi-square test, which was significant ($\chi^2(64) = 111.98$; $p < 0.01$). It should be assumed that this result is due to the large sample size (n=250), which in practice leads to high statistical sensitivity and results in the unjustified rejection of models with a good fit.

In the next step, the construct's reliability and validity were assessed. The results in this regard are presented in Table 3.

Table 3: Reliability and validity indicators

	Internal Consistency Reliability				**Composite Reliability**	
	alpha	**omega**	**omega2**	**omega3**		**AVE**
EXPTech	0.7619731	0.7632550	0.7632550	0.7618204	0.762	0.319
EXP	0.7904802	0.7950938	0.7950938	0.7982980	0.798	0.397

The reliability and validity of the constructs were assessed using the following measures: Internal Consistency Reliability (α, ω), Composite Reliability (CR) and Average Variance Extracted (AVE). The alpha and omega coefficients indicate acceptable reliability for both constructs (α = 0.76–0.79; ω=0.76–0.79). The Composite Reliability values were very similar, indicating good reliability for the constructs. Convergent validity, assessed using AVE, was on the borderline of acceptability for the general approach to experimentation, i.e. at 0.397, whilst experimentation in technical terms fell below the recommended threshold (0.319). Nevertheless, as the literature on the subject demonstrates (J. F. Hair et al., 2025; J. F. J. Hair et al., 2010) high reliability indices (α, ω, CR) compensate for the lower AVE values, and the study was therefore considered to meet the validity criteria. It was assumed that the quality of the measurement was in line with accepted standards; consequently, the relationships between the latent variables were presented in the subsequent stage (Table 4).

Table 4: Standardized factor loadings (Std.all) for the measurement model

Construct	Item	Completely Standardized Estimates (Std.all.)
EXPTech	E2	0.577
	E3	0.465
	E4	0.603
	E5	0.516
	E6	0.722
	E7	0.477
	E8	0.573
EXP	E9	0.697
	E10	0.557
	E11	0.595
	E12	0.710
	E13	0.674
	E14	0.509

Table 4 presents the completely standardised estimates for each observable variable. Experimentation in the technical dimension was verified by variables E2–E8, whilst the general approach to experimentation was verified by variables E9–E14. The highest value of the indicator in the first construct was recorded for variable E6 (0.722), indicating a strong relationship with EXPTech. The lowest loading values, in turn, were for variables E3 (0.465) and E7 (0.477); however, taking the fit assessment into account, these values were deemed acceptable (modifying the model and removing the variables did not improve the fit parameters). The remaining estimate values fluctuated above 0.5, suggesting that the construct was defined correctly.

The results obtained in the next area, i.e. the general approach to experimentation, show that all variables are >0.5 and therefore reflect the latent construct well or very well. The p-value in each case is <0.001, and therefore these variables should be considered statistically significant. It was assumed that the constructs were defined correctly; consequently, the parameters of the SEM structural model are presented in the next section (Table 5).

Table 5: SEM model parameters

Path	Std.all	p
EXP→EXPTech	0.796	<0.001

The parameters presented in Table 5 enable an assessment of the strength of the relationship between the latent constructs. The value of the β coefficient in this case was 0.8, which indicates a strong, statistically significant relationship ($p<0.001$). The results obtained suggest that the popularity of the general approach to experimentation explains experimentation in a technical sense. An increase in interest in experimentation in business activities leads to a rise in practical activities focused on technical experimentation.

A graphical summary of this interpretation is presented in Figure 1.

Figure 1 presents a graphical representation of the SEM model, highlighting the strong positive relationship: $\beta = 0.796$ ($p<0.001$) between the latent constructs, namely general experimentation and technical experimentation (the constructs are represented as circles). The factor loadings of the individual observed variables (represented as squares) ranged from 0.465 to 0.722 for the EXPTech construct and from 0.509 to 0.710 for EXP. Although the loadings for two variables fell below the recommended threshold of 0.5, they were deemed acceptable, as their removal did not improve the model's fit to the variables.

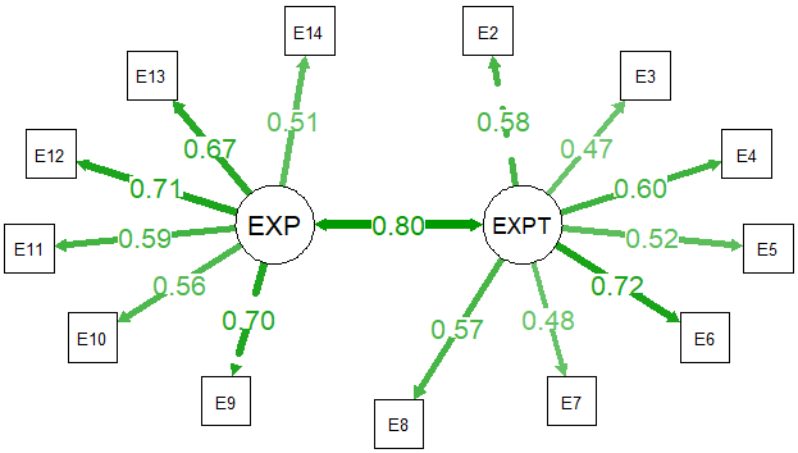


Figure 1: Graphical presentation of the SEM model

4. Conclusions

The results of the analysis indicate that both of the examined areas (latent constructs) were adequately explained by the observable variables. The general approach to experimentation was defined as:

- actively engaging employees and stakeholders in the business process,
- developing multidisciplinary teams,
- creating innovation,
- relying on a process of continuous learning when experiments fail.

Experimentation in technical terms is, in turn, presented as the application of diverse business practices, including: social media, AI, Design Thinking, Lean Startup, Agile, Agile Scrum and Kanban.

Experimentation plays a key role in the modern approach to doing business, particularly in light of the changes taking place in a turbulent environment. These activities are regarded as unconventional, and their primary aim is to improve efficiency, which ultimately enables a company to stand out from the competition. As noted above, experimentation takes place at various levels of an organisation's operations and may concern customers, stakeholders, innovation, as well as the specific nature of the business.

High factor loadings for the variables "employee engagement in the business process" and "introducing product and process innovations" constitute a strong and accurate indicator of the latent construct of "general approach to experimentation." It can be assumed that these aspects most closely reflect the perception of experimentation among the surveyed companies. In turn, the construct of "technical experimentation" was best reflected by the promotion of Design Thinking (focused on understanding customer needs, based, among other things, on empathy) and Agile (a solution that divides the project into stages, i.e., according to individual tasks). The weakest factor loadings (<0.5, but considered significant) were observed for AI and Agile Scrum. This result suggests that for many IT companies, these are not experimental solutions aimed at seeking unconventional methods of progress, but merely tools to improve organizational functioning. They can be perceived as a standard of digital development (artificial intelligence), the implementation of which seems essential to maintaining current market position, or as common operational practices (Agile Scrum) aimed at improving performance indicators. Differences in approaches to experimentation may, in this case, stem from the varying levels of maturity of the companies studied in this regard. This is evidenced, among other things, by the fact that two variables were eliminated from the model at the initial stage of its development, i.e., variable matching. It can be assumed that companies with high maturity consider the use of Big Data commonplace. A similar situation occurred with the variable: abandoning subsequent experiments if previous ones were unsuccessful.

Experimentation drives learning, and therefore all companies that experiment actively participate in the process of continuous learning. This, in turn, impacts the effectiveness of strategy planning, formulation, and implementation.

The dissemination of experimental activities is characteristic of learning organisations focused on permanent development. Taking initiatives in a general sense creates the conditions for implementing more specific experiments, and therefore, a higher level of experimentation in general fosters experimentation in the technical dimension. This confirms the previously posed research question.

5. Limitations and Directions for Further Research

The limitations of this study include its exclusive focus on a single industry, IT. Including an additional sector in the analysis could provide a broader perspective on companies' experimentation approaches. Furthermore, the results obtained in this area are dictated by the turbulent environment. The dynamic development of digital technologies, particularly the significant emphasis on AI, largely determines pro-innovation behaviour. Limitations may also result from varying levels of experimentation culture within companies, both in general and technical aspects.

The studied constructs were narrowed to a few variables, so it seems reasonable to expand them later to include additional aspects of experimentation. It is assumed that subsequent research will verify the impact of experimentation on specific areas of an organisation's strategic management.

Ethics Declaration*:* Consent was not required to conduct this research.

AI Declaration*:* AI tools such as ChatGPT were used during the development of this article. This tool was used for supporting purposes only.

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Future-proof Knowledge Management for Regenerative Value Ecosystems

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Abstract: Current societal developments increasingly prioritise social well-being and intergenerational responsibility, as evidenced by the growing emphasis on sustainability, circularity, and planetary stewardship. Since contemporary societies depend on knowledge accumulated over time, knowledge management has traditionally drawn on relatively stable repositories of past experience and established insights. However, the transition from linear, single-organisation models of value creation to regenerative, multi-partner value ecosystems challenges these assumptions. In such settings, relevant knowledge is no longer sourced solely from organisational memory but must be continuously generated, validated, and integrated across multiple contexts and stakeholders. This opinion paper argues that the resulting uncertainty amplifies the demands placed on knowledge management. The core challenge extends beyond capturing explicit and tacit knowledge: it lies in combining diverse, context-dependent perspectives into actionable understandings within an evolving social environment. As knowledge requirements become increasingly dynamic, organisations and networks must build resilience and develop the agility to respond to shifting conditions, emerging risks, and evolving societal expectations. We contribute by synthesising key societal developments shaping the knowledge landscape and its related requirements. Additionally, we propose revised principles for knowledge creation, valuation, and use that align with regenerative and circular approaches, and outline mechanisms to address the continuous emergence of new insights necessary for a well-functioning society. Finally, recognising that actors interpret and apply knowledge through the lens of their own contextual realities, we introduce the concept of a future-proof ecosystem orchestrator, also referred to scientifically as a circularity knowledge broker: a facilitating role that supports adaptive knowledge exchange, orchestrates multi-contextual sensemaking, and enables collaboration under conditions of uncertainty. This role is crucial for enhancing the collective capacity to navigate uncertain futures while maintaining social and ecological well-being.

Keywords: Future-proof knowledge management, Change, Value, Regeneration, Ecosystem orchestrator

1. Introduction: The Great Change: From Extraction to Regeneration

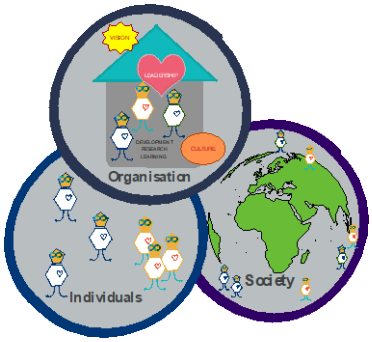


Figure 1: The 'Me-We-All' approach (Abcouwer, Takács, Schilstra, et al., 2022)

The global economic order is in a phase of reorientation, revising traditional values of growth and success due to planetary boundaries and social instability. Historically, value has been tied to extraction for profit, viewing nature as an endless resource and waste sink, leading to the "illusion of vitality'—a temporary wealth boost masking systemic exhaustion (HEC Paris, 2025). The regenerative economy contrasts this by emphasising restoring the world and fostering multiple capitals (Mentcon, n.d.). The key shift for businesses is moving from profit maximisation to contributing to systemic vitality. To align with this worldview, knowledge management must evolve from a sole focus on individual welfare and short-term gains to a balanced approach that incorporates societal and organisational perspectives (Capitals Coalition, 2024; Mentcon, n.d.). This shift involves moving from an individualistic, anthropocentric model to a 'Me-We-All' relational framework, which balances diverse needs within social-ecological systems (Takács & Abcouwer, 2025; Takács et al., 2022). The perspectives we further explore in this paper are defined as follows:

- Me (Individual): Personal well-being, skills, and fulfilment.

- We (Collective/Organisational): The health, trust, and resilience of communities, networks, and organisations.
- All (Societal/Planetary): The integrity of the biosphere and the flourishing of future generations.

This approach exemplifies the differences but also leads to a potential conflict stemming from the contradiction between the mechanics of extraction and the logic of regeneration. To be able to value these developments, we need to understand the underlying mechanisms and gather the appropriate knowledge to develop a grand view on the future impact of this (r)evolution, leading to future-proof KM for regenerative value ecosystems.

2. The Ontological Conflict: Mechanics of Extraction vs. Logic of Regeneration

The tension between extractive and regenerative models reflects their roots in economy and system design. 'Extractive,' from Latin 'extrahere,' means 'to remove,' indicating a linear process where value is taken from elsewhere, externalising ecological and social costs, causing diminishing returns and fragility (CE Delft, 2023). This model is 'locked-in' by debt-based systems and legal structures prioritising shareholder value. In contrast, 'regeneration,' from 'generare,' means 'to create.' It aims beyond sustainability, focusing on self-renewal and positive impacts on the biosphere and society, similar to natural systems' restorative processes (Central Bureau of Statistics, 2022). The goal is not just to do "less bad," but to generate a net-positive impact on the biosphere and society (Mentcon, n.d.).

3. Comparison of Economic Paradigms

Table 1: Economic paradigms (Abcouwer, Takács, Schilstra, et al., 2022; CE Delft, 2023; Central Bureau of Statistics, 2022)

Feature	Extractive Economy	Regenerative Economy
Primary source of value	Extraction of resources and labour.	Restoration and strengthening of ecosystems.
Primary focus	Individual welfare	Balancing individual, organisational and societal needs
Measurement focus	GDP and financial profit (Quantitative).	Well-being and system health (Qualitative).
Time horizon	Short-term (Quarterly results).	Intergenerational and adaptive.
System approach	Linear (Take-Make-Waste).	Circular and self-healing.
Relationship with Nature	Nature as a commodity and input.	Humans as an integral part of the biosphere.
Power structure	Concentration of wealth and power.	Participation, reciprocity, and local ownership.
Paradigm-shift	IST	SOLL
Me-We-All	ME/WE	WE/ALL

3.1 The Business Model Transformation: From Profit Maximisation to System Flourishing

For a modern company, shifting to regeneration requires a complete overhaul of strategy and operations, recognising that success depends on social and ecological network health (Mentcon, n.d.)Regenerative institutions mitigate risks by strengthening underlying capital, often through the Community Capital framework (Flora, 2018), aiming to foster flourishing across domains with the Me-We-All framework. The "Me" perspective emphasises individual well-being and purpose, driving motivation and creativity. The "We" perspective considers collective health, trust, and resilience of organisations and communities. The "All" perspective focuses on societal and planetary health, ensuring biosphere integrity and future well-being (Flora, 2018; Takács & Abcouwer, 2025; Takács et al., 2024). A regenerative company aligns the flourishing of each domain:

- **Natural Capital:** The stock of natural assets (air, water, soil, biodiversity) that provide crucial ecosystem services. The treasures of the Earth should be wisely used with equal access to ALL the members of the Society and respecting nature's right.
- **Social Capital:** The networks, trust, and relationships that bind communities and economies. The treasures of the community's treasures should benefit every member of the WE-setting equally.
- **Human Capital:** The individual skills, knowledge, health, and creativity of people. Every person has a specific value - Values of the persons (ME) that can contribute to the needs of their communities (WE) and the society and the world (ALL).

- **Cultural Capital:** The collective wisdom, traditions, and stories that provide identity and resilience (Coolset, n.d.). The values of the community – WE / ALL.
- **Physical Capital:** Human-made infrastructure and technologies, which must be circular and supportive (CE Delft, 2023; Coolset, n.d.). Human creations – WE.

This approach views the world not as a series of problems to be solved, but as a dynamic system in constant transition (Mentcon, n.d.). A regenerative company acts as a "co-evolutionary actor", aligning its purpose with the needs of the location and ecosystem in which it operates.

Transitioning from the currently dominant extraction model to a regeneration model for future societies can lead us down uncertain, unfamiliar paths, where we confront unforeseen challenges and the need for boundless creativity grounded in people's empowerment. Understanding this development requires gathering knowledge and insights that cannot be based solely on past experiences. Knowledge management must shift from capturing the past to exploring the future. We must shift from the possession-based view of knowledge as an object to a holistic, dynamic understanding. In a regenerative ecosystem, knowledge is a continuous, evolving flow of sense-making and relationships, negotiated by stakeholders within their contexts.

4. Traditional Frameworks of Knowledge and Knowledge Management

To understand new knowledge management requirements, we review the traditional discipline of KM, which developed in the industrial and post-industrial eras mainly to improve organisational efficiency and innovation within an extractive framework. Traditional KM is retrospective, focusing on capturing, codifying, and sharing existing insights to boost performance and competitive edge.

4.1 The SECI Model and the Dynamics of Knowledge Conversion

The most established theoretical foundation for traditional KM is the SECI model (Nonaka et al., 1996). This framework conceptualises knowledge creation as a continuous spiral of interaction between tacit knowledge: the unwritten, experience-based insights held in the mind, and explicit knowledge: the articulated, documented information that can be easily shared. It identifies four primary modes of knowledge conversion that allow an organisation to leverage its intellectual assets.

Table 2: Modes of knowledge conversion

Mode	Conversion Direction	Mechanism and Characteristics
Socialisation	Tacit to Tacit	Knowledge is shared through observation, imitation, and direct practice. This often occurs in apprenticeships or informal social meetings where proximity facilitates the transfer of skills.
Externalisation	Tacit to Explicit	Individual insights are articulated into concepts, models, or written documents. This crystallisation makes personal knowledge available to the collective as the basis for new insights.
Combination	Explicit to Explicit	Different sources of documented knowledge are integrated, edited, or processed to form new, complex sets of information. Computerised networks and databases frequently support this phase.
Internalisation	Explicit to Tacit	Individuals receive and apply explicit knowledge through learning-by-doing and reflection. This process converts documented rules into shared mental models and technical know-how.

Traditional Knowledge Management (TKM) systems aim to facilitate this cycle, ensuring that an organisation can "know what it knows" and avoid the loss of vital expertise. By focusing on these interactions, organisations endeavour to improve decision-making and foster innovation within their boundaries. TKM isn't just about explicit repositories. Frameworks like Nonaka and Takeuchi's SECI model focus on systemic and tacit knowledge but mostly serve within organisations for competitive advantage. Moving to a regenerative economy expands these models, requiring integration of tacit and explicit knowledge across ecosystems, aiming for collaborative planetary stewardship.

5. Repository Logic and the Focus on Stability

TKM views knowledge as a resource stored in repositories, serving as organisational memory to help managers leverage past successes for current challenges. This works well in stable economies for standardising processes and expanding successful models, with success measured by fast, accurate retrieval of relevant knowledge.

However, this approach is increasingly inadequate for modern societal challenges, as it treats knowledge as static, which does not work well in highly dynamic environments. (Abcouwer, Takács, & Banga, 2022; Meijering et al., 2020).

5.1 The Procedural Engine: the Adaptive Cycle of Resilience (ACoR)

The transition to regeneration within the **Adaptive Cycle of Resilience (ACoR)** framework (Abcouwer, Takács, & Banga, 2022; Meijering et al., 2020) is illustrated by a lemniscate (infinity loop), explaining how social-ecological systems evolve through four distinct phases:

- **Equilibrium (Certainty):** The starting state of the extractive model where operations are optimised and managers work well within established norms (Want-Must-Can alignment (Heene, 2002)).
- **Challenge (Disturbance):** Internal or external disruptions (e.g., climate crisis, resource scarcity) move the system away from its certainty in existing abilities ("Can").
- **New Combinations (Adaptation/Uncertainty):** A phase of creative search where leadership is required to find regenerative solutions and new ways of creating value.
- **Operationalisation:** Setting the new regenerative model into practice to reach a new, more resilient equilibrium.



Figure 2: The ACoR model (ref: ECKM 2024)

Within the ACoR framework, the process of adaptation is driven by the "Want-Must-Can" dilemma(Heene, 2002). This involves balancing what stakeholders desire (Want), what ecological boundaries and regulations require (Must), and what resources and skills permit (Can). Traditional KM excels when the "Can" is well-established. However, regenerative KM is necessary when the "Must" (planetary boundaries) and the "Want" (societal well-being) shift radically, rendering existing capabilities obsolete.

5.2 Systemic Traps and the Role of the Ecosystem Orchestrator

Regenerative transitions are often obstructed by specific **systemic traps** within the adaptive cycle (Holling (Holling, 1996; Takács & Abcouwer, 2021):

- **Lock-in trap**: Management fails to perceive the ecological crisis or the "economic invisibility" of nature.
- **Poverty trap**: A lack of creativity or non-monetary metrics to develop circular business models.
- **Isolation trap**: The inability to align diverse stakeholders across the **Me-We-All** scales.
- **Rigidity trap**: Resistance to changing traditional extractive ownership and governance structures.

Dealing with these traps demands significant effort from those involved. They must contribute to the best of their abilities, operating in a world where the emphasis shifts from an individualistic focus to a more societal one. The IKIGAI framework helps individuals understand their role and motivations.

6. The Ikigai Framework

The Ikigai framework (Dipolitto, 2023; Sone et al., 2008) is a Japanese conceptual tool used to define a "reason for being" or "a reason to wake up in the morning". The term is derived from the Japanese words iki (life or alive) and gai (value or worth). Traditionally, it is represented as a Venn diagram exploring the intersection of four core dimensions:

- ***What you love***: Your internal passions, interests, and activities that bring joy or "flow".
- ***What you are good at:*** Your specific skills, natural talents, and professional expertise.

- ***What the world needs***: Urgent societal, community, or ecological requirements that you resonate with.



Figure 3: The IKIGAI framework (Abcouwer, Takács, Schilstra, et al., 2022)

What you can be paid for: Professions and roles that offer financial compensation or sustainable revenue.

The framework promotes alignment among these elements to create a life that is both productive, meaningful, and satisfying. Within a regenerative economy, the "what the world needs" aspect, together with what the world is willing to pay you for, is often regarded as a fundamental, non-negotiable anchor, driving a shift from solely personal or financial ambitions towards contributions that support planetary well-being.

6.1 Mechanisms for fair Value Alignment: The Ikigai-Me-We-All Lens

To achieve a stable system, exchange must go beyond zero-sum competition. The Ikigai framework, applied within the Me-We-All

approach, offers a purpose-driven way to create value (Abcouwer, Takács, Schilstra, et al., 2022; Dipolitto, 2023). This approach shifts KM focus from structural capture to motivational alignment, centred on 'Ikigai,' which motivates knowledge creation. At the 'Me' level, Ikigai influences willingness to share tacit knowledge; without it, knowledge hoarding occurs. When Ikigai aligns with organisational (we) and societal (All), see Kalro (2023); Sone et al. (2008)) goals, KM becomes a purpose-driven mechanism that naturally propels the flow of insights from the individual out to the regenerative ecosystem.

This multidimensional alignment is protected by Steward-ownership, which ensures that the system's "reason for being" (All) remains prioritised over private extraction (Manelli et al., 2025).

7. Governance Models for a Regenerative Future

The shift towards regeneration demands new governance structures that safeguard value for the "All" level within the Me-We-All framework. These models ensure that the system's "reason for being" remains central over private extraction.

7.1 Steward-ownership

Steward-ownership separates control from economic rights. In this model, the organisation is "owned" by its mission rather than by shareholders seeking to maximise their individual returns. Profits are reinvested in the mission or shared with stakeholders, ensuring that the organisation remains a co-evolutionary actor within its ecosystem.

7.2 Asset Locks

Societies use statutory constraints called asset locks. These locks prevent the privatisation of residual assets, ensuring that the value generated by the community is retained for future generations rather than being taken during liquidation or sale. This mechanism directly safeguards the "All" level of the system.

7.3 Decentralised Value

Traditional organisations utilise a "Value In = Value Out" principle within a Decentralised Holonic Organisation (DHO) (Mathews, 1996). Members are not traditional employees; they are value creators who are responsible for discovering their own "Regenerative Ikigai"—the intersection of what they love, what they are good at, what

the world needs, and what they can be paid for. Compensation is aligned with systemic responsibility rather than time spent, encouraging a shift from reactive tasks to proactive orchestration.

8. Beyond Euros: Non-monetary Quantification of Biodiversity

In daily regenerative practice, monetary valuation, often used as a building block for knowledge and management, is frequently insufficient to capture complex ecological dynamics. Scientists and policymakers are increasingly turning to robust physical metrics within the System of Environmental-Economic Accounting (SEEA) framework (United Nations, 2021). A key metric is **Mean Species Abundance (MSA)**, which characterises ecosystem intactness on a scale from 0% (locally extinct) to 100% (undisturbed) (Amundi Research Center, 2025). By multiplying MSA by the area of impact, businesses can use **MSA.km²** as a "CO2-equivalent for biodiversity" (Schneider Electric, 2021). This allows for scientific consistency and aggregation across different regions and sectors without reducing nature's value to a mere price tag (Amundi Research Center, 2025). Furthermore, Science Based Targets for Nature (SBTN) provide guidelines for companies to set measurable goals aligned with ecological thresholds and planetary boundaries (Science Based Targets Network, 2023).

9. Management, Leadership, and Stewardship: Knowledge Governance

As organisational environments shift from certainty to risk and radical uncertainty, management styles and the utilisation of knowledge must also adapt. TKM fits well with conventional management, but regenerative ecosystems demand the integration of leadership and stewardship.

9.1 The Three Modes of Governance

Research distinguishes these three modes based on the nature of the challenges they address and the competencies they require.

Table 3: Governance modes (Takács & Abcouwer, 2024)

Mode	Focus and Context	Role of Knowledge and KM
Management	Certainty; optimising current operations.	Focuses on knowledge transfer and rational optimisation of known processes.
Leadership	Risk; developing new strategies to meet challenges.	Focuses on creativity, innovation, and the generation of new insights.
Stewardship	Uncertainty; preparing for the unforeseeable future.	Focuses on resilience, ethics, and care for the Me-We-All ecosystem.

Stewardship embodies a "service mindset," emphasising the long-term well-being of all creatures rather than immediate issues. It involves shifting from owning knowledge to sharing it. In a stewardship-driven KM system, the use of information takes precedence over mere possession, and intellectual property is regarded more as a shared resource than as something to be controlled or excluded.

10. Forward Knowledge Management

Traditional KM is often "backwards-looking," drawing on a repository of past experiences. Stewardship introduces the need for "forward knowledge management," which emphasises curiosity, innovation, and the capacity to manage unpredictable future events. This approach involves "learning from the future as it emerges," a process sometimes called "Presencing" (Scharmer, 2007; Scharmer & Yukelson, 2015). It requires individuals to sense future possibilities and act on predicted outcomes rather than on historical precedents.

10.1 Addressing Stakeholder Pluralism and the Ecosystem Orchestrator Role

A major barrier to regeneration is stakeholder pluralism, in which participants, such as investors and policymakers, see challenges differently. Often, those investing in soil health or biodiversity don't receive direct benefits, a phenomenon known as the **split-incentive problem** (Crossreis, 2024; Regenerate Tampa Bay, 2025).

10.1.1 The knowledge manager as ecosystem orchestrator

The introduction of an ecosystem orchestrator is essential to bridge these gaps (Ciulli et al., 2020; Eindhoven, 2026). Acting as a Trusted Third Party (TTP), the ecosystem orchestrator manages valorisation, legal coordination, and transparency through digital dashboards or blockchain-enabled platforms.

The ecosystem orchestrator has three key roles: facilitating balanced knowledge sharing within circular networks, exchanging knowledge between networks to maximise benefits, and ensuring knowledge is available for future development in a volatile environment.

10.1.2 The role of the ecosystem orchestrator

The ecosystem orchestrators manage the interdependencies and ensure fair redistribution of costs and benefits, now and in the future (Blackburn, 2023; Ciulli et al., 2020; Parida et al., 2019). They act as a neutral intermediary through several key functions, with some examples below (Eindhoven, 2026)

- **Valorisation & monitoring:** Managing CO2 certificates, water management, and biodiversity monitoring to make regenerative value "validatable" and tradable.
- **Legal & logistics coordination:** Providing guaranteed purchase contracts, supply chain tracking, and reverse logistics optimisation to lower transaction costs for smaller stakeholders (Ciulli et al., 2020).
- **Fiscal & financial solutions:** Solving split incentive problems through MIA/Vamil schemes, financing coordination, and subsidy applications.
- **Transparency via TTP platforms:** Operating through a **Trusted Third Party (TTP)** platform, such as a digital dashboard or blockchain-enabled system, to provide "trust-free" verification of labels and resource flows.

10.1.3 Mechanisms for fair redistribution

To create a stable regenerative system, exchange must go beyond zero-sum competition. While scientific literature suggests using Cooperative Game Theory, such as the Shapley value, for fair benefit-sharing based on marginal contribution (Lozano et al., 2013; Peleg & Sudhölter, 2007), the Ikigai framework offers a systemic view. It shifts focus from "individual extraction" to "collective reason for being,' aligning stakeholders' passions, skills, and pay with what the world needs (Dipolitto, 2023). This turns value exchange into a co-evolutionary process in which the Planetary Ikigai guides asset deployment based on biosphere needs (Kalro, 2023). Steward-ownership further anchors the system by decoupling control from profit, prioritising the system's purpose over private gain.

To achieve a stable regenerative system, the logic of exchange must move beyond zero-sum competition. While scientific literature suggests applying Cooperative Game Theory (such as the Shapley value, a game-theoretic method for fairly allocating total gains or costs among players in a coalition by calculating their average marginal contribution across all possible coalitions to calculate benefit-sharing arrangements based on marginal contribution (Lozano et al., 2013; Peleg & Sudhölter, 2007), the Ikigai framework offers a more systemic lens for value exchange.

11. Educational Requirements: The iSolution Platform

The mindset shift needed for regeneration requires developing new educational programmes that go beyond traditional specialised training. The aim is to equip individuals with the skills and practices necessary to handle ill-defined challenges in a volatile environment.

Managers often feel unprepared for unforeseen problems, frequently relying on justified but inadequate methods, such as risk matrices, to turn ill-defined problems into well-defined ones. To address this, the iSolution environment (Takács & Abcouwer, 2020) proposes a collaborative eLearning platform that utilises resources both inside and outside organisations.

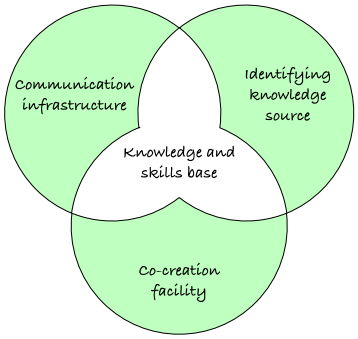


Figure 4: iSolution (Takács & Abcouwer, 2020)

The iSolution platform includes several key components:

- **Knowledge and Skills Base:** A repository that covers the priorities and needs of youth, citizens, job centres, SMEs, and NGOs, along with regional and cultural information. Note that this knowledge and skills base offers a meta-description of the information or knowledge accessible for use at a societal level.
- **Identifying sources of knowledge** to create opportunities that improve citizens' marketability through tools and resources for both traditional and self-education, focusing on digital innovation methods that facilitate co-creation. This approach unlocks the sources of knowledge, enabling better communication with them and serving as a foundation for co-creation.
- **Communication infrastructure**, to facilitate the exchange of knowledge between partners/sources.
- **Co-creation facilities** to enhance engagement in active dialogue with knowledge owners/organisations to identify future needs and facilitate co-creation to develop new insights and requirements.

As we do not know what the future will bring, the required knowledge is, due to this uncertainty, not yet known. These components facilitate the knowledge workers to:

- **Learning by doing:** Encouraging experimentation and the ability to make mistakes as a means of discovering new solutions.
- **Mentoring and training:** Focusing on generalist skills that allow managers to understand the "forest" (complexity) rather than just the "trees" (siloed tasks).

By focusing on "using and interpreting knowledge" rather than just its delivery, these programs aim to plant the seed for behavioural change at the Me-We-All levels.

11.1 The Regulatory Framework: Mandatory Transparency

The voluntary nature of natural capital reporting is disappearing with the Corporate Sustainability Reporting. Specifically, European Sustainability Reporting Standards (**ESRS** requires companies to report on biodiversity impacts and dependencies using the concept of **Double Materiality**, ensuring that nature-related risks are treated as financial realities (ABN Amro and the Impact Institute, 2025; Capitals Coalition, 2024).

11.2 The Ethical Orientation for Reorganisation

Ikigai and 'Me-We-All': In contrast to transactional logic, the concepts of **Ikigai** and the **'Me-We-All'** approach provide a more robust framework for value exchange by emphasising the **alignment of essence and necessity**.

The **Lighthouse metaphor** (Takács & Abcouwer, 2025) provides ethical orientation for a future-proof knowledge management for regenerative value ecosystems:

- The **Lighthouse** guides the Ship by foundational values and knowledge that offer stability amidst societal turbulence (All).
- The **Light beam** represents the mutual vision, the flow of motivation and knowledge (We).
- The **Sea** represents the complex and dynamic *context* of contemporary challenges.
- The **Crew on the ship** work together as an organisation within the given circumstances (Me/We).

11.3 Mechanisms for Fair Redistribution and Stewardship

To lock value within the reorganised system, organisations adopt new governance:

- **Steward-ownership:** Decoupling control from economic rights to ensure profits are reinvested in the mission (Manelli et al., 2025); (Purpose Foundation, 2020).
- **Asset locks:** Used by societies like **iFarm** (https://ifarms.me/), these statutory constraints prevent the privatisation of residual assets, protecting values for the "All" level for future generations.
- **Decentralised value (Hypha's VAR):** Organisations like **Hypha** (https://hypha.earth/) use the **"Value In = Value Out"** principle, utilising **Complexity Bands** (B1 to B5) to align compensation with systemic responsibility rather than "selling time".

12. Conclusion: A new Grammar for Knowledge Management

This new model of Future-proof Knowledge Management is guided by the Lighthouse metaphor, prioritising ethical orientation and adaptive sensemaking over static data storage. To align with the logic of regeneration, KM must be restructured around three core principles that redefine how knowledge is perceived and deployed:

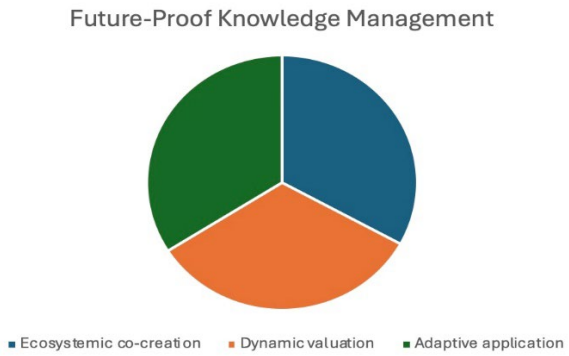


Figure 5: Future-proof knowledge management

- **Ecosystemic co-creation:** Knowledge is no longer created in isolation by internal experts. It must be continuously co-generated and iteratively validated across multi-stakeholder networks, ensuring that diverse perspectives are integrated into a collective understanding.
- **Dynamic valuation:** The value of knowledge shifts from its past utility or scarcity toward its immediate capacity to generate resilience, systemic health, and ecological or social benefits. In this paradigm, "knowing" is valued by its contribution to the flourishing of the "All."
- **Adaptive application:** Moving beyond static archives, knowledge must be deployed through agile feedback loops and "presencing." This requires replacing rigid retrieval systems with learning processes that can adapt to local contexts and evolving environmental demands in real-time.

Ultimately, Knowledge Management in a regenerative environment transcends its traditional role as a retrospective archive of organisational memory. It emerges as a dynamic orchestrator of stewardship - a purposeful engine that aligns individual motivation (Ikigai) with ecosystemic needs to facilitate the continuous flow of sensemaking required for planetary restoration and collective well-being.

Ethics Declaration: For this paper, no ethics clearance is required.

AI Declaration: AI tools are used to improve the language.

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This publication has been developed within the CE-PRINCE project, supported by the Interreg CENTRAL EUROPE Programme with co-financing from the European Union. Its content is the sole responsibility of the authors and the project partnership and does not necessarily reflect the views or positions of the Interreg CENTRAL EUROPE Programme, its programme bodies or the European Union. Neither the programme authorities nor the European Union can be held responsible for any use that may be made of the information contained herein.

Generative AI in Knowledge Management: A Comparative Mixed-methods Study of Jordan and Europe

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Abstract: Generative artificial intelligence (GenAI) is rapidly transforming organisational knowledge management (KM) processes. Yet limited research has examined how cultural and institutional contexts shape GenAI-enabled KM adoption across developed and developing economies. This study investigates the organisational, cultural, and institutional factors influencing GenAI-enabled KM practices in Jordan and Europe through a mixed-methods approach. Quantitative data were collected from 456 respondents across higher education institutions, SMEs, public-sector organisations and large enterprises. Qualitative data was collected through 36 semi-structured interviews. The findings reveal notable variations in the extent of GenAI adoption, readiness of organisational structures, maturity governance and trust in AI systems across cultures. Structural model analysis showed that technological infrastructure, AI literacy, leadership support, financial resources, and data governance positively affected GenAI adoption. Power distance and uncertainty avoidance negatively moderated adoption effectiveness. Qualitative results revealed that GenAI has high potential for supporting explicit knowledge processes, including externalisation and combination. Tacit knowledge processes such as socialisation remain dependent on people, trust and collaborative organisational culture. The study advances knowledge management theory by extending the SECI model through a GenAI-enhanced perspective that differentiates AI effects across tacit and explicit knowledge conversion processes. The study advances knowledge management theory by: (1) extending the SECI model through a GenAI-enhanced perspective that differentiates AI effects across tacit and explicit knowledge conversion processes—demonstrating process-contingency not previously specified; (2) reconceptualising GenAI capabilities as context-sensitive dynamic capabilities within the Knowledge-Based View, requiring complementary organisational resources; and (3) integrating cultural moderators into AI adoption theory, showing that cultural dimensions function as effectiveness moderators rather than just direct predictors. The study makes a novel contribution to cross-cultural AI adoption literature through a context-based model combining organisational readiness, cultural dimensions, and institutional maturity.

Keywords: Knowledge management, Cross cultural comparison, Organisational readiness, AI adoption, Jordan, Europe

1. Introduction

Organisational knowledge management (KM) is transforming rapidly with generative artificial intelligence (GenAI), but current research focuses largely on developed economies (Kudryavtsev et al., 2024). Empirical studies often assume Western findings transfer universally, overlooking how cultural and institutional conditions shape GenAI-enabled KM adoption—a critical gap for developing economies where digital infrastructure and organisational culture differ significantly from Europe.

While the SECI model (Nonaka & Takeuchi, 1995) frames tacit-explicit knowledge conversion, it lacks clarity on how GenAI interacts with cultural dimensions like power distance and uncertainty avoidance. Prior studies show GenAI enhances externalisation and combination (Sumbal et al., 2024), yet comparative evidence across divergent institutional environments remains limited. Without cross-cultural research, policymakers risk one-size-fits-all strategies.

This study addresses these gaps using a comparative mixed-methods design, exploring relationships between organisational readiness, cultural dimensions, institutional maturity, and GenAI-enabled KM practices in Jordan and Europe. Our theoretical lens integrates the SECI model, Knowledge-Based View, and cross-cultural technology adoption theory. We surveyed 456 respondents across higher education, SMEs, public sector, and large corporations, supplemented by 36 semi-structured interviews and 12 case studies. This study addresses three research questions:

RQ1: How do organisational readiness factors influence GenAI adoption intensity across Jordanian and European contexts?

RQ2: To what extent do cultural dimensions (power distance, uncertainty avoidance) and regulatory maturity moderate the readiness-adoption relationship?

RQ3: How does GenAI adoption differentially affect SECI knowledge conversion processes (socialisation, externalisation, combination, internalisation)?

Findings reveal significant cross-cultural differences, with GenAI most strongly enhancing explicit SECI processes (combination and externalisation) but weakly affecting tacit socialisation. Theoretically, we extend the SECI model by demonstrating differential AI effects, reconceptualise GenAI capabilities as context-sensitive dynamic capabilities within the Knowledge-Based View, and integrate cultural moderators into AI adoption theory. Practically, we provide guidance for policymakers to invest in infrastructure and governance, and for KM practitioners to implement GenAI as an augmentative tool supported by training and trust-building (Kumorovitzová, 2025).

2. Literature Review

2.1 Knowledge Management and Generative AI

The SECI model (Nonaka & Takeuchi, 1995) remains foundational for understanding tacit-explicit knowledge interaction (Bolisani et al., 2024). Systematic reviews confirm AI assists these conversions (Palm et al., 2025). Generative AI (GenAI) advances this further by moving beyond retrieval to active generation and contextualisation, a shift that fundamentally challenges conventional KM assumptions and requires a systematic reframing of the SECI model (Zhang Y et al., 2025). Empirical studies show that GenAI-augmented KM processes directly enhance decision-making and organisational performance by enabling firms to synthesise large knowledge repositories, codify tacit expertise, and deliver personalised learning experiences (Panizzon et al., 2024; Sumbal et al., 2024). Consequently, GenAI should be understood as a socio-technical capability embedded within broader governance and literacy structures, not merely a technological tool (Kretschmer et al., 2025; Turner, 2025; Taherdoost et al., 2023).

2.2 Cross-cultural and Institutional Influences

KM practices are consistently shaped by national and organisational culture. Hofstede's cultural dimensions are particularly relevant for technology adoption: high power distance centralises AI-related decisions and limits bottom-up experimentation, while high uncertainty avoidance fosters caution toward emerging technologies (Wang et al., 2024; Alamri, 2025). These cultural effects are amplified in AI-enabled KM because GenAI requires collaborative input and iterative refinement. The study shows that high power distance contexts show low AI readiness because of a hierarchy that stifles communication and sharing of information that is necessary for successful AI deployment (Frontiers, 2026). Institutional conditions further differentiate adoption outcomes: mature regulatory frameworks (e.g., GDPR, EU AI Act) provide governance clarity and institutional legitimacy, whereas developing economies face infrastructure and expertise constraints (AlKalbani, 2025). Middle Eastern KM adoption shows inconsistent organisational readiness. Research to date has been limited to developed economies, with comparative evidence on the role of cultural & institutional factors on the relationships between GenAI KM being minimal.

2.3 Digital Transformation and Organisational Readiness

GenAI integration into KM occurs within broader digital transformation (DT) efforts. A recent EJKM article notes that decentralised KM designs and digital transformation are closely intertwined, with DT acting as both a driver and a contextual boundary for KM innovation (Turner, 2025). Technological infrastructure, leadership commitment, digital literacy, financial resources and data governance are strongly associated with organisational readiness, and all of these factors have been a consistent predictor of successful GenAI adoption. Survey data from 778 decision-makers across multiple industries indicate that perceived benefits and readiness are the strongest enablers of GenAI adoption, while complexity represents a persistent barrier (Pokar, 2025). Leadership support and strategic alignment emerge as critical for translating technical opportunities into business value, and adoption patterns are broadly consistent across firm sizes (Pokar, 2025). GenAI is not a substitute for human skills, but rather an augmentative skill that complements human judgement and creativity (Jarrahi et al., 2025). However, significant gaps persist: empirical evidence from developing economies is scarce; existing frameworks rarely integrate organisational, cultural and institutional factors; and there is limited comparative analysis of how GenAI differentially affects SECI knowledge conversion processes. This study aims to answer these questions by conducting a comparative mixed methods research of GenAI empowered KM in Jordan and Europe.

2.4 Research gap and Theoretical Positioning

Prior literature treats GenAI primarily as a technological efficiency driver, rarely differentiating effects across SECI processes or examining cross-cultural moderators. This study addresses these gaps by proposing that GenAI-enabled KM effectiveness emerges from interactions between organisational readiness, cultural context,

and institutional maturity. We integrate three theoretical perspectives to explain this phenomenon. First, the SECI model provides the foundational mechanism for knowledge conversion, distinguishing between tacit and explicit processes. Second, the Knowledge-Based View explains why organisations differ in their capability to leverage GenAI as a dynamic capability—where AI tools represent combinative capabilities that reconfigure knowledge resources. Third, cross-cultural technology adoption theory (drawing on Hofstede's dimensions and institutional theory) explains how national and organisational cultural contexts moderate the translation of readiness into effective adoption. The integration occurs as follows: organisational readiness represents the KBV-based resource base; SECI processes are the conversion mechanisms through which GenAI creates value; and cultural/institutional factors moderate the effectiveness of both readiness→adoption and adoption→SECI pathways. This integrated perspective addresses the limitations of prior research that treated these as separate domains.

3. Conceptual Framework and Hypotheses

3.1 Conceptual Framework

The proposed framework integrates the SECI model, the Knowledge-Based View and cross-cultural technology adoption research. Organisational readiness is the most important precursor to GenAI adoption intensity, with technological infrastructure, AI literacy, leadership support, financial resources, and data governance being the primary factors. Cultural dimensions—power distance and uncertainty avoidance—together with institutional regulatory maturity moderate the readiness–adoption relationship. GenAI adoption intensity then differentially influences the four SECI processes: stronger effects are expected on explicit processes (combination and externalisation) than on tacit processes (socialisation). Enhanced SECI processes ultimately improve overall KM effectiveness (knowledge accessibility, learning, innovation capability, decision quality).

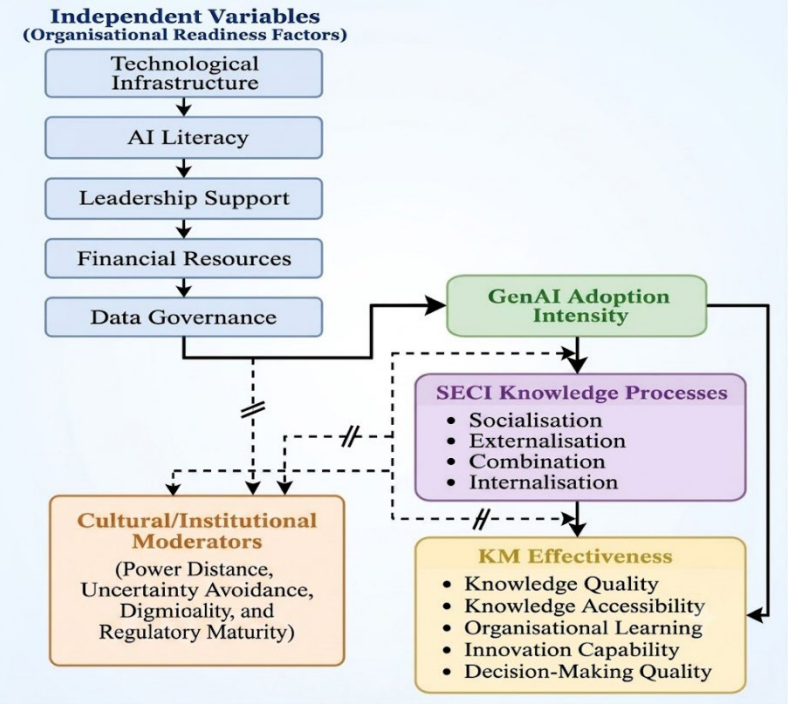


Figure 1: Conceptual Framework for GenAI-Enabled Knowledge Management Adoption

3.2 Hypotheses Development

Organisational readiness and GenAI adoption

Organisational readiness—technological infrastructure, AI literacy, leadership support, financial resources, and data governance—determines GenAI integration effectiveness. A survey of 778 decision-makers found readiness is the strongest enabler of GenAI adoption (Pokar, 2025). Hence:

> *H1: Organisational readiness (comprising technological infrastructure, AI literacy, leadership support, financial resources, and data governance) positively influences GenAI adoption intensity, with this relationship being stronger in European organisations compared to Jordanian organisations.*

3.2.1 Cultural and institutional moderators

In high power distance cultures, centralised decision-making limits bottom-up experimentation and cross-functional collaboration (Hofstede, 1983), negatively affecting AI readiness (Frontiers, 2026). Hence:

> *H2: Power distance negatively moderates the relationship between organisational readiness and GenAI adoption intensity.*

High uncertainty avoidance cultures favour predictable processes, yet GenAI's probabilistic outputs create ambiguity. This conflicts with established rules, making workers apprehensive about reliability and accountability (Alamri, 2025; Li et al., 2025). Thus:

> *H3: Uncertainty avoidance negatively moderates the relationship between the organisational readiness and the intensity of GenAI adoption.*

Regulatory maturity is the clarity, stability and enforceability of regulations and guidelines about the use of AI. Mature regulatory frameworks—such as the EU AI Act, which classifies AI systems by risk level and imposes transparency obligations—reduce legal ambiguity and build organisational confidence in adopting GenAI (AlKalbani, 2025). Clear and consistent regulations allow firms to better gauge compliance expenses, budget for compliance, and educate staff without worrying about a new set of regulations coming into effect. Lack of clarity or fluidity in regulations, on the other hand, fosters uncertainty, which inhibits investment and slows adoption. A global survey of business leaders found that nearly 80% report that unclear and evolving regulations impact the time, money and people investments they are making in AI (KPMG, 2025). Accordingly:

> *H4: Regulatory maturity positively moderates the relationship between organisational readiness and GenAI adoption intensity.*

3.2.2 GenAI Adoption and SECI knowledge processes

According to the SECI model, GenAI's capabilities map onto the four knowledge conversion processes with varying intensity (Palm et al., 2025; Zhang W et al., 2025). Accordingly, H5: GenAI adoption intensity has differential effects on SECI knowledge conversion processes—specifically, stronger positive effects on explicit processes (Externalisation and Combination) than on tacit processes (Socialisation and Internalisation). Combination is GenAI's most natural application, synthesising multiple explicit sources. Internalisation is moderately supported but requires human engagement. Socialisation remains least affected, as tacit transfer relies on trust and non-verbal cues that AI cannot replicate (Atraqchi et al., 2026; He, W. et al., 2024).

3.2.3 SECI processes and KM effectiveness

Improved knowledge conversion processes are ultimately expected to strengthen overall organisational KM effectiveness. Organisations that excel at socialisation build richer relational capital and trust networks, facilitating tacit knowledge flow across teams. Effective externalisation preserves critical expertise that would otherwise remain locked in employees' minds, reducing knowledge loss from turnover. By leveraging existing explicit knowledge, robust combination can lead to the creation of new insights, fostering innovation and strategic agility (Al-kfairy, 2025).

Lastly, employees are able to continuously learn inform the repositories and enhance their decision quality and problem solving capability by using strong internalisation. In combination, these enhanced SECI processes contribute directly to measurable KM outcomes, including faster knowledge accessibility, higher organisational learning rates, greater innovation output and improved decision-making quality (Panizzon et al., 2024; Sumbal et al., 2024). Thus:

> *H6: Enhanced SECI knowledge conversion processes positively influence overall KM effectiveness, and these SECI processes mediate the relationship between GenAI adoption intensity and KM effectiveness.*

4. Research Methodology

A sequential explanatory mixed-methods design was selected for three reasons. First, the research questions require both breadth (to establish generalisable patterns across contexts) and depth (to understand contextual mechanisms). Second, the comparative nature of the study demands quantitative comparisons of adoption rates and effects, while qualitative data is necessary to explain *why* these differences occur (Anim et al., 2025). Third, given limited prior cross-cultural research in this domain, an explanatory design allows quantitative findings to

identify patterns that qualitative inquiry can then investigate in depth. Integration occurred at the interpretation stage through joint displays and narrative synthesis (Nguyen et al., 2025).

4.1 Phase 1: Quantitative Phase

A structured online questionnaire measured GenAI adoption, organisational readiness, SECI process impacts, and cultural dimensions (power distance, uncertainty avoidance). All constructs used 7-point Likert scales adapted from validated instruments (Ribeiro, 2025).

4.1.1 Pilot testing

A first test of the survey was conducted with 36 participants, 18 from Jordan and 18 from Europe, to check clarity, cultural appropriateness and translations (Arabic and European languages). Items were revised, based on feedback. All Multi Item scales had Cronbach's alpha > 0.80 on the Reliability Testing.

4.1.2 Sampling strategy for quantitative phase

Stratified random sampling ensured representation across sector (higher education, SMEs, large corporations, public sector, non-profit), organisation size (small, medium, large), and region (Jordan: Amman, Irbid, Zarqa, Aqaba; Europe: Western, Northern, Southern, Eastern). The final sample presented in Table 1 comprised 456 respondents (Jordan n=232, Europe n=224), exceeding the minimum 200 cases required for structural equation modelling (Nguyen et al., 2025). Stratified random sampling was used to ensure representation across higher education, SMEs, large corporations, public sector, and non-profit organisations, with random selection from Jordanian and European databases. A target sample of 450 was set based on power analysis for structural equation modelling, exceeding the minimum requirement of 360 cases (10 cases per 36 parameters) with oversampling for incomplete responses.

Table 1: Sample Demographic and Organisational Characteristics

Variable	Category	Jordan (n=232)	Europe (n=224)	Total (N=456)
Gender	Male	136 (58.6%)	121 (54.0%)	257 (56.4%)
	Female	96 (41.4%)	103 (46.0%)	199 (43.6%)
Age Group	21–30	54 (23.3%)	49 (21.9%)	103 (22.6%)
	31–40	88 (37.9%)	82 (36.6%)	170 (37.3%)
	41–50	63 (27.2%)	71 (31.7%)	134 (29.4%)
	51+	27 (11.6%)	22 (9.8%)	49 (10.7%)
Sector	Higher Education	64 (27.6%)	58 (25.9%)	122 (26.8%)
	SMEs	71 (30.6%)	63 (28.1%)	134 (29.4%)
	Large Corporations	48 (20.7%)	59 (26.3%)	107 (23.5%)
	Public Sector	35 (15.1%)	28 (12.5%)	63 (13.8%)
	Non-Profit	14 (6.0%)	16 (7.2%)	30 (6.5%)
Organisation Size	Small (10–50)	76 (32.8%)	54 (24.1%)	130 (28.5%)
	Medium (51–250)	89 (38.4%)	82 (36.6%)	171 (37.5%)
	Large (>250)	67 (28.8%)	88 (39.3%)	155 (34.0%)
Current GenAI Use	Active Adoption	90 (38.8%)	152 (67.9%)	242 (53.1%)

Note: Percentages may not total 100 due to rounding.

4.1.3 Data collection procedure

Data were collected (September–December 2025) via professional networks, university partnerships, LinkedIn, and snowball sampling. Survey was translated into English, Arabic, German, French and Spanish using back translation. Multiple reminders were sent to non respondents.

4.2 Phase 2: Qualitative Phase

Semi-structured interviews (60–90 minutes each) were conducted with 36 participants (18 Jordan, 18 Europe), including KM managers, IT directors, and knowledge workers. The interviews were conducted, transcribed word

for word and structured around six thematic areas: organisational context, adoption journey with GenAI, cultural and institutional influences, human AI collaboration, benefits/challenges, and future directions.

4.2.1 Case study selection

Purposive sampling selected 12 case study organisations (6 Jordan, 6 Europe) based on variation in GenAI adoption levels (early experimentation, pilot, full deployment), sector, readiness profiles (high/medium/low), and willingness to participate.

4.2.2 Data saturation

Thematic saturation was achieved after approximately 30 interviews, with the final 6 interviews confirming no new themes emerged.

4.3 Data Analysis

4.3.1 Quantitative data analysis

IBM SPSS Statistics 29 and SmartPLS 4 for structural equation modelling were used for quantitative data analysis. The analysis sequence comprised: (1) descriptive statistics and data screening (normality, multicollinearity); (2) PLS-SEM: measurement model assessment (reliability, convergent/discriminant validity) and structural model testing (path coefficients, R^2, f^2, Q^2); (3) multi-group analysis comparing Jordan and Europe, plus t-tests and ANOVA with effect sizes (Cohen's d, eta-squared).

4.3.2 Qualitative data analysis

Thematic analysis was carried out using the steps developed by Braun and Clarke, with the assistance of NVivo 14. This coding was deductive (based on SECI constructs) and inductive. Cross-case synthesis identified patterns across the 12 case organisations.

4.3.3 Integration and mixing point

Integration occurred via: (1) quantitative results guiding purposive case selection and interview protocol refinement; (2) joint displays for interpretive synthesis and meta-inferences (Anim et al., 2025; Khan et al., 2024).

4.4 Validity and Reliability

Cronbach's alpha was used to test the reliability of the constructs and was found to be more than 0.70 for all constructs. Convergent validity was achieved when the AVE exceeded 0.50, while discriminant validity was achieved when HTMT ratios were < 0.85. Inter-coder reliability (Cohen's κ = 0.84) was used to ensure dependability of qualitative data.

5. Results

5.1 Hypotheses Testing Summary

All six hypotheses were supported. Table 2 presents measurement quality and structural model results. The quantitative results of each hypothesis are summarised below, qualitative evidence is presented in 4.3.4.

Table 2: Measurement Quality, Structural Model Results, and Hypothesis Testing Summary

Construct / Hypothesis	CR	AVE	Path Coefficient (β)	t-value	p-value	Result
Technological Infrastructure → GenAI Adoption	0.89	0.67	0.38	5.84	<0.001	Supported
AI Literacy → GenAI Adoption	0.91	0.71	0.41	6.27	<0.001	Supported
Leadership Support → GenAI Adoption	0.87	0.63	0.29	4.92	<0.001	Supported
Financial Resources → GenAI Adoption	0.86	0.61	0.33	5.11	<0.001	Supported
Data Governance → GenAI Adoption	0.90	0.69	0.36	5.66	<0.001	Supported
Power Distance × GenAI Adoption	—	—	-0.24	3.74	<0.01	Supported
Uncertainty Avoidance × GenAI Adoption	—	—	-0.19	3.18	<0.01	Supported
Regulatory Maturity × GenAI Adoption	—	—	0.31	4.83	<0.001	Supported
GenAI Adoption → Socialisation	0.84	0.58	0.19	2.41	<0.05	Supported

Construct / Hypothesis	CR	AVE	Path Coefficient (β)	t-value	p-value	Result
GenAI Adoption → Externalisation	0.91	0.72	0.46	6.82	<0.001	Supported
GenAI Adoption → Combination	0.93	0.75	0.57	8.11	<0.001	Supported
GenAI Adoption → Internalisation	0.88	0.65	0.34	4.96	<0.01	Supported
SECI Processes → KM Effectiveness	0.92	0.73	0.61	8.44	<0.001	Supported

Notes: CR = Composite Reliability; AVE = Average Variance Extracted. All CR values were above the recommended value of 0.70, and all AVE values were above the recommended value of 0.50, which indicated construct reliability and convergent validity.

5.2 Quantitative Findings

5.2.1 GenAI adoption rates (H1, H2)

H1 (higher adoption in Europe): Supported. European organisations showed 68% adoption (152/224) vs. 39% in Jordan (90/232); t(454)=7.82, p<0.001, Cohen's d=0.74 (large effect).

H2 (size/sector differences): Supported. ANOVA: F(3,452)=12.34, p<0.001. Higher education (mean=5.82/7) and large corporations (5.67/7) led adoption; SMEs (3.91/7) and public sector (4.02/7) lagged.

5.2.2 Organisational readiness differences (H3, H4)

H3 (readiness gaps): Supported. Multi group SEM: Europe scored higher on technological infrastructure (mean diff=1.82, p<0.001), digital literacy (1.31, p<0.001), financial resources (2.14, p<0.001), leadership support (0.63, p<0.05), and data governance (2.43, p<0.001).

H4 (financial resources stronger in Jordan): Supported. PLS-SEM: β=0.44 (Jordan) vs. 0.21 (Europe), p<0.001 for difference.

5.2.3 KM Process improvements: Impact on SECI model (H5, H6)

H5 (differential SECI effects): Supported. Path coefficients: Combination β=0.57 (p<0.001), Externalisation β=0.46 (p<0.001), Internalisation β=0.34 (p<0.01), Socialisation β=0.19 (p<0.05).

H6 (stronger Combination/Externalisation in Europe): Supported. Multi-group analysis: Combination Δβ=0.18 (p<0.01), Externalisation Δβ=0.12 (p<0.05) favouring Europe.

5.3 Qualitative Findings

Three dominant themes emerged from thematic analysis of 36 semi-structured interviews. First, organisational readiness emerged from first-order concepts including poor AI integration capability and weak internal datasets. Second, AI literacy and adaptation was reflected in employee fear of AI and lack of prompt engineering skills. Third, leadership and governance encompassed executive AI advocacy and unclear AI accountability. Cultural and institutional constraints appeared through fear of AI errors and hierarchical decision approval. Finally, human-AI collaboration was characterised by AI-assisted report writing and human oversight mechanisms.

5.3.1 Theme 1: Organisational readiness

Organisational readiness – infrastructure, leadership, AI literacy, governance – was the most frequently discussed factor. European participants described GenAI adoption as an extension of existing digital transformation strategies with mature IT ecosystems (Alarefi, M.A. et al., 2025). Jordanian respondents framed adoption as an emerging experiment constrained by resource limitations and uneven digital maturity.

"We already had mature digital knowledge systems before introducing generative AI tools. The transition was less about technological disruption and more about integrating AI into workflows that employees already trusted." (Senior innovation manager, German technology company)

5.3.2 Theme 2: Cultural and institutional influences

Power distance, uncertainty avoidance, and regulatory maturity significantly shaped adoption. European organisations benefited from clear governance (e.g., GDPR), providing employee confidence. In Jordanian

organisations, higher power distance centralised AI decisions, while uncertainty avoidance amplified concerns about AI hallucinations and legal accountability.

> *"Employees are more comfortable using AI tools when there are clear governance rules about accountability, data handling, and human oversight." (Compliance officer, Sweden)*

5.3.3 Theme 3: Human–AI collaboration

GenAI was viewed as augmentative rather than replacement. Employees used GenAI for synthesis, drafting, and retrieval while retaining human validation. AI literacy, trust and organisational policies were crucial for effectiveness.

> *"There is a danger that employees become passive consumers of AI-generated summaries without critically evaluating the underlying knowledge." (Policy advisor, Netherlands).*

6. Discussion

6.1 Theoretical Contributions

This study extends the SECI model in three specific ways. First, prior SECI research treats knowledge conversion as a unified process; we demonstrate process-contingency—that GenAI's effects vary significantly across conversion modes. This introduces a technology-specific boundary condition to the original model. Second, we show that SECI processes should be understood not merely as knowledge conversion mechanisms but as outcome variables that are differentially influenced by technological interventions—an extension that reframes SECI from a descriptive model to a predictive framework. Third, we identify that socialisation—typically considered the foundation of knowledge creation—may not be enhanced by GenAI, challenging the assumption that digital tools universally improve all knowledge processes. This suggests a revised SECI model where explicit processes (Combination, Externalisation) are technologically augmentable, but tacit processes (Socialisation, Internalisation) require complementary social and organisational interventions.

6.2 Practical Implications

For Jordanian policymakers, our findings suggest prioritising investment in foundational digital infrastructure—including cloud, data storage, and connectivity—as this represents a primary readiness gap (mean difference = 1.82, $p<0.001$), while simultaneously developing AI literacy programmes targeting SMEs where adoption lags significantly (mean=3.91/7 versus 5.82/7 in higher education), and establishing data governance frameworks to build trust, which our qualitative data indicates is a primary concern. For European policymakers, the emphasis should be on maintaining and refining existing governance frameworks such as GDPR and the EU AI Act, as these provide a competitive advantage ($\beta=0.31$ moderation effect), addressing the SME adoption gap through sector-specific guidance, and promoting human-AI collaboration models rather than replacement narratives to reduce uncertainty avoidance concerns. For multinational organisations, we recommend conducting cultural diagnostics before implementation, as our findings show cultural moderation effects ($\beta=-0.24$ and -0.19) that cannot be addressed through technology alone, and tailoring training approaches accordingly—with European contexts potentially emphasising compliance and governance, while Jordanian contexts may benefit more from demonstrating practical value and securing leadership advocacy.

6.3 Limitations and Future Research

The study's cross-sectional design, while appropriate for exploratory comparative analysis, prevents establishing causal direction—longitudinal research is needed to confirm that readiness precedes adoption and that adoption drives SECI enhancement. Self-reported perceptual data may introduce common method bias, although Harman's single-factor test (28% variance) suggests this is not a significant concern. The treatment of Europe as a monolithic entity masks considerable within-region heterogeneity, particularly between Northern and Southern European contexts; however, sub-regional sample sizes (n=45-90) were insufficient for meaningful disaggregation. Additionally, the sectoral focus excludes manufacturing and healthcare, where GenAI applications and knowledge management challenges differ markedly from the sectors examined. Finally, while we measured cultural dimensions at the individual/organisational level using adapted Hofstede items, these may not perfectly correspond to national-level cultural indices, suggesting value in future multi-level modelling to disentangle individual, organisational, and national cultural effects (Storey, 2025; Sun et al., 2025).

7. Conclusion

This comparative mixed-methods study reveals substantial adoption gaps (68% Europe vs. 39% Jordan), with GenAI more strongly enhancing explicit SECI processes (externalisation, combination) than tacit ones (socialisation, internalisation). Financial resources drove adoption more in Jordan, while data governance maturity gave Europe a clear edge. Theoretically, we refine the SECI model by demonstrating technology-process interaction effects—showing GenAI's differential impact on knowledge conversion modes—extend KBV through a dynamic capabilities lens, and identify cross-cultural moderators of AI adoption. Practically, findings urge infrastructure and governance investment, culturally adaptive strategies, and treating GenAI as augmentation backed by training and trust. Future research should adopt longitudinal designs, broaden regional scope, and address ethical implications.

Ethical Considerations: The research was approved by the lead researcher's Institute's Review Board. The informed consent was obtained for all the participants and anonymity was guaranteed by using pseudonyms and keeping encrypted and password-protected servers. The study adhered to GDPR in Europe and Jordanian data protection laws.

9AI Declaration: During the preparation of this work, the authors used DeepSeek for the purpose of language refinement and grammar checking. The authors reviewed and edited all content and took full responsibility for the publication.

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Integrating Generative AI into Knowledge-intensive Environments: Insights from Agile Workers

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Abstract: Generative AI (GenAI) is transforming how knowledge-intensive professionals work by generating new content and processing vast amounts of data, impacting knowledge creation. This phenomenon is widely acknowledged by scholars and practitioners, as evidenced by the growing body of literature on the topic. However, research remains in its early stages, and there is a pressing need to deepen our understanding of how these technologies are being adopted in specific contexts. This study addresses this gap by examining how agile practitioners who operate in highly knowledge-intensive environments and are among the earliest adopters of GenAI integrate these tools into their work. We developed a questionnaire including questions about performance, effort, social influence, facilitating conditions, and risks. The survey was distributed among participants at the 2025 edition of the Italian Agile Days, a two-day event that gathers Italian agile professionals. Based on responses from 91 participants, we identified three distinct user clusters: sceptical GenAI explorers, confident adopters, and cautious power users. Our findings contribute to an understanding of how GenAI is being integrated into agile practices and what facilitates or hinders its adoption among these knowledge-intensive professionals. Finally, we discuss implications for how organizations might tailor support, training, and governance to the different clusters to allow more effective and responsible GenAI use.

Keywords: Generative artificial intelligence, Knowledge management, Technology adoption, Agile, Knowledge workers

1. Introduction

Generative AI (GenAI) is deeply and rapidly transforming the landscape of knowledge-intensive work, fundamentally reshaping how professionals create, process, and leverage their cognitive assets. The technology's remarkable ability to generate novel content and analyse vast amounts of data across multiple formats is significantly impacting knowledge creation processes, collaborative workflows, and decision-making practices. This transformative phenomenon has garnered widespread recognition among both scholars and practitioners, as evidenced by the exponentially growing body of literature exploring its multifaceted implications (Purba et al., 2024; Yan et al., 2026). However, despite this burgeoning interest, research remains in its nascent stages, and there is an increasingly pressing need to deepen our understanding of how these powerful technologies are adopted, adapted, and integrated within specific organizational contexts and professional domains (Prasad Agrawal, 2024; Kirchner et al., 2025).

To address this critical knowledge gap, we conducted an empirical investigation into how practitioners working in agile contexts are adopting and utilizing GenAI tools to support their diverse agile-related tasks and activities. Our decision to focus on this professional community is motivated by two compelling, interrelated reasons. First, agile organizations epitomize knowledge-intensive environments, where continuous learning, rapid adaptation, and information sharing are paramount, and agile workers represent knowledge-intensive professionals who consistently engage in complex problem-solving and collaborative knowledge creation (Centobelli et al., 2025). Second, evidence suggests that agile practitioners are positioned among the earliest adopters and most intensive users of GenAI technologies, demonstrating both enthusiasm and sophistication in leveraging these tools within their daily workflows (Wolpers and Bergmann-Gering, 2026).

To this end, we developed a comprehensive questionnaire and strategically distributed it to participants at the 2025 edition of Italian Agile Days. This prominent two-day conference convenes Italian agile professionals, practitioners, and thought leaders from diverse industries and organizational contexts. We got inspired by other surveys examining the specific determinants and barriers influencing GenAI adoption across various professional settings (Kim et al., 2024; Chen et al., 2025; Chou, 2025). We carefully adapted questions to our specific research context and strategically added a risk perception factor, recognizing that perceived risks—including concerns about data privacy, output accuracy, ethical implications, and organizational policies—appear to particularly and significantly influence GenAI adoption decisions and usage patterns (Kim et al., 2024).

This paper presents and discusses preliminary, yet insightful analysis results derived from the collected responses (91 participants), focusing particularly on the emerging theoretical contributions and practical managerial implications of our findings. Our results provide valuable insights into how GenAI is being strategically integrated into agile practices, which specific use cases are emerging as most valuable, and which organizational, technological, and individual factors facilitate or hinder its successful adoption among these knowledge-intensive professionals.

The paper is structured as follows: Section 2 provides the background of the study, while Section 3 outlines the research objectives and methodology. Section 4 presents the results of the study, which are discussed in Section 5. This final section also includes conclusions and addresses the limitations of the study.

2. Background

2.1 Agile Professionals as Knowledge Workers and their use of GenAI

Agile methodologies represent a comprehensive suite of project management and product development frameworks specifically designed to enable teams to operate iteratively, collaboratively, and adaptively within dynamic environments characterized by frequently evolving requirements and rapidly changing conditions. While Agile methodologies initially emerged from and were predominantly associated with the software development movement, formally codified through the publication of the Agile Manifesto (Beck et al., 2001). These approaches have increasingly transcended their original domain and gained substantial traction across a diverse array of non-IT sectors (Alam et al., 2017; Ciric et al., 2018).

Contemporary organizational landscapes demonstrate that enterprises confronting complex, ambiguous, and uncertain operational environments are progressively embracing and implementing agile principles as strategic responses to volatility and complexity. Empirical evidence indicates that agile practices have been successfully adopted and deployed across various sectors, supporting critical functions such as product development, continuous process improvement, and large-scale organizational change initiatives (Noleto et al., 2023). Systematic literature reviews substantiate that, agile frameworks, particularly Scrum, can effectively facilitate continuous improvement cycles and foster innovation in non-IT contexts, though such applications frequently necessitate contextual adaptations and modifications, given that the original methodologies were predominantly architected for software development projects with their distinct characteristics and constraints.

Professionals who adopt and implement agile methodologies are typically classified as knowledge workers, since their principal assets and sources of value creation reside in their knowledge, competencies, domain expertise, and advanced problem-solving capabilities rather than physical labour or routine task execution. These individuals typically collaborate within cross-functional teams to conceptualize, develop, and deliver sophisticated solutions to complex organizational challenges. This characteristic profile positions agile practitioners among the earliest and most intensive adopters of GenAI technologies (Wolpers and Bergmann-Gering, 2026). Consequently, agile knowledge workers constitute a particularly compelling and theoretically rich context within which to systematically investigate and analyse the multifaceted factors, mechanisms, and dynamics that influence and shape the adoption patterns of this transformative emerging technology among knowledge-intensive professionals.

2.2 GenAI Adoption

To analyse the factors influencing the use of GenAI by agile workers, we resort to the Unified Theory of Acceptance and Use of Technology (UTAUT) because other authors have already used it as a theoretical framework to investigate the adoption and use of this technology. This widely applied theory explains and predicts individuals' attitudes and intentions to use technology based on their perceptions (Venkatesh et al., 2003). This theory has been the most widely used to investigate the adoption of GenAI across multiple domains, as evidenced by Chen et al. 's (2025) recent literature review on users' attitudes toward GenAI. The adoption and use of a new technology by individuals are affected by four main factors as follows:

- Performance expectancy: refers to the degree to which an individual believes that using new technology will help to improve their job performance. Various studies have proven that this is one of the most influential factors in technology adoption.
- Effort expectancy: refers to the user's perception of the amount of effort required to use new technology. The easier the technology is perceived to be to use, the higher the intention to use it.

- Social influence: refers to social pressures or expectations regarding technology use, including the influence of supervisors, colleagues, organizational culture, etc., on technology acceptance. The higher the social influence, the higher the intention to use.
- Facilitating conditions: refer to the existence of organizational and technical infrastructure that supports the use of technology. Such conditions are deemed crucial for successfully adopting new technology.

Coming back to its use in analysing the determinants of adoption and use of GenAI, it must be preliminarily underlined that most studies have applied this framework to examine the adoption of GenAI in the education (students and educators) domain (Chen et al., 2025) and therefore may not provide very useful indications about items for our study.

As concerns the use of the UTAUT model to investigate the adoption of GenAI in non-educational contexts, the analysis of the still limited literature has highlighted how some scholars have used this model in its original version (Kim et al., 2025; Chou et al., 2025; Tang et al., 2025), while others have preferred to use an expanded version, including additional factors, to take into account some specific aspects of GenAI (Hu et al., 2024; Lee et al., 2024; Xia and Chen, 2024; Kang et al., 2025; Li, 2025; Li et al., 2025).

Among the additional factors, perceived risk, i.e., the potential negative consequences associated with using GenAI, is of particular interest to scholars. This is confirmed by the literature review of Chen et al. (2025), which ranks perceived risk fourth among the top ten independent variables considered in GenAI adoption studies.

3. Data and Methodology

3.1 Participants

For this study, we developed a questionnaire and distributed it to participants at the 2025 edition of Italian Agile Days, a two-day event that gathers Italian agile professionals. The survey was conducted online, and respondents' personal information was anonymized. Only professionals who had used GenAI for business and/or personal purposes were allowed to complete the questionnaire. The aims of the survey and information on the confidentiality of the collected data and their use were included at the beginning of the questionnaire and also illustrated by one of the authors when the survey was presented at the event. Table 1 summarises participants' demographics.

3.2 Questionnaire Design and Variables

The survey instrument for this study was developed based on factors from previous literature (see Table 2 for an overview), including questions about performance, effort to use and learn, social influence from others, facilitating conditions in the organization, and technology risks. The items were intentionally limited to 4 per factor to keep the questionnaire short.

The questionnaire consisted of two sections. The first gathered demographic information, as seen in Table 1. The second section focused on the key constructs of the study (Table 2). A 5-point Likert scale was used to measure respondents' agreement with each statement, with values ranging from 1 (strongly disagree) to 5 (strongly agree).

3.3 Analysis Methodology

Given that the adoption and use of GenAI by knowledge workers is a relatively recent phenomenon, and with the aim of conducting a preliminary analysis of the collected data, we decided to perform a cluster analysis to verify whether different usage patterns exist among users of this new technology and, if so, what factors may drive such behaviours. Actually, this methodology seems particularly appropriate for exploratory research, where a new phenomenon is studied.

Specifically, we grouped similar cases using Ward's hierarchical clustering method (Ward, 1963) with factorization. The method starts with each case as its own cluster and repeatedly merges pairs of clusters to make the groups as consistent as possible. The analysis uses squared Euclidean distances to measure similarity between cases (Murtagh and Legendre, 2014). To decide how many clusters to keep, we inspected the dendrogram and selected a three-cluster solution at the point where a clear jump indicated well-separated groups. Clusters were formed from responses to the influencing factor items (4 items per factor, for a total of 20 variables) using the Enginius platform.

Table 1: Sample demographics

Items		**Frequency (Percentage)**
Gender	Male	72 (79.1%)
	Female	19 (20.9%)
Age	20 -29 years old	12 (13.2%)
	30 – 39 years old	20 (22.0%)
	40 – 49 years old	34 (37.4%)
	50 -59 years old	20 (22.0%)
	60+ years old	5 (5.5%)
Education	High School	23 (25.3%)
	Bachelor Degree	10 (11.0%)
	Master Degree	55 (60.4%)
	PhD	1 (1.1%)
	Other	2 (2.2%)
Job role	Clerk	41 (45.1%)
	Middle Manager	14 (15.4%)
	Manager	14 (15.4%)
	Owner/Shareholder/CEO	11 (12.1%)
	Freelance	8 (8.8%)
	Other	3 (3.3%)
Department/ sector	Production	14 (15.4%)
	Information Systems	33 (36.3%)
	HR	10 (11.0%)
	Sales	4 (4.4%)
	Administration	4 (4.4%)
	R&D	13 (14.3%)
	Marketing	1 (1.1%)
	Purchasing/Logistics	1 (1.1%)
	Consulting	6 (6.6%)
	Other	5 (5.5%)
Industry	Primary	1 (1.1%)
	Manufacturing	24 (26.4%)
	Professional services	46 (50.5%)
	Public Administration	6 (6.6%)
	Logistics	4 (4.4%)
	Finance/Insurance	7 (7.7%)
	Other	3(3.3%)
Company size	< 10 employees	10 (11.0%)
	10 -49 employees	14 (15.4%)
	50 – 249 employees	27 (29.7%)
	250 – 999 employees	12 (13.2%)
	1000 – 4999 employees	22 (24.2%)
	5000+ employees	6 (6.6%)

Items		Frequency (Percentage)
GenAI experience	0 – 6 months	17 (18.4%)
	7 – 12 months	32 (35.2%)
	13 – 18 months	13 (14.3%)
	19 – 24 months	18 (19.8%)
	> 24 months	11 (12.1%)
Most used system	ChatGPT	41 (45.1%)
	Copilot	16 (17.6%)
	Gemini	13 (14.3%)
	Claude	19 (20.9%)
	Perplexity	2 (2.2%)

Table 2: Questionnaire's items

Factor	Items	References
Performance Expectancy (PE)	PE1: The use of GenAI in an agile context contributes to increasing the efficiency of activities PE2: The use of GenAI in an agile context contributes to increasing the quality of activities PE3: The use of GenAI in an agile context contributes to solving complex problems PE4: The use of GenAI in an agile context contributes to generating innovative ideas	Kim et al. (2025) Cao & Peng (2024)
Effort Expectancy (EE)	EE1: GenAI is simple to use EE2: GenAI doesn't take long to become an advanced user EE3: GenAI can meet the many needs of its users EE4: GenAI integrates well with my current work methods	Kim et al. (2025) Cao & Peng (2024)
Social Influence (SI)	SI1: The use of GenAI in an agile context is encouraged by my supervisor SI2: The use of GenAI in an agile context is positively evaluated by my colleagues SI3: The use of GenAI in an agile context is widely adopted within my team/organization SI4: The use of GenAI in an agile context is widely adopted among my company's competitors	Kim et al. (2025) Chen et al. (2025)
Facilitating Conditions (FC)	FC1: GenAI is compatible with the technology systems currently in use at my organization FC2: My organization is providing sufficient training, technical support, and assistance regarding the use of GenAI FC3: I can easily find help from colleagues if I encounter difficulties using GenAI FC4: My organization has sufficient resources to equip itself with advanced GenAI systems	Kim et al. (2025)
Perceived Risk (PR)	PR1: I am very concerned that daily use of GenAI could reduce my creative capabilities PR2: I am very concerned that daily use of GenAI could reduce collaboration with colleagues PR3: I am very concerned that GenAI could produce unreliable content PR4: I am very concerned about the potential negative consequences in terms of ethics and confidentiality of business information resulting from the use of GenAI	Cao & Peng (2024) Chen et al. (2025) Li et al. (2025)

4. Findings

Our analysis revealed three clusters. Table 3 summarises the results of the cluster analysis. For each variable, the mean values in the overall dataset and in each cluster are shown.

Table 3: Overview of the 3 clusters

Factor	Overall Population (N=91)	Cluster 1 (N=20)	Cluster 2 (N=38)	Cluster 3 (N=33)
PE1	4.13	3.60	4.16	4.42
PE2	3.62	3.10	3.53	4.03
PE3	3.53	2.80	3.53	3.97
PE4	3.63	3.10	3.74	3.82
EE1	3.70	3.55	3.63	3.88
EE2	3.34	3.05	3.32	3.55
EE3	4.11	3.90	4.24	4.09
EE4	4.19	3.60	4.37	4.33
SI1	3.69	2.65	3.95	4.03
SI2	4.13	3.55	4.47	4.09
SI3	3.84	2.80	4.13	4.12
SI4	3.86	3.45	3.76	4.21
FC1	3.86	2.80	4.03	4.30
FC2	3.29	2.50	3.21	3.85
FC3	3.68	2.55	3.84	4.18
FC4	3.60	2.60	3.82	3.97
PR1	2.86	3.05	2.05	3.67
PR2	2.55	2.40	1.92	3.36
PR3	4.20	4.35	3.92	4.42
PR4	3.76	3.80	3.21	4.36

Table 4 presents the demographic values (see Table 1) assumed by the three clusters, excluding descriptors with low presence. We could not find any differences in age, gender or months of using GenAI, but we did find differences in the sector and education in which participants work. These factors are shown in Table 4.

Table 4: Demographic factors in each cluster

	Population	Cluster 1	Cluster 2	Cluster 3
Age	43.2	43.1	42.5	43.9
Gender	0.791	0.700	0.868	0.758
Education	2.33	2.70	2.21	2.24
Months of using GenAI	16.8	17.3	16.9	16.3
Information Systems	36.3%	25.0%	28.9%	51.5%
Production	15.4%	15.0%	13.2%	18.2%
R&D	14.3%	5.0%	23.7%	9.1%
HR	11.0%	25.0%	13.2%	0.0%
Clerk	45.1%	35.0%	47.4%	48.5%
Mid Manager	15.4%	20.0%	7.9%	21.2%
Manager	15.4%	20.0%	15.8%	12.1%
Freelance	8.8%	10.0%	10.5%	6.1%
Owner/Shareholder/CEO	12.1%	15.0%	13.2%	9.1%
Manufacturing	26.4%	40.0%	23.7%	21.2%
Professional Services	50.5%	50.0%	50.0%	51.5%
Public Administration	6.6%	0.0%	5.3%	12.1%

	Population	Cluster 1	Cluster 2	Cluster 3
Logistics	4.4%	5.0%	2.6%	6.1%
Finance/Insurance	7.7%	5.0%	13.2%	3.0%

Based on the results from the cluster analysis in Tables 3 and 4, we can describe the three clusters as "sceptical explorers", "confident adopters" and "cautious power users" (see Table 5).

Cluster 1 "sceptical explorers" see fewer benefits from using AI in their work than the other clusters, and have more concerns. Cluster 1 employees have higher levels of education than people in the other two clusters. In particular, it consists of employees working in HR or as middle managers, who need to make decisions about people (e.g., about hiring, firing, evaluations), so they might be more concerned about AI hallucinations that could lead them to wrong decisions. Furthermore, the cluster has more manufacturing employees who might face compliance and procedural constraints, and thus have less autonomy to make free decisions in their daily work. As IT and R&D employees are underrepresented in the cluster, it does not have many technical experts who can more easily understand how GenAI works.

Cluster 2 "confident adopters" gain higher efficiency when using GenAI at work. They are mainly knowledge workers (R&D, Finance, Clerks, and Freelancers), who can use GenAI to get support in routine tasks or standardized processes in finance. These tasks are not directly connected to people's responsibilities, which might cause them to be less concerned about GenAI.

In Cluster 3 are "cautious power users", which contains more IT, public administration, and logistics. Especially IT people are capable of using AI and are aware of risks. People working in public administration can use GenAI well for their work; however, they need to be cautious users when decisions about people have to be made.

Table 5: Clusters description

Cluster 1: Sceptical explorers	**Cluster 2: Confident adopters**	**Cluster 3: Cautious power users**
20 people (22% of the sample) See fewer benefits from GenAI use Feel the least supported when using GenAI, e.g., by training and help from colleagues Have concerns about their GenAI use above average overrepresented people from HR and manufacturing, middle managers Underrepresented IT and R&D	38 people (42% of the sample) Have a supportive environment when using GenAI, e.g., most help from colleagues and supervisor support Have the lowest concerns toward GenAI use Gain from GenAI use, e.g., higher efficiency Overrepresented people from R&D, finance, clerks, and freelancers	33 people (36% of the sample) Perceive the highest benefits: efficiency, quality, can solve complex problems the best, ... have the highest support at their workplace (helping colleagues, most training, ...) have the greatest concerns about GenAI use Overrepresented IT, public administration, and purchasing logistics

A closer examination of the demographic profiles reveals further nuance. The sceptical explorers (Cluster 1) are dominated by HR professionals (25%) and manufacturing workers (40%), whose roles involve people-related decisions and compliance constraints where AI errors carry serious consequences. This explains their high risk concern scores (PR3=4.35, PR4=3.80). Counterintuitively, this cluster has the highest education level (2.70), suggesting that more educated users critically evaluate AI limitations rather than uncritically embracing the technology. The underrepresentation of IT and R&D workers (5%) means the cluster also lacks internal advocates who could model effective GenAI use. The confident adopters (Cluster 2) are primarily R&D (23.7%), finance (13.2%), and clerical workers (47.4%), whose tasks are routine and standardized, making AI errors easy to detect and consequences manageable. This explains the lowest risk scores across the sample (PR1=2.05, PR2=1.92). The cautious power users (Cluster 3) present the most theoretically interesting profile. IT professionals dominate (51.5%), and despite reporting the highest perceived benefits (PE1=4.42), they also show the highest risk concerns (PR4=4.36). This challenges the assumption that technical familiarity reduces risk perception; instead, deeper technical knowledge appears to heighten awareness of GenAI's failure modes such as hallucinations and data leakage.

5. Discussion and Conclusion

This study provides early empirical insights into how knowledge-intensive professionals working in agile contexts adopt and use GenAI in their daily tasks. Based on a survey of 91 practitioners at the Italian Agile Days 2025, we identify three distinct user clusters: sceptical explorers, confident adopters, and cautious power users, each characterized by different levels of engagement, perceived benefits, effort expectancy, social influence, and risk awareness. These findings show that GenAI adoption in agile environments is not uniform but unfolds through diverse sense-making processes, competence levels, and perceptions of value. The distribution of roles across clusters highlights how occupational context shapes adoption. Notably, Cluster 3 challenges a common assumption: rather than technical expertise reducing risk concern, IT professionals' deeper understanding of GenAI's failure modes, hallucinations, data leakage, output unreliability appears to heighten their caution, suggesting that capability and critical scrutiny co-evolve. Sceptical explorers are concentrated in HR, middle management, and manufacturing, where responsibility for people-related decisions and procedural constraints increase concerns and reduce the perceived benefits of GenAI. In contrast, confident adopters are primarily knowledge workers in R&D, finance, and freelance roles, where GenAI is used to support routine and standardized tasks, enabling efficiency gains with fewer concerns. Cautious power users illustrate how technical capability and work context interact, while their roles enable effective use of GenAI, their awareness of risks leads to a more critical and cautious engagement. These findings highlight a central tension between organizational support and risk perception. While training, collaboration, and enabling conditions can facilitate movement from scepticism to more confident use, increased experience does not eliminate perceived risks. Most UTAUT-based studies implicitly assume a linear adoption trajectory, where increased experience and organizational support progressively reduce barriers and lead to more confident use (Venkatesh et al., 2003; Bagozzi, 2007; Kim et al., 2024). Our findings challenge this assumption. While Cluster 2 broadly fits this pattern, Cluster 3 demonstrates that higher technical capability does not reduce risk concern but intensifies it. This suggests that GenAI adoption is better understood as a branching process shaped by occupational context and domain expertise, rather than a single pathway toward confident use (Kim and Kim, 2026). This aligns with prior research indicating that experienced users adopt more critical evaluation practices (Kirchner et al., 2025) and that perceived risk remains a persistent factor in GenAI use (Kim and Kim, 2026). It also contributes to research on human–AI collaboration by showing that effective use of GenAI depends not only on technical capability but also on users' ability to interpret, question, and validate AI-generated outputs (Jarrahi et al., 2023).

These findings suggest that organizations should move beyond one-size-fits-all adoption strategies and instead design differentiated support mechanisms that account for users' roles, experience levels, and evolving perceptions of risk. As GenAI becomes increasingly embedded in knowledge work, understanding these nuanced adoption dynamics will be critical to realizing its potential while mitigating its limitations.

5.1 Academic and Managerial Implications

From a theoretical perspective, our study contributes to the literature on AI adoption in knowledge-intensive contexts by offering an empirically grounded typology of GenAI user groups within agile work. Practically, our findings indicate that organizations may need to tailor support strategies to the specific needs and concerns of each cluster to facilitate effective and responsible GenAI use.

In the first cluster with sceptical explorers, organizations should better support these employees by providing sufficient training about how they can successfully employ GenAI for benefitting their work, validating the results, and changing their sceptical to cautious usage behaviour.

The confident adopters in the second cluster who regularly use GenAI for their work could benefit from scaling up, for example, by creating a prompt library with standard prompts they can use to optimize their daily tasks with GenAI and gain more benefits than only efficiency. Furthermore, they could support employees in cluster 1 to get more familiar with GenAI and understand the pitfalls.

Lastly, the cautious power users in cluster 3 could evaluate different GenAI tools to give advice to the organization and help with drafting organizational policies for GenAI use. The employees working in IT in this cluster might be able to help with fact-checking processes, so that employees can better check that the generated AI-content is correct.

5.2 Future Research Directions

Future work should collect data from more agile professionals, which would enable the validation of the three-user-cluster model. Since GenAI tools evolve rapidly, longitudinal research is needed to understand how

perceptions, adoption levels, and user clusters shift over time. Building on our clusters, researchers could design and test interventions, such as onboarding programmes, peer learning, or GenAI-risk awareness workshops, to examine their effectiveness in supporting effective and responsible GenAI use.

5.3 Limitations

This study presents several limitations. First, data were collected exclusively from participants at the Italian Agile Days 2025, which limits the generalizability of the findings to other cultural and professional contexts. Second, only professionals who had already used GenAI were eligible to participate, introducing a self-selection bias that excludes non-users who might exhibit different adoption patterns. Third, the cross-sectional design captures perceptions at a single point in time, making it impossible to observe how adoption behaviours and risk perceptions evolve over time. Finally, the three-cluster solution is exploratory in nature and based on a relatively small sample of 91 participants; future confirmatory studies with larger and more diverse samples are needed to validate and refine it.

Ethics Declaration: All participants gave their informed consent before participating in our study. We did not require ethical clearance for the research described in this paper.

AI Declaration: We used GenAI to revise and correct the written text.

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Impact of Tacit Knowledge on Management Students by Experiential Learning Using Business Games

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Abstract: The purpose of this article is to observe how explicit knowledge acquired in a Management program is applied in an experiential learning exercise through the study of a business game. We are interested in identifying and analysing their perception of how students' explicit knowledge can be transformed into tacit knowledge through a simulated competitive environment and whether they consider this form of learning useful for developing managerial skills. The research is a replication of research conducted last year on another group of students, and we want to compare whether there are changes in perceptions regarding the accumulation of tacit knowledge between two generations of students (2025 vs 2026). Applying Kolb's learning cycle in such a context allows the study of different learning behaviours and the discovery of practical aspects that can allow the accumulation of a high volume of tacit awareness in an educational context in which technology generates the behaviour of rejecting classic forms of explicit knowledge transfer, students prefer role-playing games, games such as printable games, etc.

Keywords: Knowledge, Explicit knowledge, Tacit knowledge, Transfer, Experiential learning

1. Introduction

Tacit knowledge from an epistemological point of view, is a concept that appears similarly formulated in Michael Polanyi's work Tacit Dimension, which considers that, “human knowledge by starting from the fact that we can know more than we can tell” (Polanyi, 1966, p4). The author addresses the problem of the accumulation of tacit knowledge through two psychological experiments conducted by Lazarus and McCleary (1949), who presented a human subject with a series of meaningless syllables and then applied an electric shock, and Eriksen and Kuethe (1958), who applied shocks associated with words about shocks to the human subject, with the aim of appearing to observe. According to Grant, tacit knowledge is difficult to articulate — it’s deeply internalized and hard to put into words or but can’t describe it (Grant, 2025). Nazim and Mukherjee consider that “tacit knowledge is a kind of personal knowledge that is learned by members of an organization through experience and learning by doing and is used to perform their work (Nazim and Mukherjee, 2016). Nonaka and Takeuchi, defined tacit knowledge is subjective and experience-based knowledge which is difficult to articulate or write down and communicate but gained through experience and knowledge linked to their mental schemas (Nonaka and Takeuchi 1995), because this type of knowledge is acquired individually from peoples who learned and in many cases unconsciously, but when he finds himself in a similar situation as in the examples studied by Michael Polanyi, he will know how to react and decide in the same context. Finally, Bratianu et al. (2026), consider that tacit tacit knowledge is personal knowledge that is created through direct experience and expressed through body language (Bratianu, et al., 2026). In other words, according to Dreyer, is a medley of competencies and experiential recollections something that is done reflexively and instinctively (Dreyer, 2018). According to Zait (2021), tacit knowledge originates in the mind of “knowers”, derived from personal experiences. It is inherently intangible and fluid, rather understood than ever stated, difficult to express, and sometimes even difficult to be perceived or realized (Zait, 2021). Because the objective of this study is to identify the impact of experiential learning in transferring tacit knowledge this aspect depends on the individual's capacity to accumulate tacit knowledge through personal experiences. With this context, business games offer the student the practical foundation necessary to complete the managerial learning curve, providing the framework in which he can practice the explicit knowledge accumulated in other disciplines and apply it in economic events proposed through the game that ensures the transfer of knowledge. This makes knowledge diffusion slow and expensive; and is why some human experts can command high returns for their unique knowledge (Grant, 2025). Types of

tacit knowledges are classified in five categories: (i) “concealed knowledge” (such as knowledge that is kept secret); (ii) “ostensive knowledge” (such as knowledge that is transmitted by pointing); (iii) “mismatched saliences” (such as knowledge that is not expressed because the knower does not realize that it needs to be revealed to a recipient); (iv) “unrecognized knowledge” (knowledge that is actually used but not expressed and even not known to be possessed by the user); (v) “un cognized/unrecognizable knowledge” (knowledge that is not articulated and not explicable in a given stage of human history, and that is perhaps humanly impossible to explicate) (Soler and Zwart, 2025, p 10, after Collins, 2001a). For explain this five categories Collins introduced sub-types of tacit knowledge: *relational* (tacit due to how individuals interact), *somatic* (tacit because it is tooted in the human body) and *collective* (tacit as it is embedded within the social environment) (Chin 2026 citing Collins, 2001). But according to Soler and Zwart, (2025), of the three new categories useful for the proposed study tacit knowledge in experiential learning context is collective or strong because it is required to act appropriately and creatively within a specific collective (Soler and Zwart, 2013) or practical framework.

2. Experiential Learning and Tacit Knowledge

Experiential learning is defined by Kolb (1976), as a process whereby knowledge is created through the transformation of experience. This approach shifts away from passive learning instruction, instead converting concrete experiences after reflection in knowledge. Experiential learning is an essential strategy for engaging students in critical academic content and developing key skills, projects, and internships. In higher education, both formal and informal experiential learning reinforce learning endeavours, thereby improving student success (Brodowicz, 2025). When implemented through various practical exercises, role-playing games, the use of design applications, product conception or - as in the case of this research, business games, experiential learning enables student to transition from the explicit knowledge obtained from individual study or participation in didactic activities to their application in a simulated context in which, through involvement and understanding of the context, they effectively accumulate tacit knowledge. According to Nakitiikwa and Baagala (2024), the main benefits of experiential learning for students are: opportunities for immediate application knowledge, promotion of teamwork, improved motivation and opportunities for reflection. These benefits are significantly stimulated through the use of business games because the students have the opportunity to apply explicit knowledge accumulated by other program courses and transform it into tacit knowledge. The advantages of business games in this learning process also stem from the fact that learners participate in a company's development over multiple simulated years. This longitudinal structure grants them the necessary time between decision periods to analyse the results (opportunity to reflect) and to consult with the game partner (team work) regarding the decisions to be considered in the next round. Ranken et al. (2025) analyses how students accumulate knowledge by drawing on Kolb framework, which extends Dewey's (1938) original theory of experiential learning. They note that “concrete experiences serve as the foundation for observation and reflection, which are then transformed into abstract concepts. These concepts inform future actions and guide the creation of new experiences.” The Association of Experiential Education (2012) defines experiential learning as “engaging with learners in direct experience and focused reflection in order to increase knowledge, develop skills, clarify values, and develop people’s capacity to contribute to their communities”. Jump Foundation (2025), analyses the benefits of experiential learning in actual context when students have difficulty to concentrating, 7 seconds era, multiple screens are: i) enhance academic performance (National Society for Experiential Education (NSEE) demonstrate a 20% improvement), ii) improved critical thinking and problem-solving skills (Association for Experiential Education (AEE), 85% of students in experiential programs make substantial gains in critical thinking and problem-solving skills); iii) superior retention rate (experiential learning can lead to retention rates as high as 90%, compared to just 5% from traditional lectures); iv) development of essential soft skills (teamwork, leadership, communication); v) preparing for the future careers – prepare practical, hands-on skills that directly translate to their future careers; vi) fostering lifelong learning, experiential education isn’t just about teaching facts—it’s about cultivating a mindset; vii) creating global citizens immersive experiences are catalysts for personal growth and cultural understanding. Based on the aforementioned analysis, we can argue that experiential effectively facilitates the transfer of tacit knowledge to students. Active participation in often competitive business games fosters a strong sense of psychological ownership over the virtual business. Consequently, this immersion mitigates typical classroom distraction – such as smartphone usage, while encouraging students to communicate and understand with teammates and decide in the context of the game and eagerly await the results obtained after each round, in order to discover and understand the results.

3. Methodology

3.1 Nature of the Study

The purpose of the study is to identify how students have accumulated a series of managerial skills or tacit knowledge by participating in a business game. Being repetitive experiential learning, for six periods, we want to identify how the repetition of the experience generates a change in the way they have learned tacitly from the previous experience, elements of the management decision. The objective will be achieved through quantitative analyses with two distinct researches, implemented in two different periods, on the same proposed group: (1) at the beginning of the game after the animator has presented and detailed all the necessary elements to be applied and the target group has to go through the decision-making process specific to the first period of the games and (2) at the end of the specific decision-making to simulate all the proposed periods to simulate their children: healthy and resilience to the conditions of the competitive environment. The two tools used are to a significant extent similar, containing many of the results proposed by Kolb to be achieved through the experiential learning cycle: actions, interpersonal, reflection, wilful, strategic, skills, etc.

3.2 The Research Instrument

The research instruments that we are proposing and testing are two questionnaires, with a certain level of similarity that contains the following:

- The declaration of consent regarding participation in this study, and the way in which the students were explained how to use the information transmitted, if there were any questions clarified by answers provided by the research team.
- One question about the extent to which they consider that they will apply the knowledge gained in previously studied disciplines that have implications for participation in simulation through business games;
- Five questions about the extent to which participation in the game allows the development of managerial skills such as: re-evaluation of beliefs about the way they learn (Learning_change_mode), discovery of entrepreneurial skills (Entrep_skills), discovery of manager (Manager_skills), ability to experiment (Experimental_skills). These five question are similar to the second questionnaire applied to the end of the business games:
- The scale was Likert range from one to five: strongly disagree, disagree, neither agree or disagree, agree, strongly agree, which allowed us to identify the way in which students collect and use the knowledge transmitted for the development of skills and capacities specific to Kolb's Experiential Learning Cycle (Kolb, 1984).
- The survey has been conducted online. Google Forms was used and data has been collected between 16th and 19th of March 2026 and the second research in the period 4th and 7th of May 2026. For the proposed comparative analysis, data collected between the 17th and 21st of March 2025 will also be considered.

3.3 The Sample

The respondents are the students in the third year, last semester of the Management specialization, who have the business games discipline in their curriculum. In the research context at the first questionnaire, we have 73 responses from 98 students enrolled and the second we have 67 responses from 98 students. The percentage represents approximately 75% of the number of students participating in the business games. The number of students participating in the study in 2025 was 86, representing about 78% of all the 110 students enrolled.

3.4 Methods and Techniques Used for Data Analysis

Microsoft Excel and R Stata, were used for data analysis. In order to measure the impact of applying tacit knowledge in training students through experiential learning, we will try to statistically analyse the differences in the variables that were common in the two studies proposed to students by applying different statistical tests.

4. Results

For the statistical analysis, the common variables from the two studies, specifically data_pre and data_post which pertained to participation in the experiential learning exercise, were considered. Table 1 and Table 2 present the descriptive statistics of the responses to the common variables (learning_change_mode, entrep_skills, manager_skills, etc.) in order to observe differences that occur in the mean, the degree of data dispersion around the mean (standard deviation), the direction of asymmetry (skewness), the standardized

value of asymmetry (Z-Skew), the degree of skewness (Kurtosis), the standardized value of skewness (Z-Kurt). We can see that the average of the responses is between 4 – 5 with a maximum value of 4,397 for the action skills variable and a minimum of 3,806 for strategic_capabilities_skills, which means that the respondents believe that they will develop their ability to react to changes in the competitive environment proposed by the game, but the minimum for strategic capabilities demonstrates that at the beginning of the game they do not have a vision of how such an experience can develop their strategic abilities. The standard deviation shows us that the participants' responses do not deviate much from the average, but the asymmetry is negative, which demonstrates that the responses to the variables obtained high and above average scores, but there were some respondents who gave answers of the very little and little type, which led to the lowering of the average, also demonstrated by the Z-Skew values. From the point of view of the kurtosis (Kurtosis) the distribution of the responses to some variables is normal, for others the distribution is high or for some it is flattened. For example, the Learning change mode variable has a value of 1.463, which means that students believe that it will be a different way of learning, but there are also some who do not trust the form of learning through experience, possibly having never heard of such methods or being scared of what they have to achieve following the explanations of the animator who in a short period of time explicitly transferred a lot of information (perhaps being considered boring in the context in which you do not see their immediate applicability). We specify that for each form of learning based on a business game, the animator must present and interpret the game's rules to the participants. If we analyse from the Z-Kurt perspective, we observe that in most cases the vaulting is negligible, only in the case of the same variable learning change mode, the value is 2.551, the distribution being very sharp at the top, most of the answers being very close to the mean (Table 1)

Table 1: Descriptive statistics regarding the respondents' opinions about how the game will improve the following skills (after explanations and the first round – pre experiential learning)

	N	Media	Dev.Std	Skewness	Z-Skew	Kurtosis	Z-Kurt
ID_student	73	37	21.217	0	0	-1.249	-2.179
Learning_change_mode	73	4.082	0.812	-0.914	-3.188	1.463	2.551
Entrep_skills	73	4.164	0.834	-0.875	-3.052	0.977	1.704
Manager_skills	73	4.233	0.773	-0.77	-2.687	0.105	0.183
Experimental_skills	73	4.192	0.776	-0.864	-3.014	0.593	1.034
Reaction_skills	73	4.137	0.751	-0.61	-2.129	0.086	0.151
Interpersonal_managent_skills	73	4.233	0.717	-0.364	-1.269	-1.04	-1.814
Reflection_skills	73	4.164	0.746	-0.465	-1.621	-0.487	-0.849
Wilfull_skills	73	4.342	0.711	-0.813	-2.836	0.189	0.33
Information_colect_analyse	73	4.384	0.719	-0.92	-3.208	0.267	0.466
Ideea_manipulation_skills	73	4.301	0.845	-1.01	-3.524	0.202	0.352
Action_skills	73	4.397	0.682	-0.928	-3.236	0.65	1.133
Decision_concequences_skills	73	4.219	0.837	-0.839	-2.927	-0.025	-0.043
Objective_conception_skills	73	4.301	0.758	-0.736	-2.567	-0.3	-0.524
Strategic_capabilities_skills	72	3.806	0.85	-0.578	-2.004	0.472	0.817

The descriptive statistical analysis of the responses obtained to the same variables after completing the business game (table 2) highlights the fact that the average of the responses is also in the range of 4-5, with a value of 4.537 for the variable decision_consequences_skills, which means that the students tacitly understood the impact that it can have on some businesses, the decisions made, because the business game offers them a series of results, performance indicators from different perspectives (financial - accounting, investments, production, marketing, human resources, cost). The minimum average value was obtained by the variable learning_change_mode, which in the first part of the study had obtained the maximum value. From the point of view of the standard deviation, a normal distribution is observed, it does not deviate much from the average, only in the case of the manager skills variable, the deviation is 0.37, which means that there are large differences

between the subjects' responses, probably some consider that by participating in the game they developed some managerial skills, others consider it not very useful (some do not even understand this decision-making process) or they did not want to get involved in the business game. Another variable with a large standard deviation is information_colect_analyse, very relevant for decision-making analysis, even if the students disregarded its importance. In the case of asymmetry, the distribution deviates from normality for the manager skills variable, - 3.132, meaning that most subjects have answered little or very little but there are a few "outliers" on the left, who answered very differently with very low scores, which means that the game did not form managerial skills for them. In addition, we can see that for the same variable the Z-Skew is – 10.466, which suggests a pronounced ceiling effect, the tail of the distribution being pulled down strongly by a series of minimal responses. Similar effects on both the asymmetry of the distribution and the vaulting are also observed for the entrepreneurial_skills variable, with some students considering that the game does not form these skills.

Table 2: Descriptive statistics regarding the respondents' opinions about how the game will improve the following skills (after the final of the game – post experiential learning)

	n	mean	sd	skew	z_skew	kurtosis	z_kurt
ID_student	67	34	19.485	0	0	-1.254	-2.095
Learning_change_mode	67	3.627	0.624	-1.771	-5.918	3.442	5.75
Entrep_skills	67	3.731	0.665	-2.703	-9.032	7.079	11.828
Manager_skills	67	3.881	0.37	-3.132	-10.466	9.817	16.403
Experimental_skills	67	4.478	0.587	-0.58	-1.939	-0.68	-1.136
Reaction_skills	67	4.254	0.766	-1.249	-4.172	2.99	4.995
Interpersonal_managent_skills	67	4.418	0.781	-1.608	-5.375	3.633	6.07
Reflection_skills	67	4.224	0.714	-0.342	-1.144	-1.036	-1.731
Wilfull_skills	67	4.164	0.751	-0.692	-2.313	0.281	0.47
Information_colect_analyse	67	4.433	0.633	-0.634	-2.119	-0.623	-1.041
Ideea_manipulation_skills	67	4.075	0.926	-0.933	-3.119	0.608	1.016
Decision_concequences_skills	67	4.537	0.559	-0.656	-2.191	-0.69	-1.152
Action_skills	67	4.418	0.655	-0.658	-2.197	-0.647	-1.082
Objective_conception_skills	67	4.418	0.655	-0.658	-2.197	-0.647	-1.082
Strategic_capabilities_skills	67	4.388	0.673	-0.917	-3.063	0.818	1.367

Table 3 highlights data obtained with the same instrument in 2025, on a group of students from the same study program, but this time the instrument applied was the one from the beginning of the learning experience. As can be seen, the distributions are somewhat similar to the data from 2026, students being convinced that through the game they will develop managerial, decision-making, strategic skills and less the ability to react to environmental changes in the game for example, or to act in a certain context.

Table 3: Descriptive statistics regarding the respondents' opinions about how the game will improve the following skills (after explanations and the first round – pre experiential learning)

	N	Media	SD	Skewness	SE-Skew	Z-Skew	Kurtosis	SE-Kurt	Z-Kurt
ID_student	86	43.5	24.97	0	0.264	0	-1.242	0.528	-2.351
Learning_change_mode	86	3.907	0.863	-0.911	0.264	-3.448	1.409	0.528	2.668
Entrep_skills	86	4.174	0.785	-0.742	0.264	-2.809	0.15	0.528	0.284
Manager_skills	86	4.267	0.789	-1.068	0.264	-4.045	0.973	0.528	1.841
Experimental_skills	86	4.267	0.742	-0.802	0.264	-3.037	0.317	0.528	0.6
Reaction_skills	86	3.942	0.845	-0.47	0.264	-1.779	-0.399	0.528	-0.756
Interpersonal_managent_skills	86	4.116	0.788	-0.63	0.264	-2.386	-0.049	0.528	-0.093
Reflection_skills	86	4.105	0.651	-0.102	0.264	-0.385	-0.698	0.528	-1.321
Wilfull_skills	86	4.07	0.748	-0.277	0.264	-1.05	-0.722	0.528	-1.366

	N	Media	SD	Skewness	SE-Skew	Z-Skew	Kurtosis	SE-Kurt	Z-Kurt
Information_colect_analyse	86	4.279	0.662	-0.604	0.264	-2.286	0.315	0.528	0.596
Ideea_manipulation_skills	86	4.035	0.758	-0.536	0.264	-2.03	0.073	0.528	0.138
Action_skills	86	3.942	0.886	-0.892	0.264	-3.378	0.724	0.528	1.37
Decision_concequences_skills	86	4.465	0.627	-1.003	0.264	-3.799	1.231	0.528	2.33
Objective_conception_skills	86	4.279	0.762	-0.82	0.264	-3.104	0.152	0.528	0.288
Strategic_capabilities_skills	86	4.349	0.748	-1.485	0.264	-5.621	3.712	0.528	7.027

In table 4, we present only the averages of the proposed variables in order to identify differences between the average value of the proposed variables and the analysis. It can be seen that for the first variable learning change mode, where both in 2025 and 2026, the average of the answers was high, for the question after completing the game in 2026, 3.627 is lower than initially, which may mean that through the game the mode of knowledge accumulation has not changed significantly compared to classical learning methods. In contrast, significant increases are observed in the ability to react or act.

Table 4: Descriptive statistics regarding the respondents' opinions about how the game will improve the following skills (2025, 2026 – pre gaming, 2026 – post gaming)

	2025-pre	2026-pre	2026-post
Learning_change_mode	3.907	4.082	3.627
Entrep_skills	4.174	4.164	3.731
Manager_skills	4.267	4.233	3.881
Experimental_skills	4.267	4.192	4.478
Reaction_skills	3.942	4.137	4.254
Interpersonal_managent_skills	4.116	4.233	4.418
Reflection_skills	4.105	4.164	4.224
Wilfull_skills	4.07	4.342	4.164
Information_colect_analyse	4.279	4.384	4.433
Ideea_manipulation_skills	4.035	4.301	4.075
Action_skills	3.942	4.397	4.537
Decision_concequences_skills	4.465	4.219	4.418
Objective_conception_skills	4.279	4.301	4.418
Strategic_capabilities_skills	4.349	3.806	4.388

To measure how knowledge transfer changed from one year to another or from the beginning period to the end of the game, since the data are numerical but not normally distributed, we will apply the Wilcoxon Signed-Rank statistical test for analysis, which measures whether the median of the differences between the two periods is different from 0. Thus, we applied it for two of the specified variables, Manager_Skills, because the differences were very large between the means, resulting in a V = 578.5, p-value = 0.8756, we observe the absence of a statistically significant difference, but the p-value is very high, as there is the high asymmetry presented previously, due to the Ceiling Effect (Figure 1).

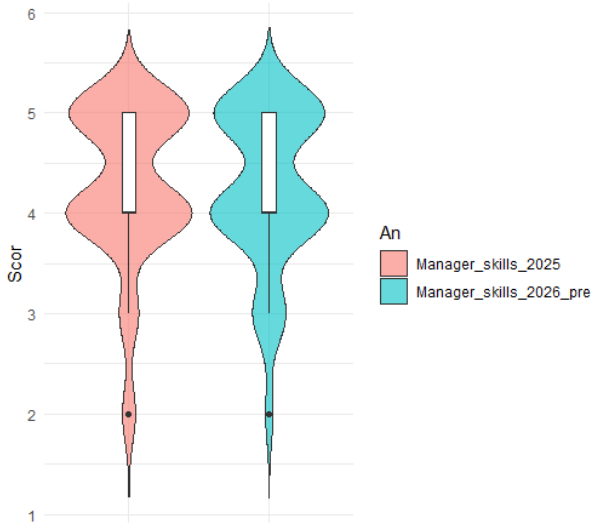


Figure 1: Distribution of scores regarding the perception of change in managerial skills

Figure 2, highlights the graphical representation obtained by applying the same test for the variable decision_consequences_skills. For the analysis of the links between the results of 2025 and 2026, the value of V = 579, with a significance threshold p-value = 0.08892, means that there is a marginal evolution of the scores that cannot be generalized, and although the test is not significant there is some connection. If we interpret the result of applying the Wilcoxon Signed-Rank test for the results of the first questionnaire in 2026 and the second of the same year, the value of V = 232, p-value = 0.034, which means a significant difference between the students' abilities to understand the decisional consequences at the beginning of the game and those at the end. Considering the significance threshold obtained, p-value = 0.034 less than 0.05, we can state that there was a change in the way students improved their understanding of the effects of decisions through business games.

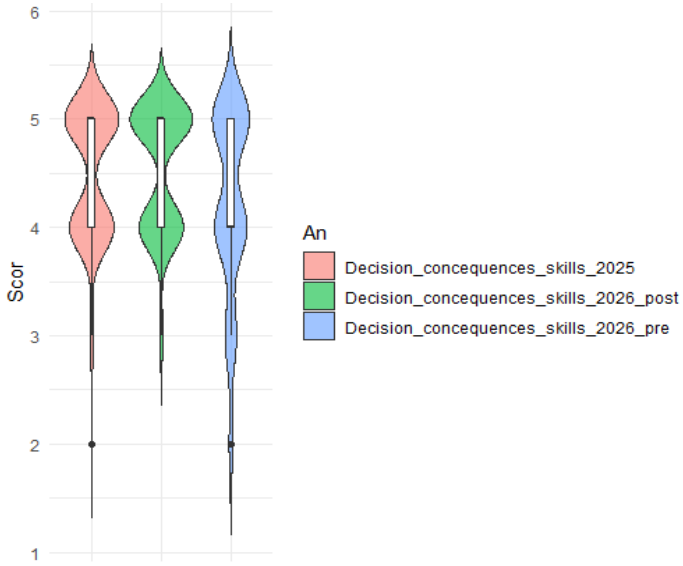


Figure 2: Distribution of scores regarding the perception of change in the abilities to understand the consequences of decisions

5. Discussion

The transfer of knowledge through experiential learning highlights several critical insights regarding the participating students. First, business games offer students a unique opportunity to understand the consequences of decisions made at the organizational context. Because these simulations operate in real time, students are forced to adapt and implement a series of adjustments and across corporate functions, including production, investments, marketing, human resources and quality management. All of these are subsequently visible and interpreted in the results section. In this manner, the game stimulated the understanding of the impact of the decisions made – an excellent form of tacit knowledge for the training of future management

specialists. However, a large dispersion in the variable *information_colect_analyse* signifies that undergraduate economic education at our faculty has not fully developed students' data analysis capabilities. In the game situation, when the volume of information provided often prevents them from analysing and interpreting it in the simulated context. This finding suggests that previously studied foundational disciplines such as financial accounting, financial management, investments, production and operations management, human resources management, quality management should place a high emphasis on the interpretation and analysis of the data obtained. Consequently, students recommended that the facilitator focus more intensely on the diagnostic part of the results, because although they are explained in an allotted time, it would seem that their explicit presentation is boring and their high volume becomes irrelevant for the participants.

Furthermore, an improved capacity for action and reaction constitutes another form of tacit knowledge obtained as a result of the game. This highlights the students high level of engagement, as they continuously reflected on different situations obtained through the game in order to increase the quality of decisions and the performance of the simulated organization. The business game environment according to Iftimescu and Tiţă, (2026) offers a simulation of reality, not reality itself, which has a practical advantage: reducing economic reality to a limited set of parameters allows the essential market mechanisms and their interactions to manifest within a compressed timeframe. Conversely, it also introduces a practical limitation, as any modelling regardless of its realism is subject to simplifying and reductionist rules, but nevertheless offers the student the opportunity to make decisions in a context that is over 60% similar to the real market. In addition to the competition between students, which is very attractive, much of the knowledge is transmitted tacitly, such as: the importance of granting salary increases, the investment moment, the ability to understand costs, it is cheaper to store products with a low cost, compared to a high one, etc. But the main tacit knowledge transmitted through the game following individual discussions with each participating team was the ability to think. From the analysis of the variables presented, it can be seen that for many of them there is an increase in the average between the first stage of the analysis and the second, which is why we could state that after participating in experiential learning through a business game, students tacitly accumulated a series of skills regarding achieving objectives, pursuing strategies, etc.

6. Conclusion

The comparative analysis of data collected in two distinct dimensions: (1) two consecutive years 2025 and 2026 and (2) the evolution of responses between the initial phase of the game and its completions after six rounds, clearly highlights that students tacitly accumulate vital management specific skills. In the current era of rapid technological expansion driven by artificial intelligence (AI), the tacit knowledge acquired through business games proves particularly essential. Because the simulations require active engagement within a highly competitive peer-driven environment, they develop cognitive skills and critical thinking without relying on AI assistance. Because it's a competitive context participants, cannot control or predict the visions or strategies of opposing teams, which is why each team must think through their own decisions in an environment with a high level of chaos. Consequently, business games serve as a highly beneficial and student approach learning mechanism for the transfer of tacit knowledge, providing a practical arena where learners can effectively operationalize the explicit knowledge acquired from other faculty disciplines.

Acknowledgement

The European Commission's (EACEA) support to produce this publication, through Jean Monnet Module. Project 101127556 — EU Resilience Digital Skills - EU-ReDiSkills — ERASMUS-JMO-2023-HEI-TCH-RSCH, does not constitute an endorsement of the contents, which reflect the views only of the authors. Neither the European Union nor the granting authority can be held responsible for them.

Ethics Declaration: Ethical clearance was not required for the research.

AI Declaration: AI tools have not been used for the creation of the paper.

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Is Artificial Intelligence a Better Researcher than Humans?

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Abstract: In the last few years Generative Artificial Intelligence (GenAI) has taken universities by storm. This does not only affect the way what and how to teach and how to assess knowledge and competences in exams, but it also impacts the way how to do research. On one hand, GenAI has fast access to a huge amount of wide-ranging (explicit) knowledge and the capability to extract and combine knowledge that seems to be relevant in the context of certain research. On the other hand, research is closely linked to the human capability of being creative showing curiosity, care, collaboration, and critical thinking. Against this background, the paper addresses a question of immense social and also ethical relevance: May we use (Gen)AI as tool for scientific research and if so to what extent? The paper starts analysing the problem from a theoretical and conceptual point of view by comparing capabilities of GenAI with those of a good researcher. Based on this the complete research cycle is investigated to understand which capabilities are more helpful to achieve research results of high quality and novelty, but in an effective way. To gather empirical data from a self-experiment, the setup of an unexperienced researcher (e.g. PhD student) with just a rough idea about the intentional research focus was chosen. Addressing the first and fundamental phase of any research process, idea generation, by comparing performance of an AI researcher with a human one, results demonstrate the usefulness of combining strength of both worlds mandatorily keeping the human researcher in the loop. With this, the paper focusses on chances and challenges coming with the highly dynamic evolution of AI within a complex, knowledge-intense application area where human experience, problem-solving capability and creativity is decisive. It contributes to discussions about necessary adjustments in how organizations (and particularly universities) manage their knowledge generating potential considering artificial and human intelligence.

Keywords: Generative artificial intelligence, Knowledge, Research quality, Research efficiency, Human-in-the-loop

1. Introduction

Artificial Intelligence (AI) is one of the most promising technological advancements, but also one of the most ambivalently discussed topics these days. The latter starts with its definition already, as there are two different perspectives, a psychological and a computational one. Gignac and Szodorai (2024) elaborated operational definitions of both artificial intelligence and human intelligence (HI). They differentiate AI from HI just by referencing to an artificial system and computational algorithm instead of a person and his/her perceptual-cognitive processes for completing a novel standardized task. The latter is a task (or test) with limited chances for preparation, as it neither was introduced before nor awareness was risen that this type of questions should be solved. This is typically the case when it comes to answering a research question. As this is a particularly challenging task to human researchers, might they be young ones (newcomers, typically PhD students) or experienced ones (researchers well recognized in a certain community), any kind of approach, method, methodology, source of inspiration, or even tool is welcome to provide support.

With the advent of generative Artificial Intelligence (GenAI), it suddenly seemed to be easy to speed up research. GenAI refers to integrating machine-learning models to fabricate novel content based on large datasets that train the generative model (Dwivedi et al, 2023). To understand the power of this not so new, but suddenly widely available tool, AI is benchmarked by putting its performance in competition to HI performance when dealing with the same tasks. The AI index report 2025 (Maslej et al, 2025) uses different benchmarks to monitor technical progress of AI systems over time. Results show that AI systems continuously improve exceeding human performance at many previously challenging tasks already (see Figure 1).

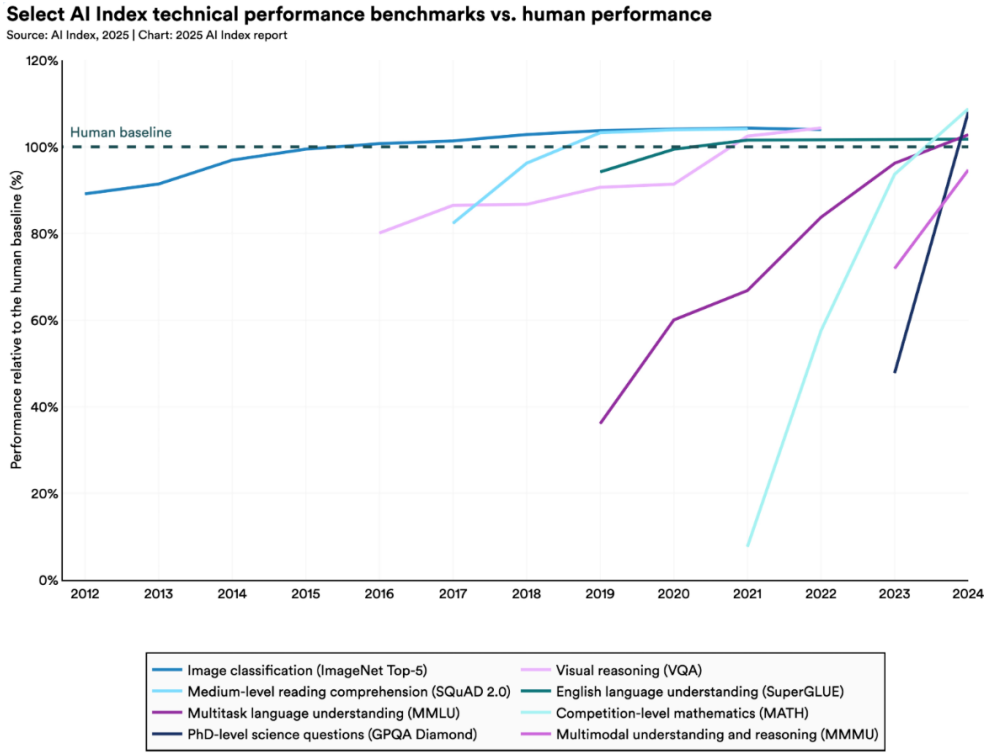


Figure 1: State of AI performance (Maslej et al, 2025, p. 94)

These new opportunities felt particularly welcome as *"… researchers are under extreme pressure to publish high-quality research"* (Lindgreen et al, 2021, p. A13). Consequently, the interest in applying AI techniques and technology in research has been increasing from a growing number of disciplines (Madanchian and Taherdoost, 2025); research employing GenAI is anticipated to accelerate and transform scientific knowledge (Benbya et al, 2024). There are various studies investigating GenAI use in research. They mainly focus on the impact of AI-based or AI-supported research on its productivity (i.e. research efficiency – see e.g. Madanchian and Taherdoost, 2025) or quality (i.e. research integrity – see Andersen et al, 2025, for example) and how to assess them. Those studies are based on literature review or surveys in the field and reflect the situation in that particular moment. Because of the ongoing rapid development and highly dynamic evolution of GenAI, including the immensely growing knowledge base underlying Large Language Models are trained with, on one hand, but also due the raising awareness of researchers of ethics challenges, bias, or risk of failure on the other, there is no comprehensive picture on the extent to what GenAI might be beneficial alongside the research cycle, yet.

Against this background, the paper analyses the potential of GenAI application in a certain research context throughout the entire research process. Are we on the way towards fully automated research solely run by GenAI or will there still be the need for human intervention, i.e. for human researchers? When answering this question, the future need for human capabilities is in focus. The following sections will analyse both, capabilities of GenAI (Section 2) and capabilities of (good) researchers (Section 3). Findings from both sections are brought together and applied to a specific case with regard to the kind of researcher and the chosen research problem to specify what in the research process could or should be taken over by GenAI and what could or should remain in hands of the human researcher (Section 4). Section 5 summarizes discussions and draws conclusions on both, the use of GenAI and the future role of human experts in scientific research.

2. Capabilities of Generative Artificial Intelligence

In recent years, *Generative AI (genAI)* and open access AI tools like ChatGPT, Gemini, DeepSeek, or CoPilot provided a more common user interface moving the use of AI from an expert's competence to an almost everyday tool. Schneider (2025) characterizes GenAI as an AI system based on a foundation model that generates and transforms content based on specific user interactions. In other words, GenAI can generate new data similar to the training data it has seen. Generative models learn the underlying probability distribution of the (enormous amount of) training data and can then generate new samples from this learned distribution (Baum, 2024). *Large Language Models (LLMs)* are specific applications of GenAI designed to understand human language and to

generate intelligent, creative responses similar to human-produced content when queried. Because of the ability of processing natural language, AI is capable already to assist humans in many different ways:

- AI-powered *translation systems* use artificial neural networks to translate texts in various languages at high quality of language.
- GenAI tools create *new content* as text, image or video usually in response to human prompts.
- AI chatbots simulate *human-like conversation* through text or speech interfaces to help in customer service, manage appointments, or support travellers in booking trips.

Bots are the simplest form of AI assistance. These automated systems are typically rule-based and designed to carry out predefined tasks without human intervention. Bots can manage repetitive tasks, answer basic questions, and execute straightforward functions. They follow scripts and rely on if-then-else logic, meaning their responses are limited to the scenarios they have been programmed to handle (Alosious, 2024). The integration of LLMs with retrieval mechanisms enhances their response generation to answer precise questions from large databases or address customer queries using information from different company documents. This *Retrieval Augmented Generation (RAG)* is another increasingly common capability of AI combining the strengths of information retrieval and GenAI (Maslej et al, 2025): The model first retrieves relevant information from databases, files or documents and then combines them to generate a response tailored to the user's query based on retrieved content. Because of using those (relevant) external sources instead of training data purely, responses are more accurate and up-to-date.

Co-pilots represent a collaborative approach between AI and humans. Acting as assistants, they provide real-time, contextually aware support, allowing users to complete complex tasks more efficiently. Co-pilots excel in roles requiring decision support and act as an "extra set of hands" that brings data-driven insights and recommendations directly into workflows. This way, they enhance human judgment enabling more nuanced and strategic decision-making (Alosious, 2024).

The latest boost of development moved AI application from those sophisticated communicators or task-oriented AI to agentic AI allowing for autonomous, goal-driven decision-making. With this, AI evolved from prompt-driven content generation (GenAI) via tool-based task execution (AI agents) towards orchestration of full-fledged workflows (agentic AI). *Agentic AI* enables autonomous decision-making, automates processes, and enhances efficiency though transition from assisted (co-pilot) to autonomous (autopilot) models (Hosseini and Seilani, 2025). Agentic AI (or multi-agent) systems composed of multiple, specialized agents that coordinate, communicate, and dynamically allocate sub-tasks within a broader workflow to achieve a common goal are comparable to human experts working in teams. Those agents, i.e. more advanced AI applications with a degree of autonomy and cognitive capability beyond that of a bot, can interpret data, learn from interactions, and make independent decisions within set parameters. They are crucial for tasks that require context-awareness, data analysis, and ongoing adaptability (Alosious, 2024). This constitutes a paradigm shift in AI enabling to act independently, pursue broad objectives rather than isolated decisions, and carry out complex tasks that require reasoning elements such as planning and reflection (Sapkota et al, 2025; Schneider, 2025).

An IBM Think Circle (IBM, 2025) identified a number of use cases despite implementation challenges:

- *Document retrieval and analysis*: Intelligent agents search unstructured data in documents such as product documents, sales documents, contracts and identify what is the best document to choose.
- *Complex data querying*: Code models are used to create SQL queries.
- *Proactive outlier detection*: Intelligent agents look at sets of data, scan them, run and find outliers overnight. They send back results as a morning briefing.

These examples and first use cases underline the potential proper AI integration might have.

These different kinds of GenAI techniques do not only form levels of evolution, but provide a set of tools to support human knowledge processes. They offer different capabilities (and come with different levels of complexity) we can (and should) choose from according to what might be most appropriate and beneficial in a certain application context as, for example, scientific research. To provide a basis for selection the following section analyses what capabilities are required (by a human researcher so far) throughout the research process.

3. Capabilities of a Good Researcher

In order to identify capabilities a researcher (and particularly a good one) should possess, it is helpful to start from identifying the steps and phases of any research process. Literature contains various models for how to

conduct research within different contexts and for different purposes. Zapata and Velásquez (2008), for example, present a *conceptual model for writing a research article*. It shows main elements of a research article (i.e. problem, objectives, solution, and future work) and how they are related to each other in order to assure consistent structure and flow in writing. This way the model also indicates elements of the research process the article is based upon. However, to derive what is required from a researcher this model is too generic. Other authors focus more on how to actually research. Alphonse (2023) derives eight *main stages of the research process* from a literature review and puts them in a cyclical process from identifying a research question to presenting findings which might trigger new or further research questions. This proposal considers research as a complex and challenging process which cannot be performed in vague, unprepared, and surprising way. Instead, a researcher needs to define and structure the process to follow well; s/he must be capable to work in a systematic and organized way according to prior planning. Saunders et al (2023) explain the *research process in the field of business* discussing 13 steps in detail from generating a research idea and developing a research proposal to writing and presenting the research report. They particularly point on the necessity to follow a systematic approach moving forward step-by-step instead of jumping in and out or over as it might feel good. Depending on the initial research problem it might also be quite helpful to substructure a complex problem into smaller less complex or more focussed ones. The more a researcher is capable in doing so, the better researcher s/he will be.

Andersen et al (2025) base their survey on GenAI use cases in research at Danish universities on *five phases of a research process* from idea generation to writing and reporting research results. When analysing survey results, they identified *three clusters of GenAI use* in Danish academia that were assessed also as good research practices:

- "GenAI as a work horse" – using GenAI
- *to create and edit software codes for analysis and simulation*
- *to support statistical analysis*
- *to help recognize patterns in data*
- "GenAI as language assistant only" – using GenAI
- *to edit language, e.g. of research proposals*
- *to transcribe recordings of research material*
- *to propose titles, keywords, or abstracts*
- *to edit research articles for readability and formatting references*
- "GenAI as a research accelerator" – using GenAI in almost all use cases, particularly for data analysis and research design, except the creation of synthetic datasets and identifying ethical issues in research.

These clusters of GenAI use show that researchers mainly see benefits for activities that are somehow formal, analytical and repetitive requiring a certain level of accuracy and preciseness from the researcher. On the other hand, activities that require more creative thinking or moral assessment should remain in human responsibility. In terms of research fields, authors saw a closer relation of researchers from technical sciences, especially those ones from experimental technical sciences, and researchers from quantitative social sciences to GenAI usage than of researcher from other domains with more qualitative research. This finding to some extent confirms a general expectation that researchers used to work with software to plan, gather, analyse and interpret data have a lower barrier to give technological advancements a chance and to imagine that and how they might be beneficial in their research. This does not differentiate per se a good researcher from a normal or even bad one, but this capability of being open-minded to new tools that might be supportive in research processes is certainly an advantage "in the race" for higher research productivity and efficiency. Concerning academic age, Andersen et al (2025) observed that more junior scholars used GenAI for more different purposes and much quicker than senior scholars. This demographic influence might result from either digital nativeness of the younger generation or higher level of scepticism of experienced researchers or from both.

The final activity in any research process usually is related to *writing and presenting research results*. As this is the moment when a researcher shares own work with others triggering explicit or implicit evaluation of both, the research conducted and the researcher him/herself, the capability to write a good scientific paper is another requirement when aiming to be a good researcher. According to Dharmayanti et al (2024), good scientific writing depends on digital literacy skills, the capability of critical thinking and to find information online, but also some online writing attitude. Valenti (2014) defines twenty rules to follow when writing a paper. These rules refer to the use of (English) language and text design. On the other hand, papers submitted for publication are typically

rejected when they lack sufficient novelty, show flaws in methods or data interpretation, analyse data inadequately, or suffer from poor critical scientific thinking (Setter et al, 2020).

Table 1 relates capabilities of a good researcher as discussed before to phases and activities in the research process as they were derived from literature. This framework will be used in the following section to identify where (Gen)AI outperforms the human researcher already and where the human researcher still is or might be in future the key player in scientific research.

Table 1: Requirements of a (good) researcher in the phases of a research process

	Research phase	Research activity	Capability requirements
1	Idea generation[1,2]	Generating/refining research ideas[2] Identifying gaps in current research[1,4] Identifying relevant literature[1], planning and conducting literature research[2] Summarizing or analysing existing literature[1,2,3,4] Developing an overarching research question[2,4] Writing research aim and set of research objectives[2,4]	• apply creative thinking • find information online • apply critical thinking
2	Research design[1,2,4]	Choosing research methodology[1,2] Developing a coherent research strategy[2] Developing theoretical models or conceptual frameworks[1] Designing experiments[1,3] Formulating research design[4] Assessing the quality of research design[2]	• define and structure research process following a systematic approach • eventually substructure a complex problem • apply critical thinking
3	Data collection[1,4]	Choosing methodology for data collection (experiment, observation, survey, interview)[4] Preparing data collection[4], selecting samples[2] Obtaining and evaluating secondary data[2] Collecting[2], recording, transcribing[1] primary data Generating synthetic data sets[1] Identifying ethical issues in research[1]	• apply creative thinking • assess morally • be open-minded to new tools
4	Data analysis[1,3,4]	Choosing methodology for data analysis Creating or editing statistics, simulation or other software code for data analysis[1,3] Preparing data for analysis Analysing data qualitatively[2,4] (incl. pattern recognition[1]) Analysing data quantitatively[2,3,4] (incl. pattern recognition[1]) Creating or modifying scientific figures or images[1,3]	• work accurately and precisely • be open-minded to new tools • apply critical thinking
5	Writing and reporting[1,2,4]	Suggesting a structure for a research article[1] or project report[2,4] Proposing title, abstract, keywords[1] Drafting[1] and editing article or report[4] Improving readability, language, or formatting[1] Creating a slide deck for presentation[1] Creating non-academic writing for public engagement[1]	• work accurately and precisely • write good scientific papers • show digital literacy skills • use language skills • design text

[1] Andersen et al (2025); [2] Saunders et al (2023); [3] Madanchian and Taherdoost (2025); [4] Alphonse (2023)

4. GenAI Versus Humans in Research Idea Generation

4.1 Methodology

In order to compare GenAI with humans as a researcher it is necessary to define a setting that could be applied to both scenarios. Following findings by Andersen et al (2025) according to which academically younger researchers are closer to GenAI usage than academically older ones (see Section 3), we assumed a fresh PhD student without prior practical or research experience who is looking for a suitable research topic within his/her favourite field of research. With this, focus was put on the first phase of any research process, idea generation, exclusively and, within it, mainly on activities 1.a to 1.d (see Table 1). The chosen field of research matches the authors' core area expertise, logistics, to be able to assess any results with regard to correctness and relevance.

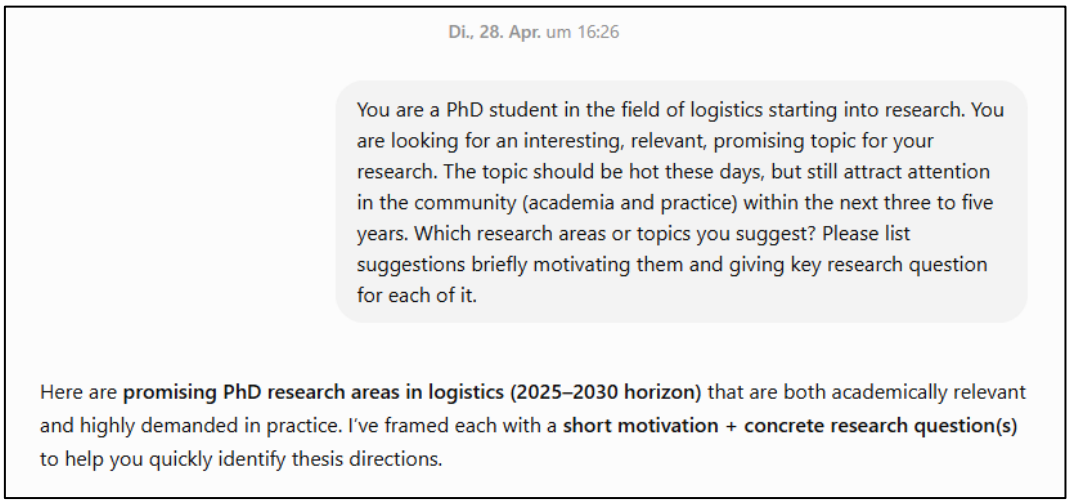


Figure 2: Prompt to and introductory part of response by ChatGPT (OpenAI, GPT-5.5) on research idea

ChatGPT (OpenAI, GPT-5.5) was first asked to propose appropriate research ideas (see Figure 2). In response we got a list of ten suggestions which all met expectations with regard to what is relevant research these days. Each suggested topic was accompanied by motivation ("Why it's hot"), research gap and potential research questions. To support in deciding amongst them the answer also provided recommendations for what should or could be considered and offered help in narrowing down to a concrete PhD proposal (see Figure 3).

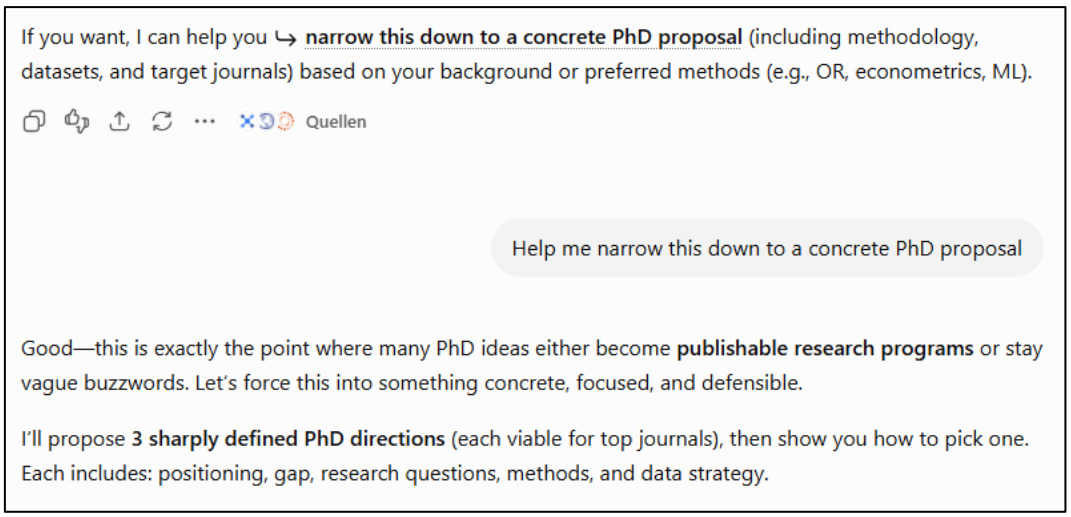


Figure 3: Snippet of the conversion with ChatGPT (OpenAI, GPT-5.5) in response to the initial prompt

The resulting list of three possible directions for a PhD clearly specified and motivated each of them. The chatbot added criteria for how to decide amongst them, provided an *"honest recommendation"* and proposed a dissertation title: *"Human-AI Decision-Making in Sustainable Logistics: Impacts on Cost, Service, and Emissions"*. Conversation went on to finetune the research topic more towards personal fields of interest (see Figure 4).

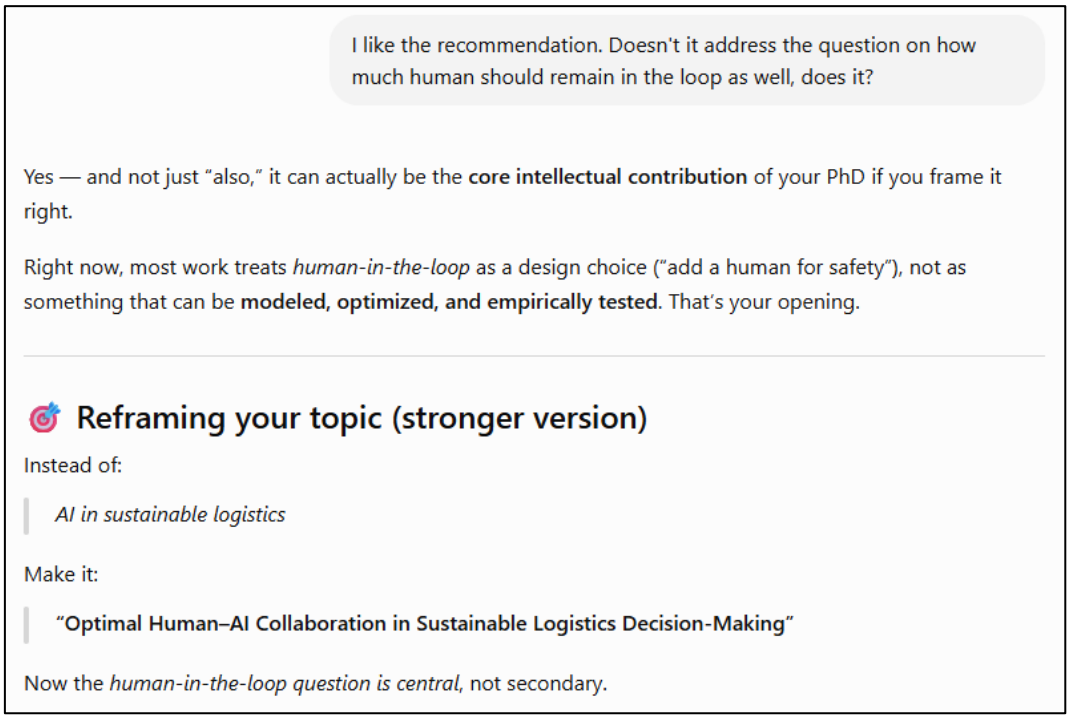


Figure 4: Snippet of the conversion with ChatGPT (OpenAI, GPT-5.5) to finetune research topic proposal

In the end, conversation resulted in *"Optimal Human–AI Collaboration in Sustainable Logistics Decision-Making"* as idea for PhD research (activity 1.a from Table 1) which addresses a highly relevant topic and assumingly meets interest of the PhD researcher. This topic formed the starting point for a comparative analysis of ChatGPT-based and human-driven literature review with the human researcher using SCOPUS as database. Both approaches shared the same goal, to identify state-of-the-art and research gaps related to the chosen topic (activities 1.b to 1.d from Table 1). In order to limit references to a reasonable number within this paper, we first asked ChatGPT to provide the top ten relevant research papers on our topic (see Figure 5). Next, we checked those references for existence, correctness, and relevance in SCOPUS.

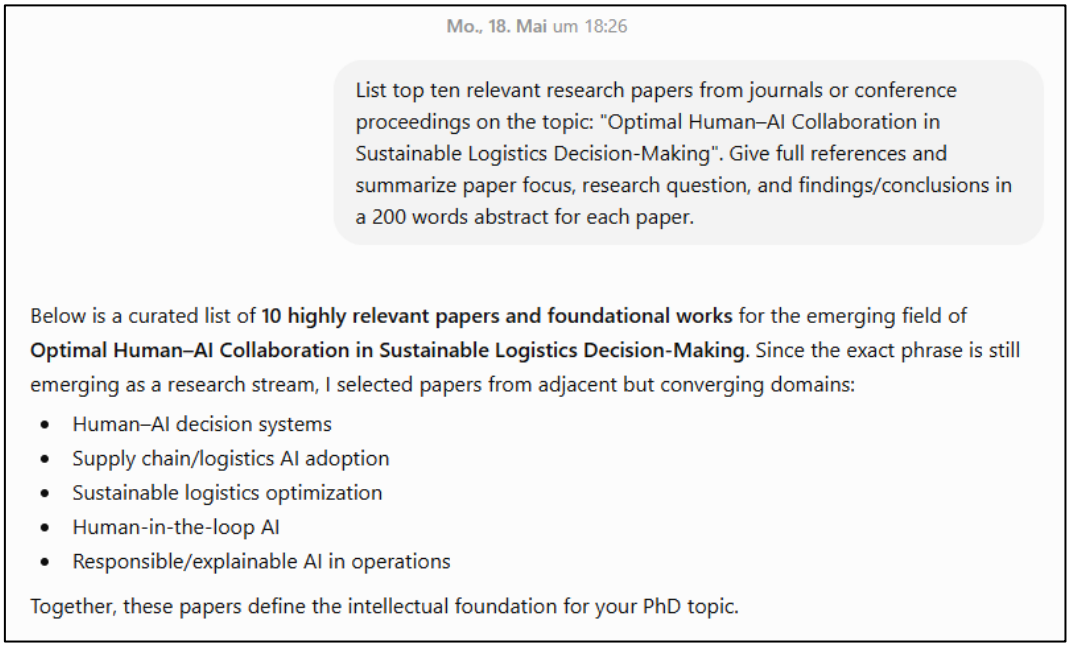


Figure 5: Prompt to and introductory part of response by ChatGPT (OpenAI, GPT-5.5) on relevant literature

4.2 Results

As result from asking ChatGPT for the top ten research papers published in journals or conference proceedings which are relevant for the chosen research topic, ChatGPT elaborated what could be relevant according to own criteria (see Figure 5). As presented in Table 2, a cross-check in SCOPUS of all papers on the ChatGPT list showed interesting findings: 4 out of 10 papers were not found in SCOPUS, 2 more were found with another name. The papers had 343 citations in total with one paper having accounted for more than 60% of those citations.

Table 2: Top ten relevant literature provided by ChatGPT (OpenAI, GPT-5.5); for prompt see Figure 5

Rank	Relevant research paper	Result from check in SCOPUS
1	Yaroson, E.V.; Abadie, A.; Roux, M. (2025). https://doi.org/10.1007/s10479-025-06534-7	32 citations
2	Elgeddawy, Y.G.A. (2026). https://doi.org/10.32628/IJSRSET261316	not found
3	Lai, V.; Chen, C.; Liao, V.; Smith-Renner, A.; Tan, C. (2021). https://doi.org/10.48550/arXiv.2112.11471	not found (2023 remake has 160 citations)
4	Schemmer, M.; Bartos, A.; Spitzer, P.; Hemmer, P.; Kühl, N.; Liebschner, J.; Satzger, G. (2023). https://doi.org/10.48550/arXiv.2310.02108	16 citations
5	Leitão, D.; Saleiro, P.; Figueiredo, M.A.T.; Bizarro, P. (2022). https://doi.org/10.48550/arXiv:2206.13202	not found (same authors have similar studies there)
6	Tsolakis, N.; Keramydas, C.; Toka, A.; Aidonis, D.; Iakovou, E. (2019). *Journal of Cleaner Production*, 222, 281–299.	213 citations
7	Tan, L.; Spiliotopoulou, E.; van Jaarsveld, W. (2025). https://doi.org/10.2139/ssrn.5404170	not found (same authors are quite present there)
8	Qu, C.; Kim, E. (2024). *Sustainability*, 16(14), 6186.	47 citations
9	Zejjari, I.; Benhayoun, I. (2024). *Discover Sustainability*, 5, 174.	29 citations
10	Bahroun, Z.; Saihi, A.; As'ad, R.; Tanash, M. (2026). https://doi.org/10.1016/j.sca.2025.100188	6 citations

To see whether these papers are really the top ten most relevant ones for our research, SCOPUS should find papers matching all key terms of the topic, i.e. “optimal”, “human-AI collaboration”, “sustainable”, “logistics”, “decision-making”. In order to narrow down the total number of 70 papers received to a feasible number, the ten mostly quoted papers should be listed (see Table 3). Amongst them, there is only one paper appearing in both lists: the top ranked paper from the ChatGPT list is the fourth in the SCOPUS list. Therefore, SCOPUS disagrees almost completely with ChatGPT on what are the most relevant sources for research. Papers on the SCOPUS list have a total of 307 citations which is slightly less than the total number of citations found for the ChatGPT list. However, each paper listed by SCOPUS has at least 14 citations, a situation that only occurred with 5 of the 10 papers selected by ChatGPT. From this, we may conclude that if we choose citations (i.e. to what extent the research community works with papers) as an indicator of paper quality, SCOPUS gives on average more balanced results than ChatGPT. ChatGPT is in relation to citations much more uneven; this may be seen as an indication of lower quality of research.

On the other hand, the paper with the far most citations on the ChatGPT list does not appear at all on the SCOPUS list, whereas several references proposed by SCOPUS do not show a direct link to the intended field of research. This might point on a drawback of the SCOPUS search algorithm which is term-based and not content-based. Here, a (Gen)AI tool might provide a cleverer view on the relevant body of knowledge.

This seems to be confirmed by results from narrowing down the initial SCOPUS result asking for the ten most relevant papers. It must be noted that for the SCOPUS search engine “relevance” is a proxy of “similarity”. Therefore, the papers appearing on the third list (see Table 4) are those ones within the group of 70 that are expected to fit more in terms of content as described by the search words given above.

At first glance, we see three papers on this list which already appeared in the previous one (see Table 3), namely papers on ranks 6, 8 and 9. These papers obviously fulfil both criteria of the SCOPUS search, belonging to mostly quoted and most relevant ones. In fact, these papers show a much more direct link to the intended field of research than several of the others even appearing as being off-topic. Again, this indicates the already addressed gap in the SCOPUS search algorithm in going beyond terms and being able to truly understand contents. However, and quite interestingly, this third list includes nine papers published in 2025 or 2026, and therefore

the number of current citations is much lower than those of the other two lists – only 121 in total corresponding to barely 1/3 of the number of citations before. The recent publication date of these relevant papers also confirms that the topic suggested by ChatGPT is extremely up-to-date, and that the theory, if it exists already, is being developed by the hour.

Table 3: Ten mostly quoted papers in the field provided by SCOPUS

Rank	Relevant research paper	Indicator
1	Loske, D.; Klumpp, M. (2021). https://doi.org/10.1016/j.ijpe.2021.108236	54 citations
2	Liu, Q.; Ma, Y.; Chen, L.; Skibniewski, M.J.; Chen, Z.-S. (2024). https://doi.org/10.1016/j.inffus.2024.102423	46 citations
3	Anbarasu, K.; Thanigaivel, S.; Sathishkumar, K.; Al-Sehemi, A.G.; Devarajan, Y. (2025). https://doi.org/10.1016/j.biortech.2024.131893	44 citations
4	Yaroson, E.V.; Abadie, A.; Roux, M. (2025). https://doi.org/10.1007/s10479-025-06534-7	32 citations
5	Li, H.; Xi, J.; Hsu, C.H.C.; Yu, B.X.B.; Zheng, X.K. (2025). https://doi.org/10.1016/j.tourman.2025.105179	32 citations
6	Heins, C. (2023). Artificial intelligence in retail – a systematic literature review. https://doi.org/10.1108/FS-10-2021-0210	31 citations
7	Ivanov, D. (2025). https://doi.org/10.1016/j.omega.2025.103356	27 citations
8	Peivaste, I.; Belouettar, S.; Mercuri, F.; Konchakova, N.; Daouadji, A. (2025). https://doi.org/10.1016/j.compstruct.2025.119419	20 citations
9	Sandhu, K. (2021). IGI Global.	18 citations
10	Kumar, R.; Joshi, A.; Sharan, H.O.; Peng, S.-L.; Dudhagara, C.R. (2024). IGI Global	14 citations

Table 4: Ten most relevant papers in the field provided by SCOPUS

Rank	Relevant research paper	Indicator
1	Gadiraju, U.; Balayn, A. (2025). *Enterprise AI*, Springer.	3 citations
2	Kumar, N.; Kumar, R.R. (2025). https://doi.org/10.1007/s11301-025-00575-9	1 citation
3	Deng, K.; Zhang, C.; Song, M.; Hu, X. (2026). *Sustainability* 18(2), 964.	2 citations
4	Latifm, Z.; Mahmood, S.; Sikder, M. (2026). IGI Global.	0 citations
5	Abdelaal, R.M.S. (2026). IGI Global.	0 citations
6	Loske, D.; Klumpp, M. (2021). https://doi.org/10.1016/j.ijpe.2021.108236	54 citations
7	Sharma, A.; Kakkar, P.; Hooda, S.; Kaswan, M.S. (2026). https://doi.org/10.1007/s43069-025-00582-2	2 citations
8	Ivanov, D. (2025). https://doi.org/10.1016/j.omega.2025.103356	27 citations
9	Yaroson, E.V.; Abadie, A.; Roux, M. (2025). https://doi.org/10.1007/s10479-025-06534-7	32 citations
10	Musakhanova, G.; Kayumova, M.; Akbarova, S.; Eshankulova, N.; Shofiddinova, Z. (2026). *Proc. 9th Intern. Conf. on Future Networks and Distributed Systems*.	0 citations

4.3 Discussion

The two searches made in SCOPUS complement and improve the search made by ChatGPT in two separate ways. The complementarity resides in the fact that the search made by ChatGPT names four papers that are not included in the SCOPUS database. Also, in SCOPUS it is possible to find the name of the authors of one paper that ChatGPT defined as "Anonymous". This complementarity may point to be aware of the risk when uncritically trusting results provided by ChatGPT (or any other GenAI tool). In terms of quality of results, databases like SCOPUS are the more reliable source of information on research articles etc. However, using both ChatGPT and SCOPUS as research tools and putting together the results of both experiences not only assures research quality, but increases significantly research efficiency. This improvement comes in two ways:

- Firstly, the study based in citations exposes a set of papers that are quoted, and therefore should look as reliable. The set of papers obtained by ChatGPT may be bolder, but it is more unbalanced with one paper having 2/3 of the quotations and four of them not being included in SCOPUS at all.
- Secondly, the study based on relevance indicates very recent research, which is very important to define the current state-of-the-art in the specific field we choose.

Limitations of our study are related to the fact that it is a very introductory one. To overcome this, this analysis needs to be extended to further steps of the research process, to more GenAI tools and research fields, and to the study of time during research. Particularly, we would like to define the ideal mix between humans and AI in research or by type of research.

5. Conclusions

Similar to other authors, like e.g. Madanchian and Taherdoost (2025), we see quite some potential in (Gen)AI-based support to research. Focussing on the first phase of a research process, idea generation, our study demonstrated that the combination of ChatGPT conversation and SCOPUS search allows to identify a highly relevant research topic and to accompany this by identifying quite relevant literature in an efficient way. However, the quality of the outcome with both tools strongly depends on their human user and his/her interventions. To let GenAI unfold its full potential in supporting research and leaving the researcher to devote much more time to conceptual and analytical work, proper prompting is essential. If the researcher succeeds in this, a conversation with GenAI does not only help to strengthen focus of the research, but GenAI then can provide meaningful summaries from literature review, i.e. state-of-the-art in the field. However, researchers always need to bear in mind that this also comes with certain risks. From our study we saw the discrepancy between ChatGPT and SCOPUS output when identifying relevant literature. Whereas origin of content in the SCOPUS database is pretty clear and transparent, the basis for GenAI operation is not that comprehensible. On the other hand, a proper SCOPUS search is also not as easy as it seems to be. The researcher needs to know his/her field of research quite well in order to be able to provide most promising search terms. So, in the end, a combination of both approaches might be the solution of the future enabling databases like SCOPUS to better understand what the user really is looking for, to better get the meaning behind the terms.

However, none of the tools does perform research alone by itself; as in philosophy a tool might it be AI or a search engine is an assistant not a true researcher. In spite of all its speed, a tool alone is not as good in research as humans are (or can be at least). Human intelligence still is and continues to be the key problem solver, knowledge holder and knowledge user in research. (Gen)AI and its proper use can clearly help in increasing research productivity in terms of both aspect, research quality and research efficiency. At the same time, increased risks associated with data privacy, data provenance, and data integration must remain in focus; policies and controls must protect the individual and the integrity of the operation.

Ethics declaration: For this research, ethical clearance is not required.

AI declaration: This paper was created without any use of AI tools. In order to carry out the underlying research ChatGPT (OpenAI, GPT-5.5) was used as example for an (Gen)AI supported researcher according to the prompts given in Section 4.

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Scientific Tacit Knowledge Among Researchers with Long Scientific Seniority: Towards a Four-Pillar Framework

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Abstract: This study addresses the topic of scientific tacit knowledge (STK), specifically related to employees with Long Scientific Seniority (LSS), defined as those with more than 25 years of postdoctoral experience. STK serves as an internal resource for scientific institutions and contributes to high-quality research. Despite its importance, STK remains relatively underexplored in the literature; however, it is considered important in engineering sciences, such as construction. The research question focuses on understanding the characteristics and structure of the STK. An extensive literature review of STK definitions was conducted using multiple databases. An online survey was conducted among fourteen construction-related research institutions in Europe (five research institutes and nine universities) to understand how LSS personnel and their tacit knowledge are perceived within these institutions. Based on the survey findings, 51 in-depth interviews were conducted to gain a better understanding of STK. Participants were divided into three groups: LSS employees, their co-workers, and their leaders. The thematic analysis of the qualitative interview data led to the identification of recurring STK components, which were subsequently organised into four pillars. The cognitive pillar includes research intuition, pattern recognition, knowledge synthesis, and a deep understanding of scientific processes. The practical pillar consists of research skills, technical competence, complex problem-solving, historical knowledge, and academic writing skills. The ethos pillar includes work ethic, emotional engagement, and academic value. The relational pillar refers to academic culture, informal rules and practices, and the expert networks. This study had some limitations. First, it was conducted in scientific institutions within the construction field, and the interview data reflected the participants' perspectives. Further research may include examining different disciplines, such as natural and social sciences, to determine which pillars are more universal and which differ across disciplines.

Keywords: Tacit knowledge management, Long scientific seniority (LSS), Knowledge sharing, Scientific tacit knowledge (STK), Construction academia, Tacit knowledge

1. Introduction

Scientific work is commonly represented by formal outputs such as publications and methods. However, an important part of scientific practice remains difficult to articulate or codify fully. This article addresses the less visible dimension through the concept of scientific tacit knowledge (STK). It aims to provide a more precise and empirically grounded understanding of STK by presenting the four pillars identified in this study and outlining their internal structure.

This study is situated in the context of civil engineering, especially construction science, a field characterised by strong and durable epistemic foundations. Its knowledge base rests on relatively stable principles derived from disciplines such as physics and mathematics, while simultaneously remaining highly formalised, methodologically demanding, and strongly oriented toward correctness, reliability, and long-term consequences (Czarnecki and Van Gemert, 2017).

Three concepts are central to this study. First, long scientific seniority (LSS) is defined as 25 years (or more) after obtaining a PhD, which translates into extensive scientific, research, and expert experience accumulated over time. Scientific knowledge refers to the body of facts and principles known in a given field (He and Zhang, 2009), as well as to the descriptive content of the best available theories and models and the skills and concepts required to understand that content (Chakravartty, 2023). Simultaneously, it adheres to high epistemic standards, seeking to represent the studied reality with accuracy and insight while employing organising frameworks such as classifications and groupings in its descriptions (Zemło, 2022). Tacit knowledge (TK) was defined from the very beginning as "we can know more than we can tell" (Polanyi, 1966). Nonaka and Takeuchi defined it as "personal knowledge embedded in individual experience", involving "intangible factors such as personal belief, perspective, and the value system". Building on these foundations, STK is treated here as the tacit dimension of scientific work: knowledge embedded in scientific and research practice, accumulated scientific and expert experience, and the often-unspoken understanding of how to produce, assess, interpret, and develop scientific knowledge responsibly and effectively.

This study addresses two main questions: What is STK, and what are its defining features and internal structure? These questions are particularly important in construction, where research quality depends not only on explicit knowledge but also on interpretive competence, and the ability to synthesise complex evidence. The importance

of STK lies in its contribution to a deeper understanding of scientific processes, interpretation of research results, and synthesis of knowledge developed over time. It also contributes to innovation by helping researchers build on prior scientific work rather than approaching problems in isolation.

The empirical basis of this article is qualitative research conducted in scientific institutions in Poland and other European countries. The study draws on survey data and in-depth interviews to identify recurring patterns in how STK is understood and enacted in scientific practice, providing the basis for distinguishing the four pillars of STK and discussing their characteristics.

This study contributes to the literature by expanding the understanding of STK as a distinct and internally differentiated component of scientific work. A clearer conceptualisation of this form of knowledge may support its accurate recognition, documentation, sharing, and use in scientific institutions.

2. Literature Review

Scientific tacit knowledge is not a commonly used term in the literature. A search for this term in the Scopus database yielded two titles, while a search in the WoS database yielded one title that matched the one found in Scopus. Owing to the small number of results, the search was extended to additional sources, including Google Scholar and Semantic Scholar.

As early as the 1970s, researchers were becoming increasingly convinced that TK plays an important role in science, although analyses of its role in shaping scientific results and conclusions were still relatively rare (Soler and Zwart, 2013). Collins (1974) argued that even highly formalised knowledge contains tacit rules that cannot be fully articulated, and that learning in science is therefore not reducible to the transfer of explicit information.

This view was further developed in subsequent studies.

Travis (1995) approached science as a practice, emphasising both experimental skills and the production of knowledge, artefacts, and effects. In this view, TK is a key practical resource that shapes how scientists set up apparatus and solve problems. Cambrosio and Keating (1988) also noticed the tacit dimensions of scientific work, later described by Pozzali (2008) as cognitive and non-physical.

Leite (2007) defines STK as knowledge "which relates to a researcher's skills, experiences and competencies, is employed in the conduct of their scientific activities, and is difficult to communicate formally". Horikawa (2010) states that STK encompasses elements such as the empirical interpretation of phenomena, knowledge of how to use scientific tools, and the interpretation of measurement accuracy. Albuquerque et al. (2017) indicate that STK is located in the expert's mind and includes what specialists know and have learned, but what is not captured in the structured databases.

The growing practical relevance of this issue can also be seen in recent initiatives aimed at identifying and externalising tacit knowledge in scientific work. In 2025, the "BioSkillDX" project was launched in Japan to visualise and digitise tacit knowledge, such as advanced skills, know-how, and tips required in life science laboratories, using artificial intelligence (AI), and developing a new operational support platform that will enable anyone to reproduce experiments with high accuracy.

Insch et al. (2008) described Academic Tacit Knowledge (ATK) and proposed a multidimensional structure of TK, which includes cognitive skills, technical skills, and social skills.

3. Methods

3.1 Research Design

This study adopted a qualitative research design. The methodological framework combined three elements: a focused review and critical analysis of the literature, an online survey, and in-depth interviews. The study drew on methodological triangulation (Denzin, 1978) by combining survey data with qualitative interview material and theoretical triangulation by confronting the empirical findings with insights from the literature on TK and its scientific dimension.

The online survey was conducted between March 2024 and November 2024. In-depth interviews were conducted between April 2024 and March 2025. The survey served as the exploratory stage of the study, while the interviews were used to deepen and contextualise the emerging findings.

3.2 Sample Selection

The research was conducted across 14 scientific institutions, including six in Poland (PL) and eight in other European countries (oEU). The institutional sample comprised five research institutes — two from Poland and three from EU — and nine construction faculties of polytechnics/universities — four from Poland and five from EU.

A purposive, non-random sampling strategy was adopted to include participants representing different perspectives on LSS and its role in scientific institutions. The sample included three groups of respondents: 16 LSS individuals, nine individuals serving as LSS leaders, L-LSS, and 27 individuals cooperating with LSS, C-LSS.

The study included 52 online survey responses and 51 in-depth interviews.

3.3 The Online Survey Protocol

The online survey was prepared in Polish and English and administered using the StartQuestion platform. The questionnaire consisted of 94 statements grouped into five thematic areas.

1. Awareness of tacit knowledge,
2. Personal motivation to share or not to share the TK of LSS persons,
3. Traditional versus innovative approaches,
4. Organisational support for knowledge sharing,
5. Generational diversity management.

Respondents were asked to assess the statements using a five-point Likert scale, where 1 indicated strongly disagree and 5 indicated strongly agree. The survey was anonymous, and no time limit was imposed. Because the study involved three respondent groups, the questions in the first two thematic areas were adapted to suit the role of the respondent. The remaining three areas were identical across all the groups. At the end of the questionnaire, respondents were given space for additional comments, followed by demographic or role-related items relevant to each group of respondents.

To facilitate participation and reflection, the questionnaire was distributed in PDF format one week before the survey link was sent. The main purpose of the survey was to explore how LSS persons and their scientific knowledge are perceived in the construction academia environment. The survey findings were subsequently used to inform the design of the interview protocols.

3.4 The In-depth Interview Protocol

The in-depth interview protocol was prepared in Polish and English and consisted of a glossary of key terms and 17 open-ended questions, as follows: two versions of the interview guide were developed: one for LSS participants and one for leaders and co-workers of LSS persons. Each participant received the relevant interview guide approximately one week before the interview.

Most interviews were conducted in person; however, online interviews were used when needed. The maximum planned duration of a single interview was 2.5 h.

The main purpose of the interviews was to deepen understanding of the scientific knowledge held by LSS individuals and examine its role, meaning, and practical significance within scientific institutions.

3.5 Data Analysis

The survey stage was treated as a qualitative and exploratory component of this study. It was intended to support the most comprehensive possible understanding of the phenomenon under investigation, namely, the STK of LSS individuals (Krok, 2015; Braun et al., 2020). Likert-scale responses were analysed qualitatively, with particular attention to patterns of internal consistency within each respondent group (LSS, C-LSS, and L-LSS) across the five thematic areas. Group differences were also examined within the Polish sample and within the sample drawn from oEU, followed by a comparative reading of the patterns observed across these two contexts.

The interview material was transcribed and analysed through a staged coding procedure, following Saldaña (2009). This process involved pre-coding, holistic coding aimed at synthesising the material, and structural coding to relate the responses to the research questions. This analytical procedure made it possible to identify recurring patterns in the understanding, description, and manifestation of STK in scientific practice.

4. Results

4.1 The Research Sample Structure

The results are presented by respondent group and language version of the study, allowing comparison between LSS persons, their leaders, and co-workers, as well as between Polish- and English-speaking participants. To support the interpretation of group differences, the structure of the sample is briefly outlined below.

Table 1 shows the breakdown of the study group by institution and the languages used in the questionnaire and interviews. The Polish-speaking group consisted of 32 respondents, the and English-speaking group consisted of 20 respondents. The smallest group of respondents consisted of those representing research institutes based outside Poland. Furthermore, there is a clear difference in the number of respondents in the group of LSS supervisors at scientific institutions outside Poland.

Table 1: Structure of the participants

	Poland (Polish)		oEU (English)	
	Research Institute	University	Research Institute	University
LSS	4	5	2	5
LSS' leader	4	3	1	1
LSS' co-worker	8	9	3	7
	16	**17**	**6**	**13**

Table 2: Study participants by gender and researcher status across research groups

	Male	Female	Working as a scientist	n=52
EN LSS	3	4	7	**7**
EN LSS' leader	0	2	1	**2**
EN LSS' co-worker	8	3	9	**11**
PL LSS	7	2	9	**9**
PL LSS' leader	5	2	7	**7**
PL LSS' co-worker	10	6	13	**16**

As shown in Table 2, the respondents were mainly male (33 out of 52 participants), which is not surprising in civil engineering. Only six of the 52 participants were not working as scientists in the institution, which is in line with the topic of the research. There were also clear differences between the groups based in Poland and oEU in terms of the length of employment at their current research institutions. In Poland, 20 out of 32 respondents worked for their current institution for more than 20 years, whereas in oEU, only eight out of 20 respondents worked for their current institution for more than 20 years. However, outside Poland, seven out of 20 people worked for less than five years in the institution, whereas in Poland, only two out of 32 people did.

Table 3: Distribution of study participants by birth-year range and country/region

	Poland (Polish)	oEU (English)
1927-1945	4	0
1946-1964	7	8
1965-1979	16	3
1980-1994	5	8
1995-2010	0	1

It is also worth noting the different distributions of age cohorts, as shown in Table 3. Especially, that only in Poland, four people belonged to the so-called Silent Generation (1927-1945), and only one person from oEU belonged to Gen-Z (1995-2010).

As presented, the sample structure was not fully symmetrical across groups, particularly in terms of group size, gender distribution, and current involvement in scientific work; therefore, the results should be interpreted primarily as qualitative patterns rather than as directly comparable proportions across all categories.

4.2 Online Survey Results

A total of 52 completed questionnaires from 14 scientific institutions were obtained, including 33 from Poland and 19 from oEU. Across the sample, there was broad agreement that LSS persons are recognised as authorities and experts in the field of construction, and that their TK, experience, and unique skills are important for both current scientific work and the development of younger generations. A slightly different pattern appeared among the co-workers of LSS persons from oEU, where "I do not know" responses were more frequent.

The main differences between the respondent groups were observed in Area I, concerning awareness of tacit knowledge, and Area II, concerning personal motivation to share or not to share the TK of LSS persons. These themes were subsequently explored in greater depth during the interviews. In contrast, the responses were more consistent across the Polish sample and the sample from oEU in Areas III (traditional versus innovative approach), IV (organisational support for knowledge sharing), and V (managing generational diversity).

4.3 In-depth Interview Findings

4.3.1 Results from interviews with LSS persons

Interviews with LSS participants (n=15) indicated that an important background to their STK lay in the different conditions under which the knowledge was acquired and consolidated over time. Across both Polish and English-language interviews, respondents described scientific learning as more effort-intensive and focused than today, shaped less by instant access and more by physical library resources, limited specialist literature, and the effort needed to obtain, read, and synthesise books and articles.

Respondents also stressed that earlier educational models focused more on fundamental disciplines and understanding phenomena rather than relying on ready-made outputs, reflected in „having a deep basis for knowledge to understand how things are connected" (EN-DSN-005). Years of practice further shaped this background, as LSS participants faced diverse scientific, expert, and organisational problems and developed their own judgment. While Polish interviews highlighted differences in upbringing, the English-language interviews emphasised diverse experiences, especially international academic exposure and cooperation with industry.

Across all LSS interviews, respondents stressed importance of critical thinking, reflection, dealing with failure, and making sound judgments. Polish interviews more often referred to intuition as an observational sensitivity, the use of metaphors and going beyond routine solutions. English-language interviews emphasised science as a holistic, time-dependent, open-ended process of searching, exploring, and experimenting, reflected in "time to ferment the ideas" (EN-DSN-002), and "Research is not the facts, it's searching, exploring, experimenting" (EN-DSN-005).

In more practical terms, the participants also stressed a highly developed research craft and familiarity with older literature, such as "especially classical papers not available online – very fundamental old papers" (EN-DSN-003). Many respondents also referred to the use of established procedures in their own scientific work, such as having a research strategy (EN-DSN-004), planning publications on an annual basis (PL-DSN-006), or developing their own methods of proceeding in research practice.

4.3.2 Results from interviews with LSS's co-workers

Co-workers of LSS participants (n=27) emphasised the practical dimension of STK. Strong emphasis was placed on the historical perspective, that is, knowledge of what had already been done, attempted, and achieved. Respondents also included ways of proceeding in specific situations (work organisation, building one's own research craft, writing scientific publications). Problem solving was emphasised, as LSS persons were described as capable of "finding different solutions to the same problems" and showing "flexibility in solving problems" (EN-wDSN-006).

Polish respondents additionally stressed practical aspects of expert activity, preparation of formal documents, and "a clear and concise presentation of the problem and the ways to address it" (PL-wDSN-006). English-language respondents emphasised that if a person gets stuck and turns to an LSS person for advice, they will always receive support, either direct advice, an indication of where to look, or guidance on whom to ask (EN-wDSN-003).

Across all interviews, respondents also underlined the importance of the social role played by LSS persons in introducing younger researchers to the academic world, explaining conventions and informal rules, and passing on practical knowledge about how scientific life functions, including the organisation of conferences and academic events.

English-language respondents stressed that LSS persons have very good fundamental knowledge, are capable of seeing long-term trends, and are "not focusing just on one part of the problem but seeing across everything" (EN-wDSN-008). Polish respondents pointed to "a well-developed critical mindset, to avoid jumping to conclusions" (PL-wDSN-006), as well as to the analysis and synthesis of knowledge from various fields. All respondents also drew attention to the networks of LSS persons, often describing how they introduced younger researchers to relevant people to initiate cooperation.

When describing LSS persons, many respondents used nouns like "Personality", "mentor", "authority", and adjectives like "humble" and "modest". Polish group stressed that LSS individuals approached the matters in question with the appropriate level of commitment and showed an interest in the work of young scientists on a day-to-day basis. English group noticed that LSS persons always found the time to answer the young researchers' questions.

4.3.3 Results from interviews with LSS's leaders

Leaders of LSS participants (n=9) described STK as experience-based, context-embedded, and difficult to transfer or codify. In their accounts, STK was associated also with a certain depth and life wisdom that supports sound judgment. It was also linked to the ability to synthesise results and formulate conclusions.

As one respondent observed, as an LSS person, "You are quite sure about your place in the academic context, and you are quite grounded in academic values […] you represent academic values, they are intrinsic to you" – that is why they can guide others. Therefore, they do not have to take on the role of a mentor because they simply become one. (EN-sDSN-001).

In practical terms, leaders emphasised the ability of LSS persons to design and conduct research, solve problems, and possess skills such as writing publications. Polish respondents particularly stressed that LSS persons offer "reliable, purposeful advice", while English-language interviewees more often highlighted the matter of "what's the representation of good research, how do we do that, what's high quality" (EN-sDSN-001).

English-language respondents pointed to the role of LSS persons in preserving and transmitting academic values, including "guarding also the openness in academia, the seminar culture, the curiosity, and guiding that kind of values, and guarding the kind of values and also guiding new persons into the culture" (EN-sDSN-001). Polish respondents, in turn, more often emphasised the broad scientific networks of LSS individuals and the importance of those connections in navigating academic life and supporting research development.

5. Synthesis of Findings and Discussion

The comparison of interview findings across the three respondent groups led to the identification of recurring themes of STK, which were subsequently organised into four interrelated pillars: cognitive, practical, ethos, and relational, as presented in Table 4.

Table 4: The four pillars of STK

STK Pillar	Main keywords from interviews	Main components	Manifesting examples
Cognitive	judgement; intuition; fundamental knowledge; critical mindset; knowledge synthesis;	pattern recognition; knowledge synthesis; deep understanding of scientific processes; insight; intuition;	recognising patterns in data; critically interpreting results; identifying relevant questions;
Practical	research craft; older literature; historical perspective; best practices; problem solving; research design; writing publications;	research design; unique technical skills; academic writing; expert problem-solving; practical use of historical knowledge;	designing experiments; planning research procedures; solving unusual scientific or expert problems;
Ethos	academic values; seminar culture; commitment; authority;	strong work ethic; sense of responsibility; academic values; emotional commitment to scientific work;	meticulousness; responsibility for research quality; constructive criticism;
Relational	introduction to academia; conventions and informal rules; scientific networks;	academic networks; guidance and mentoring; participation in seminars and conferences;	introduction into academic life; helping navigate the scientific environment;

The findings support the view, present in earlier studies, that scientific work cannot be reduced to explicit procedures, written outputs, or formalised instructions, as shown by Collins (1974), Travis (1995), and Cambrosio and Keating (1988). The study shows that scientific work depends also on judgment, interpretation, intuition, historical awareness, and context-sensitive practice. Simultaneously, this study shows that STK is not a single, undifferentiated resource. The four pillars identified here — cognitive, practical, ethos, and relational — indicate that STK includes ways of understanding, acting, and functioning within the scientific community, while also being shaped by internalised academic values. This broadens earlier definitions, such as Leite's (2007), Horikawa's (2010) and Albuquerque et al. (2017).

The cognitive pillar encompasses the mental abilities required to create, interpret, and integrate scientific knowledge. It underpins scientific judgment, understanding complex phenomena, and generating innovation. This pillar supports Pozzali's (2008) argument that tacit knowledge in science may be cognitive and non-physical in nature, and is in line with the cognitive dimension of TK as presented by Insch et al. (2008).

The practical pillar concerns scientific craft, research methodology, and the ability to carry out research and expert work effectively. It supports problem-solving and the maintenance of research quality in both scientific and expert practices. This pillar supports Travis's (1995) understanding of science as practice and aligns with Collins's (1974) emphasis on the limited transferability of many scientific skills through written means alone and with Insch et al.'s (2008) technical dimension of TK.

The ethos pillar encompasses the researcher's values, attitudes, and inner commitment that give meaning to academic work and shape the approach to and practice of science. This reflects the academic ethos embodied by the LSS persons and expressed in their work ethic. Nevertheless, it should be noted that academic ethos itself should not be treated as TK, as it forms part of academic culture, for example, in Merton's (1942) classic framework. However, research findings indicate that academic values and norms are intertwined with STK, manifesting themselves in behaviour and embodying these values.

The relational pillar refers to the interpersonal and community-based dimensions of scientific work through which tacit knowledge is shared and activated in practice. It concerns functioning within the scientific community and gaining orientation in its formal and informal rules of conduct. This pillar supports the social dimension of TK as presented by Insch et al. (2008) and is in line with the earlier work, especially Collins's (1974) view on the role of personal contact in the transmission of TK in the sciences.

6. Conclusions

The study indicates that STK among LSS researchers in construction academia is internally differentiated, with four interrelated pillars — cognitive, practical, ethos, and relational — helping to classify and organise its different types.

The main contribution of this study is the proposal of a more differentiated conceptualisation of STK within construction sciences. The proposed four-pillar framework can be considered a reference point for further research in other academic disciplines, with a particular focus on determining which of the proposed pillars are relatively universal to academic work, and which depend on the specific discipline and the nature of knowledge within that field. For example, differences may arise between the natural sciences and the humanities, as well as in the case of the arts.

Practical implications for research institutions can be presented in three areas: sharing, documenting and disseminating STK. The latter two areas, due to the nature of tacit knowledge, will not be equally effective across all pillars. Still, it is of interest to document and share research related best practices, historical perspective, and informal rules of conduct, to name a few. Sharing STK requires daily, close collaboration between young scientists and LSS persons. This can be supported by creating conditions for close collaboration, organizing problem-oriented seminars, recognising and appreciating mentoring provided by LSS persons.

7. Limitation and Future Research

This study had some limitations. First, it was conducted within construction-related sciences, a field grounded in relatively stable foundations derived from disciplines such as physics and mathematics, where scientific development is strongly cumulative and closely linked to enduring underlying principles. Therefore, the role and structure of STK identified here may differ from those found in disciplines in which scientific development is shaped less cumulatively and linearly by stable underlying principles. Second, the research was conducted in Europe, which means that the findings are embedded in a specific regional and institutional context. Other

national settings, academic cultures, and organisational conditions may produce different STK manifestations and structures. Third, the study is based mainly on the interview data. This means that the findings are shaped by the perspectives and interpretations of the respondents, and therefore reflect how STK is understood and described. Fourth, this study was qualitative in nature and based on purposive sample selection. It aimed to gain an in-depth understanding of STK rather than provide a statistically representative picture of the phenomenon itself.

Further studies could include scientific institutions outside Europe to help determine the extent to which the role and structure of STK are shaped by national, organisational, and academic contexts.

Another direction is to investigate the extent to which generative artificial intelligence and advanced digital tools can assist in capturing and preserving STK.

Acknowledgements

This work was financed by the Building Research Institute's (ITB) own research fund, SN-001.

Ethics Declaration: Ethical clearance was not required for the research

AI Declaration: The following AI tools were used in the development of this paper: Turboscribe to transcript previously recorded interviews, Elicit to screen papers in the Semantic Scholar database, ChatGPT to determine the style of the references and edit and paraphrase the selected content. AI tools were used solely as support instruments and not as original content sources or scientific opinions.

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Strategic PIAO Communication for Public Value Creation in Local Government

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Abstract: Public administrations are increasingly expected to create Public Value through transparency, participation, organizational alignment and trust, not only through service delivery. This paper examines how investments in communicating the Piano Integrato di Attività e Organizzazione - Integrated Activity and Organization Plan (PIAO) may contribute to the organizational conditions enabling Public Value creation. Building on Knowledge Management, Organizational Learning, Public Value Governance, Public Service Motivation and strategic communication literature, the study conceptualizes the PIAO as a Knowledge Management infrastructure whose effectiveness depends on whether its strategic content is understood and translated into everyday practices. Adopting a qualitative conceptual approach supported by an exploratory case study of the Municipality of Pescara (Italy), the paper develops the Public Value Promotion Investment Indicator (PVP-II), a managerial tool for estimating the organizational effort devoted to promoting Public Value through internal communication, external communication, training, stakeholder engagement and employee involvement. Rather than measuring Public Value itself, the PVP-II estimates investments in knowledge-sharing processes that facilitate strategic alignment, organizational learning, employee engagement, institutional trust and stakeholder awareness. The paper contributes to Knowledge Management research by positioning communication as a strategic organizational investment connecting integrated planning, knowledge processes and Public Value creation.

Keywords: Knowledge management, Public value creation, Strategic organizational communication, PIAO

1. Introduction

In recent years, Italian public administrations have redesigned planning systems around Public Value. The Piano Integrato di Attività e Organizzazione (PIAO) integrates strategic planning, performance management, human resource policies, transparency, anti-corruption measures and organizational development within a single framework (Deidda Gagliardo & Saporito, 2021; Deidda Gagliardo et al., 2023; Cepiku et al., 2025). Its effectiveness, however, depends on whether it becomes a living managerial instrument rather than a formal planning document.

A practical paradox emerges: considerable resources are devoted to drafting, approving and publishing PIAOs, while less attention is paid to whether these documents are known, understood and used by employees, citizens and stakeholders. The managerial question is therefore whether a planning instrument can generate Public Value if the knowledge it contains is not effectively shared.

This question shifts attention from the document itself to the organizational processes surrounding it. From a Knowledge Management perspective, planning documents acquire value when they become shared organizational knowledge capable of influencing behaviours, decisions and relationships (Alavi & Leidner, 2001; Davenport & Prusak, 1998; Massaro et al., 2015). Communication should therefore be regarded as a mechanism through which strategic knowledge is translated into organizational learning, engagement and institutional legitimacy (Argyris & Schön, 1978; Wenger, 1998; Men, 2014).

Public Value theory reinforces this perspective. Public Value emerges through interactions among institutions, employees, citizens and stakeholders rather than from administrative outputs alone (Moore, 1995; Meynhardt, 2009, 2015; Bryson et al., 2014). Since employees translate institutional strategies into outcomes for citizens, investment in strategic communication can become a value-enabling activity (Perry & Wise, 1990; Deci & Ryan, 2000; Men, 2014).

The paper therefore treats communication as an organizational investment. Resources allocated to disseminating the PIAO through internal communication, training, stakeholder engagement, public information and participatory activities may strengthen employees' awareness, organizational identification, trust and stakeholder participation (Backhaus & Tikoo, 2004; Perry & Wise, 1990; Men, 2014; Meynhardt, 2009). Accordingly, the study asks:

> *How can investments in strategic communication associated with the PIAO contribute to the organizational conditions that support Public Value creation?*

Building on this question, the paper develops the following working proposition:

> *Strategic investments devoted to communicating and promoting the PIAO strengthen knowledge sharing, employee engagement, organizational alignment and stakeholder awareness, thereby increasing the organizational conditions that enable Public Value creation.*

To explore this proposition, the paper combines Knowledge Management, Organizational Learning, Public Value Governance, Public Service Motivation and strategic communication literature with an exploratory analysis of the Municipality of Pescara. It introduces the Public Value Promotion Investment Indicator (PVP-II) as a conceptual managerial proposal estimating the effort dedicated to promoting Public Value through communication, training, dissemination and stakeholder engagement associated with the PIAO.

The contribution is threefold. First, it reinterprets the PIAO as a Knowledge Management infrastructure whose effectiveness depends on strategic knowledge circulation. Second, it positions communication as an organizational investment creating conditions for Public Value generation. Third, it proposes the PVP-II as a first conceptual architecture for making communication and engagement investments visible within integrated Public Value management.

2. Theoretical Foundations

2.1 Public Value Requires Shared Organizational Knowledge

The growing emphasis on Public Value has changed how public administrations conceive planning, organizational development and institutional performance. Rather than evaluating public organizations only in terms of efficiency or service delivery, contemporary public management increasingly recognizes their capacity to generate broader social outcomes, strengthen democratic legitimacy and improve citizens' well-being (Moore, 1995; Meynhardt, 2009, 2015; Bryson et al., 2014). Public Value therefore emerges through the interaction between organizational capabilities, institutional relationships and stakeholders' perceptions of public action.

This evolution has significant managerial implications. Creating Public Value requires public organizations not only to define strategic priorities but also to ensure that these priorities are understood, shared and translated into coherent organizational behaviour. Integrated planning systems, and particularly the PIAO, aim to strengthen this alignment by connecting strategic objectives, organizational resources, human capital, governance mechanisms and performance management within a unified framework (Deidda Gagliardo & Saporito, 2021; Deidda Gagliardo et al., 2023; Cepiku et al., 2025). Strategic alignment, however, cannot be achieved through planning documents alone. It depends on whether the knowledge embedded in those documents becomes part of everyday organizational practice.

This perspective is particularly relevant in contemporary public organizations, where strategic planning depends on collaboration among managers, employees, political leaders and citizens. Knowledge Management in the public sector extends beyond information management and includes the capability to create, share, apply and preserve knowledge in support of public decision-making (Cong & Pandya, 2003; Wiig, 2002). Leadership, organizational culture and knowledge-sharing practices strongly influence this capability (Pee & Kankanhalli, 2016). KM should therefore be understood as a managerial capability that aligns people, knowledge and institutional objectives around Public Value creation.

Consequently, integrated planning cannot be evaluated only by examining the quality of planning documents or the coherence of strategic objectives. The crucial issue is how strategic knowledge is disseminated, explained and internalized. Only when planning becomes shared organizational knowledge can it influence employees' behaviour, strengthen organizational alignment and create the conditions for Public Value generation (Argyris & Schön, 1978; Wenger, 1998; Men, 2014).

2.2 Strategic Communication as a Knowledge Management Process

Knowledge Management literature shows that knowledge generates value only when it is communicated, interpreted, shared and applied (Nonaka, 1994; Davenport & Prusak, 1998; Alavi & Leidner, 2001; Massaro et al., 2015). Communication is therefore a mechanism through which strategic knowledge becomes coordinated action, learning and collective understanding.

This interpretation is particularly relevant for integrated planning systems such as the PIAO. Although the document defines strategic priorities, organizational objectives, performance indicators and Public Value goals, its managerial effectiveness depends on whether these contents become understandable and meaningful for

those responsible for implementation (Deidda Gagliardo & Saporito, 2021; Deidda Gagliardo et al., 2023; Cepiku et al., 2025). Publishing the PIAO does not ensure that its strategic vision becomes embedded within the organization. Planning becomes operational only when communication transforms formal objectives into shared organizational knowledge.

Communication supports the interpretation of strategic priorities, reduces informational asymmetries, facilitates organizational learning and aligns individual behaviours with institutional objectives (Alavi & Leidner, 2001; Men, 2014). In public organizations, this process is especially important because employees represent the primary interface between institutional strategies and citizens. Public servants translate strategic priorities into administrative decisions, services and everyday interactions with stakeholders. Their awareness of organizational objectives is therefore a strategic asset, influencing internal coordination and the perceived quality, coherence and legitimacy of public action (Perry & Wise, 1990; Deci & Ryan, 2000; Men, 2014). Strategic communication also extends beyond organizational boundaries, contributing to transparency, accountability, stakeholder awareness and legitimacy in collaborative governance environments (Bryson et al., 2014; Meynhardt, 2009).

Communication should therefore be interpreted as a core Knowledge Management process: investing in communication means investing in the capacity to transform planning into shared understanding, coordinated behaviour and collective commitment.

2.3 From Communication Activities to Communication Investments

Communication is often treated as a supporting function, yet public management and KM literature suggest that it is a strategic capability shaping the conditions under which Public Value is generated (Bryson et al., 2014; Meynhardt, 2009, 2015; Alavi & Leidner, 2001; Massaro et al., 2015).

Despite this recognition, communication is still rarely treated as an organizational investment within public administrations. Resources devoted to communication are usually considered operational expenditures rather than strategic assets. Consequently, while considerable attention is devoted to measuring outputs, outcomes and performance indicators, less attention is paid to the investments required to ensure that strategic priorities are understood, shared and enacted.

This observation is particularly significant in the context of the PIAO. Preparing an integrated planning document requires strategic analysis, performance planning, human resource policies, governance design and Public Value objectives. Yet this effort may remain partly unrealized if the strategic contents of the PIAO are not disseminated among employees, managers, citizens and institutional stakeholders. Drafting the PIAO is therefore only the first stage of a broader organizational process whose effectiveness depends on communication.

KM literature shows that organizational knowledge generates value only when it becomes actionable knowledge influencing behaviour and decision-making (Davenport & Prusak, 1998; Alavi & Leidner, 2001; Wiig, 2002). Investments in internal communication, training, participatory processes and stakeholder engagement should therefore be interpreted as mechanisms converting strategic knowledge into organizational capabilities.

The same reasoning applies to human capital. Employees translate institutional strategies into operational practices; their understanding of priorities and contribution to collective goals influences organizational action (Perry & Wise, 1990; Deci & Ryan, 2000; Men, 2014). Communication investments also reinforce transparency, stakeholder awareness, trust and participation (Bryson et al., 2014; Meynhardt, 2015).

These considerations suggest that communication investments are enabling investments. They do not directly create Public Value; rather, they strengthen the organizational conditions through which Public Value can emerge. This shifts managerial attention from communication outputs to the contribution of communication to alignment, knowledge sharing, employee engagement and stakeholder involvement.

An important gap therefore remains. Although many studies recognize the strategic importance of communication, there is still no conceptual framework capable of estimating the organizational effort devoted to promoting Public Value through strategic communication activities associated with integrated planning systems such as the PIAO. Addressing this gap provides the rationale for the conceptual proposal developed below.

3. Conceptual Framework: Strategic PIAO Communication as a Knowledge Management Infrastructure

The central argument of this paper is that the Public Value potential embedded within the PIAO cannot be realized through drafting and formal approval alone. Integrated planning defines strategic priorities, organizational objectives, governance mechanisms and expected societal impacts, but these elements generate organizational value only if they are understood, shared and translated into everyday behaviour. Public Value is therefore not produced by the existence of the PIAO itself, but by the organizational processes that transform its strategic content into collective action (Moore, 1995; Meynhardt, 2009, 2015; Bryson et al., 2014; Deidda Gagliardo & Saporito, 2021).

This observation shifts attention from planning to implementation and, more specifically, from producing strategic documents to managing organizational knowledge. Knowledge Management literature argues that organizations create value when knowledge is generated, interpreted, shared and applied by organizational actors (Nonaka, 1994; Davenport & Prusak, 1998; Alavi & Leidner, 2001; Massaro et al., 2015). An integrated planning system such as the PIAO can therefore be interpreted as a repository of strategic organizational knowledge whose effectiveness depends on dissemination, internalization and operational use.

If the PIAO represents the strategic knowledge architecture of the organization, a further question arises: how can public administrations ensure that this knowledge reaches employees, managers, citizens and stakeholders? Communication is one of the primary mechanisms through which knowledge becomes coordinated action, organizational learning and shared understanding (Alavi & Leidner, 2001; Wenger, 1998; Men, 2014). In integrated planning, it is therefore a deliberate managerial activity requiring resources, attention, capabilities and governance arrangements.

For this reason, communication is conceptualized as a strategic organizational investment rather than a post-planning activity. Internal dissemination, training, explanatory materials, digital communication, participatory events and stakeholder engagement transform planning into shared organizational knowledge.

The expected return on these investments should not be interpreted as immediate Public Value creation. Instead, communication investments strengthen intermediate organizational conditions that make Public Value more likely to emerge. Knowledge sharing increases employees' understanding of institutional priorities and facilitates organizational learning (Argyris & Schön, 1978; Wenger, 1998). A clearer organizational mission may reinforce motivation, commitment and Public Service Motivation (Perry & Wise, 1990; Deci & Ryan, 2000). External communication may also improve transparency, legitimacy, stakeholder trust and awareness (Men, 2014; Bryson et al., 2014).

Existing studies discuss integrated planning, effective PIAOs and the benefits of Knowledge Management (Deidda Gagliardo et al., 2023; Massaro et al., 2015; Pee & Kankanhalli, 2016), but rarely estimate the effort required to transform strategic planning into shared organizational knowledge. These investments remain largely invisible within planning and performance systems.

To address this gap, the Public Value Promotion Investment Indicator (PVP-II) is proposed as a conceptual managerial tool. It does not measure Public Value itself or replace existing indicators; rather, it estimates the intensity of organizational investment devoted to promoting PIAO contents through communication, training, dissemination and stakeholder engagement.

Conceptually:

$$\textbf{PVP-II} = f(\textbf{IC}, \textbf{EC}, \textbf{T}, \textbf{SE}, \textbf{EI})$$

where IC is internal communication, EC external communication, T training and organizational development, SE stakeholder engagement, and EI employee involvement. The formula is intentionally conceptual: each dimension should be calibrated according to organizational context, strategic priorities and future empirical validation. The proposed variables are scalable and may be adapted to organizational size, financial investment per PIAO action, number of employees involved and stakeholder heterogeneity.

The PVP-II has a dual function. Ex ante, it estimates the investment devoted to communicating PIAO objectives at the time of publication. Ex post, it supports reflection on whether these investments contributed to employee engagement, organizational learning, performance improvement and the broader conditions enabling Public Value creation.

Figure 1 summarizes the model, showing how strategic investments in PIAO communication activate Knowledge Management processes, generate organizational and relational outcomes, and strengthen conditions for Public Value creation.

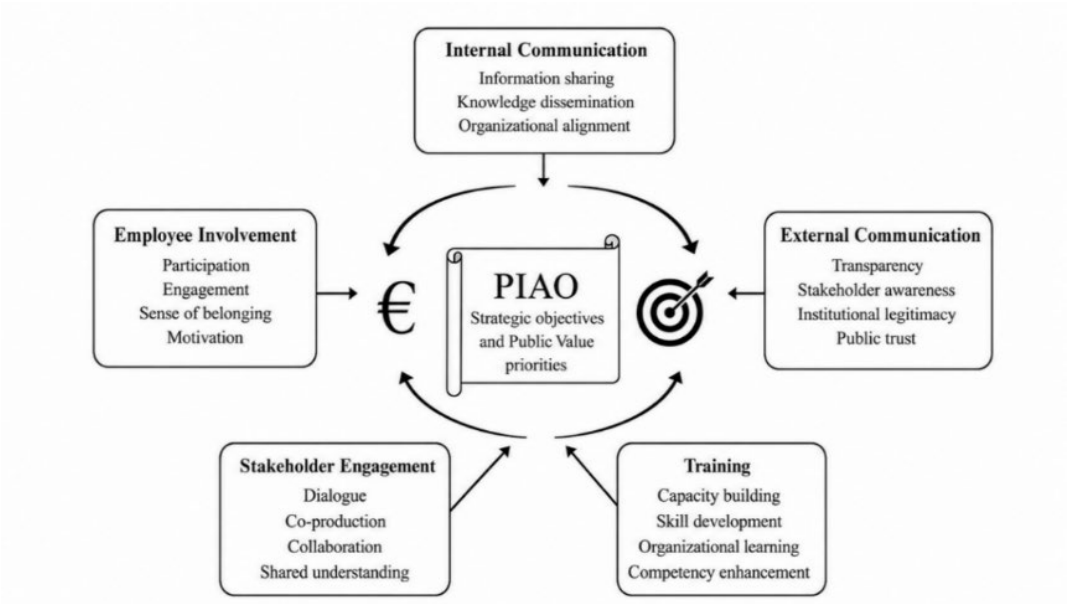


Figure 1: Conceptual Framework: strategic PIAO communication as a Knowledge Management infrastructure for Public Value creation (authors' elaboration)

4. Methodology

This study adopts a qualitative conceptual design supported by an exploratory case study. It does not seek to demonstrate a causal relationship between communication activities and Public Value creation, nor to validate a new performance indicator statistically. Rather, it develops a theoretically grounded managerial framework explaining why investments in communicating integrated planning represent an overlooked organizational dimension and how they may become measurable. The paper therefore adopts a theory-building perspective in which conceptual development precedes empirical operationalization (Alavi & Leidner, 2001; Moore, 1995; Meynhardt, 2009).

This methodological choice is consistent with Knowledge Management research, where conceptual studies have anticipated empirical developments by proposing interpretative models, constructs and managerial tools before operationalization (Nonaka, 1994; Alavi & Leidner, 2001; Massaro et al., 2015). Similarly, Public Value research has developed conceptual frameworks intended to guide managerial practice before empirical measurement (Moore, 1995; Meynhardt, 2009; Bryson et al., 2014). The paper should therefore be understood as a theory-building contribution centred on the PVP-II.

To support the framework, the study employs an exploratory case study of the Municipality of Pescara. The case does not function as empirical validation; rather, it provides a real organizational setting in which the assumptions of the framework can be examined. The case selection follows a purposive logic based on theoretical relevance. Pescara has adopted the PIAO as the central governance instrument integrating strategic planning, performance management, organizational development, human resource policies, transparency and Public Value objectives. The municipality has also expressed interest in strengthening PIAO dissemination among employees and stakeholders, making the case suitable for exploring communication as an organizational investment.

The empirical analysis primarily relies on documentary evidence. The principal source is the Municipality of Pescara's PIAO 2026-2028, examined with particular attention to Public Value, strategic planning, organizational development, performance management, human capital, stakeholder participation, transparency, internal communication, training and governance mechanisms. Document analysis was complemented by consideration of institutional communication initiatives, organizational practices and managerial reflections concerning PIAO dissemination. Rather than assessing effectiveness, the analysis identified the organizational resources

potentially invested in transforming strategic planning into shared knowledge. This distinguishes the study from approaches that evaluate only document quality or organizational outcomes.

The documentary analysis followed a structured qualitative procedure. First, the PIAO 2026–2028 and the related institutional documentation were systematically examined to identify recurring themes concerning Public Value, strategic planning, communication, human capital, governance and stakeholder engagement. Second, these themes were grouped into broader analytical categories and interpreted through the theoretical lenses of Knowledge Management, Organizational Learning and Public Value. Finally, an iterative comparison between the documentary evidence and the literature allowed the refinement of the conceptual framework and the identification of the dimensions composing the proposed PVP-II. Therefore, the Municipality of Pescara was not used to validate the framework empirically, but to inform and theoretically ground its conceptual development.

Following an abductive logic, theoretical concepts from Knowledge Management, Organizational Learning, Public Value, motivation and strategic communication literature were compared with documentary evidence from the case. This iterative comparison refined the conceptual framework and identified the principal dimensions of the PVP-II, allowing the model to remain connected to the operational characteristics of the PIAO. The indicator follows a conceptual rather than statistical logic: it estimates the intensity of investment devoted to promoting strategic objectives through internal communication, external communication, training and organizational development, stakeholder engagement and employee involvement.

Consequently, the contribution is not the validation of a new performance measure, but a theoretically grounded pathway for future operationalization of the relationship between communication investments and the conditions supporting Public Value creation.

5. The Municipality of Pescara: Towards the Public Value Promotion Investment Indicator (PVP-II)

The Municipality of Pescara offers a meaningful setting because its PIAO 2026-2028 identifies Public Value as the overarching objective of municipal action and links strategic planning, organizational development, human resource management, transparency, digital transformation, participation and performance management within a unified strategy aimed at improving local economic, social, environmental and institutional well-being.

From a strategic management perspective, the document represents more than a statutory planning requirement. It codifies the municipality's institutional vision, strategic priorities, expected impacts and organizational commitments. In Knowledge Management terms, the PIAO is the principal repository of strategic organizational knowledge, concentrating information that should guide managerial behaviour and collective action (Nonaka, 1994; Davenport & Prusak, 1998; Alavi & Leidner, 2001). Yet this does not automatically mean that its contents become shared or influence employees, managers, citizens and stakeholders. Its effectiveness depends on the organization's capacity to transform strategic planning into shared knowledge and collective awareness.

From this perspective, communication becomes a managerial issue rather than a purely informational one. Internal dissemination activities - leadership communication, staff meetings, onboarding, training, workshops and digital communication - help employees understand the strategic meaning of the PIAO and their contribution to its objectives (Men, 2014; Perry & Wise, 1990; Deci & Ryan, 2000). External communication directed towards citizens, associations, businesses, schools and institutional partners may increase transparency, accountability and awareness of municipal priorities. These activities require financial resources, managerial time, competences and organizational commitment, yet such investments remain largely invisible within planning and performance systems.

Knowledge Management explains why these investments matter. Strategic knowledge generates value only when it is shared, interpreted and incorporated into routines (Nonaka & Takeuchi, 1995; Alavi & Leidner, 2001; Massaro et al., 2015). Organizational Learning theory similarly suggests that employees develop coherent behaviours when institutional objectives are collectively understood (Argyris & Schön, 1978; Wenger, 1998). Motivation theories reinforce this view by showing that individuals become more engaged when they understand the purpose of their work and perceive their contribution to collective goals (Perry & Wise, 1990; Deci & Ryan, 2000).

Building on these considerations, Pescara can be interpreted as an exploratory laboratory for the conceptual development of the PVP-II. The indicator does not quantify Public Value or replace existing performance

measures. Rather, it estimates the organizational investment dedicated to promoting the strategic contents of the PIAO among employees and external stakeholders, shifting attention from outcomes alone to the effort required to make those outcomes achievable. In its conceptual formulation, the PVP-II assumes that investments in strategic communication create enabling conditions - knowledge dissemination, organizational learning, employee engagement, institutional trust, stakeholder awareness and organizational alignment - that increase the probability that PIAO objectives are translated into behaviour and, ultimately, Public Value outcomes.

The case illustrates an overlooked managerial dimension: transforming strategic planning into shared organizational knowledge requires resources, competences and sustained communication. Recognizing and progressively measuring this effort is the primary contribution of the PVP-II and the foundation for Figure 2.

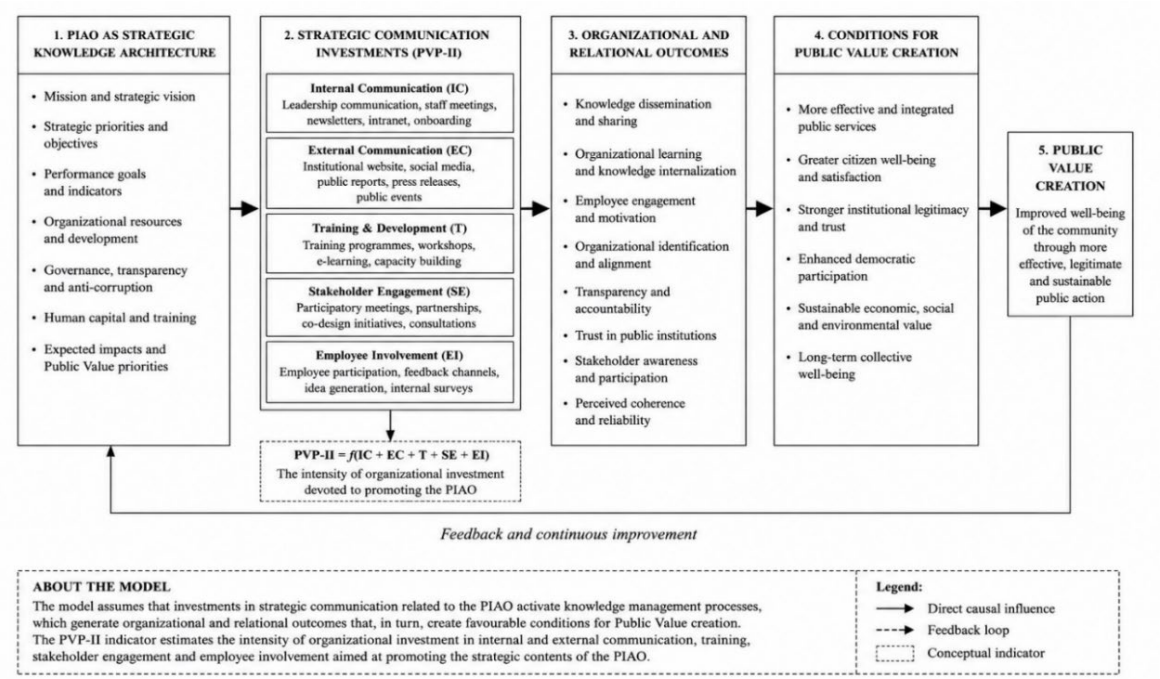


Figure 2: The PVP-II Conceptual Model (authors' elaboration)

6. Managerial Implications: The Public Value Promotion Investment Indicator (PVP-II)

The conceptual framework and the exploratory analysis of Pescara suggest that one managerial dimension of integrated public planning remains overlooked: the effort required to ensure that strategic priorities become understood, shared and translated into coordinated organizational behaviour. The central proposition advanced in this paper is that strategic communication should be interpreted as an organizational investment rather than as downstream dissemination. Internal communication campaigns, leadership engagement, employee training, stakeholder consultation, participatory initiatives, digital communication and public dissemination require financial resources, managerial commitment and organizational capabilities. They are therefore not ancillary to planning; they create the conditions through which planning can influence behaviour and performance.

Building upon this premise, the PVP-II is introduced as a conceptual managerial construct. The indicator does not measure Public Value itself or replace performance measurement systems. Its purpose is to estimate the organizational effort devoted to promoting, communicating and disseminating the strategic contents embedded within the PIAO, thereby supporting the knowledge-sharing processes that precede Public Value creation. It is organized around five investment domains: internal communication, external communication, training and organizational development, stakeholder engagement and employee involvement. Together, these dimensions describe the extent to which an organization invests resources in transforming strategic planning into shared organizational knowledge.

The scalability of the model may be refined by relating PVP-II components to contextual parameters, including territorial extension, resident population, employee-to-population ratios, investment per PIAO action, the number of trained or informed employees and the stakeholders involved in specific communication actions. This formulation is a conceptual aggregation of the principal investments supporting Public Value promotion, not a definitive measurement equation. Future research may refine the model through weighting coefficients,

normalization factors or organizational parameters according to the size, complexity and strategic priorities of different public administrations.

From a managerial perspective, the indicator encourages public managers to ask whether sufficient resources are being invested to ensure that strategic priorities are understood by employees, managers, citizens and stakeholders. The Municipality of Pescara is an appropriate context because its PIAO already links organizational health, participation, governance quality, human capital and Public Value. The PVP-II extends this logic by making communication investment visible.

Figure 2 positions strategic communication investments at the centre of the relationship between integrated planning and Public Value creation, interpreting communication as the mechanism through which strategic knowledge is disseminated and organizational learning is fostered.

7. Concluding Remarks

This paper addressed a practical yet theoretically underexplored question: how can public administrations ensure that the strategic knowledge embedded within integrated planning systems contributes to Public Value creation?

Responding to this question required moving beyond the interpretation of the PIAO as a planning and compliance instrument and reinterpreting it as a Knowledge Management infrastructure whose effectiveness depends on transforming planning into shared organizational knowledge. Drawing on Knowledge Management, Organizational Learning, Public Value, motivation and strategic communication literature, and using Pescara as an exploratory context, the paper argues that investments devoted to communicating the PIAO constitute an overlooked managerial dimension.

Rather than producing Public Value directly, these investments strengthen knowledge sharing, organizational alignment, employee engagement, institutional trust and stakeholder awareness, thereby reinforcing the conditions through which Public Value may emerge. The principal contribution is the conceptual development of the PVP-II. Unlike traditional performance indicators, it does not quantify Public Value itself; instead, it makes visible the resources devoted to making strategic planning understandable, actionable and collectively shared. The proposed framework should be interpreted as a conceptual starting point rather than a definitive measurement model.

Future research may operationalize the PVP-II dimensions, explore weighting schemes, investigate relationships with employee engagement and organizational learning, and test applicability across public administrations.

Ethics Declaration: No ethical approval was required for this study.

AI Declaration: AI tools were used solely for language editing and stylistic refinement. The authors retain full responsibility for the final manuscript.

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Transforming Environmental Knowledge Into Business Opportunity Through Circular Economy Practices Mediation

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Abstract: In conditions of increasing environmental turbulence, organisations must continuously transform environmental information into strategic and operational responses. This study examines whether circular economy (CE) practices mediate the relationship between environmental scanning and business opportunity. Drawing on dynamic capabilities and the knowledge-based view, environmental scanning is conceptualised as a sensing capability, while CE practices represent organisational mechanisms transforming knowledge into value-creating actions. The study distinguishes between Sustainable Product Design and Circular Resource Management to explain how different CE dimensions contribute to business outcomes. Quantitative data were collected from 300 medium and large enterprises operating across 19 industrial sectors in Poland. Structural Equation Modelling (SEM) was used to examine direct and indirect relationships. The results show that environmental scanning does not directly influence business opportunity. Instead, its impact is primarily indirect and mediated through CE practices. The strongest effect was identified for Circular Resource Management, indicating that operational circular practices are critical for transforming environmental knowledge into business value. The study contributes to research on environmental scanning and circular economy by demonstrating that environmental knowledge creates value only when embedded in organisational capabilities enabling resource reconfiguration and operational implementation. The findings also provide managerial implications for firms seeking to translate environmental signals into competitive advantage.

Keywords: Environmental scanning, Knowledge transformation, Circular economy, Business opportunity, Organizational learning

1. Introduction

In an environment of growing complexity and uncertainty, the ability of firms to monitor regulatory, technological, economic and social changes has become a key determinant of long-term competitiveness. Global transformations—including digitalisation, climate policies and resource volatility—require organisations not only to possess resources but to continuously reconfigure them in response to environmental signals.

Environmental scanning is widely recognised as a component of dynamic capabilities, enabling sensing, seizing and reconfiguring (Teece, 2007; Sun et al., 2021; Koparan and Aksaray, 2025). It is primarily instrumental, supporting opportunity identification, risk mitigation and strategic decision-making. Firms scan their environment not to pursue normative goals but to recognise and exploit opportunities.

At the same time, the circular economy (CE) is gaining importance as a direction of industrial transformation. Practices such as eco-design, resource loop closure and material efficiency are increasingly perceived not only as responses to regulatory pressure but also as sources of cost efficiency, innovation and new revenue models.

Importantly, firms do not scan their environment with the primary aim of implementing CE. However, many environmental signals—such as regulatory changes, increasing material costs or technological developments—relate to circular transformation. CE may therefore represent one possible strategic response, but not an automatic one.

This raises a key research question: does environmental scanning directly lead to improved business outcomes, or is its effect mediated through specific organisational practices such as CE implementation? Existing research rarely addresses this mechanism in an integrated manner. Environmental scanning studies focus on direct effects, while CE research typically treats implementation as a response to external pressures. Few studies analyse CE as a mediating mechanism or distinguish between its design and operational dimensions.

This study addresses this gap by examining whether Sustainable Product Design and Circular Resource Management mediate the relationship between environmental scanning and business development trends. Unlike previous studies that treat circular economy implementation as a single construct or as a direct response to external pressure, this research conceptualises CE practices as organisational mechanisms transforming environmental knowledge into business opportunity.

The study contributes to the literature in three ways. First, it integrates environmental scanning and circular economy research within a single analytical framework grounded in dynamic capabilities theory. Second, it distinguishes between design-oriented and operational circular practices, showing that they generate different value creation mechanisms. Third, it empirically tests the mediating role of CE practices using Structural Equation Modelling based on data from 300 firms.

The following hypotheses are proposed:

H1: Environmental scanning positively influences the implementation of CE practices.

H2: CE practices positively influence business opportunity.

H3: CE practices mediate the relationship between environmental scanning and business opportunity.

2. Literature Review

2.1 Environmental Scanning and Business Outcomes

Environmental scanning is defined as the systematic monitoring and interpretation of environmental signals to support strategic decision-making (Beal, 2000; Choo, 1996; Choo, 2001). It is conceptualised within dynamic capabilities as part of the sensing process (Teece, 2007).

Empirical studies show that environmental scanning supports innovation, adaptability and performance, particularly under conditions of high turbulence (Sun et al., 2021; Stelmaszczyk et al., 2023; Zhou et al., 2025). However, most research models scanning as a direct predictor of performance or as mediated by general constructs such as innovation or flexibility (Otache, 2024; Yu et al., 2022).

At the same time, literature reviews emphasise that studies rarely examine the specific operational mechanisms through which scanning translates into economic outcomes (Magnano et al., 2024; Nassou & Kamar, 2025). As a result, concrete organisational practices remain underexplored as intermediary links

2.2 Circular Economy and Firm Performance

Research on CE shows positive relationships between circular practices and financial performance, resource efficiency and organisational resilience (Centobelli et al., 2020; Khan et al., 2022). CE is also associated with business model transformation and cost reduction.

The literature identifies key drivers of CE implementation, including regulatory pressure, stakeholder expectations, environmental orientation and access to resources (Velenturf & Purnell, 2021; He et al., 2022; Aryee & Kanda, 2024). Consequently, CE is often interpreted as a response to external pressure rather than as an outcome of knowledge processes.

Moreover, many studies treat CE as a single construct, overlooking differences between design-level practices (eco-design) and operational practices (resource circulation). These dimensions may generate distinct value creation mechanisms (Aryee & Kanda, 2024).

2.3 Towards an Integrated Mechanism

Recent literature calls for integrating information processes with implementation mechanisms (Magnano et al., 2024). CE can be viewed not only as a response to external pressures but also as a mechanism for commercialising environmental signals.

However, there is still a lack of research that simultaneously treats environmental scanning as an antecedent of CE, distinguishes between CE dimensions, and analyses their mediating effects on business outcomes.

3. Materials and Methods

The study adopts a quantitative research design to examine both direct and indirect relationships between environmental scanning, CE implementation and business development trends.

The model includes two dimensions of environmental scanning: Macro-Environment Scanning (ME) and Industry Environment Scanning (IE), as well as two dimensions of CE implementation: Sustainable Product Design (CE Design) and Circular Resource Management (CE Operations). The dependent variable is Business Development Trend.

Data were collected in January 2025 from 300 medium and large enterprises operating across 19 industrial sectors in Poland. The study used a CATI survey administered to senior managers (CEOs, technical directors, financial directors).

All variables were measured using five-point Likert-type scales. The reliability of the constructs was satisfactory, with Cronbach's alpha values of 0.87 for environmental scanning and 0.78 for CE practices.

Structural Equation Modelling (SEM) was employed to analyse direct and indirect effects, enabling the simultaneous examination of mediating relationships.

Several limitations of the research design should be acknowledged. First, the use of perceptual measures may introduce common method bias, as all responses came from single respondents. To mitigate this risk, anonymity was ensured and questionnaire items were separated conceptually. Furthermore, Herman's Single-Factor Test was conducted, which showed a proportion of total variance of 31.08%. This result does not indicate a problem with common method bias. Second, the cross-sectional character of the study limits causal interpretation, as relationships were measured at a single point in time. Consequently, the findings should be interpreted as associative rather than strictly causal.

The conceptual model is presented in Figure 1.

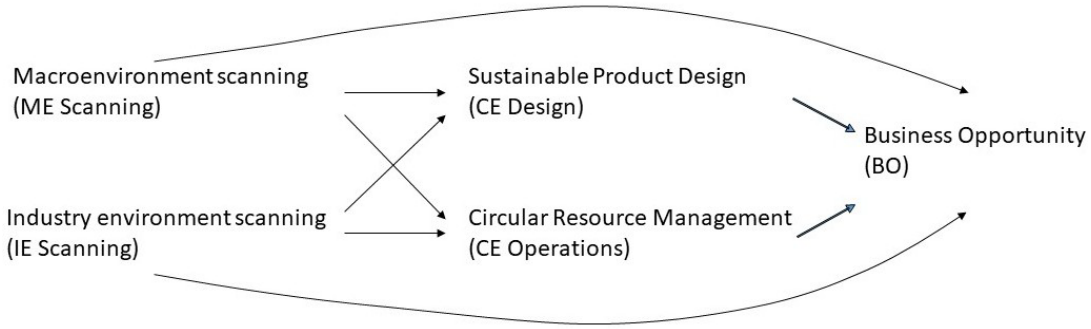


Figure 1: Research model

4. Results

4.1 Frequency of Responses

The descriptive analysis indicates that firms most intensively monitor technological, regulatory and customer-related environmental changes. In contrast, socio-demographic and environmental trends are scanned less frequently (Table1). Regarding CE implementation, firms more commonly adopt design-related practices, particularly environmentally friendly materials and recycling-oriented design, whereas operational practices based on internal waste reuse remain less developed (Table 2).

Table 1: Environmental Scanning (N = 300)

Segment		LOW (1;2)	LOW (%)	HIGH (4;5)	HIGH (%)
ME Scanning	E1	77	25,7%	118	39,3%
	E2	55	18,3%	143	47,7%
	E3	79	26,3%	88	29,3%
	E4	61	20,3%	147	49,0%
	E5	56	18,7%	179	59,7%
IE Scanning	E6	34	11,3%	191	63,7%
	E7	46	15,3%	170	56,7%
	E8	74	24,7%	130	43,3%

Table 2: Circular Economy Practices (N = 300)

Principle		LOW (1;2)	LOW (%)	HIGH (4;5)	HIGH (%)
CE Design	C1	74	24,7%	147	49,0%
	C2	50	16,7%	155	51,7%
	C3	91	30,3%	119	39,7%
	C4	63	21,0%	147	49,0%
	C5	119	39,7%	100	33,3%
CE Operations	C6	90	30,0%	118	39,3%
	C7	150	50,0%	82	27,3%
	C8	96	32,0%	128	42,7%

Table 3 shows the distribution of assessments of business development trends (Business Opportunity – BO). A positive trend (responses 4–5) was reported by 47.3% of enterprises, whilst 13.3% indicated a negative trend (responses 1–2). This means that almost half of the surveyed companies perceive their growth dynamics as favourable.

Table 3: Business Trend

Category N		%
BO (1–2)	40	13.3%
BO (4–5)	142	47.3

In order to preliminarily identify the relationship between environmental scanning and the implementation of CE principles and the business development (BO) trend, two extreme configurations were compared (Table 4): low engagement in scanning changes in the sociodemographic segment and the use of own production waste (E3 and C7), and high engagement in scanning the customer segment and the use of environmentally friendly materials (E6 and C2).

The proportion of firms declaring a positive business development trend (BO 4–5) was significantly higher in the strong configuration (19.7%) than in the weak configuration (6.0%), indicating a link between the co-occurrence of engagement in scanning and implementing CE principles and more favourable business dynamics.

Table 4: High and low engagement in environmental scanning and the implementation of circular economy principles versus business trend

Configuration	BO (1–2) %	BO (4–5) %
Low E3 and Low C7	3.0%	6.0%
High E6 and High C2	3.7%	19.7%

4.2 Correlation Analysis

To determine whether there is a correlation between the variables: environmental scanning (E1–E5; E6–E8), application of Circular Economy principles (C1–C5; C6–C8) and business development trends (BO), a Spearman's rank correlation test was conducted (Table 5).

Correlation analysis revealed statistically significant positive relationships among environmental scanning variables, CE practices and business opportunity. Strong correlations within the scanning and CE dimensions suggest that firms tend to apply these practices systematically rather than selectively.

Table 5: Spearman's rank correlation

Variable	E1	E2	E3	E4	E5	E6	E7	E8	BO	C1	C2	C3	C4	C5	C6	C7	C8
E1	1,000	0,561	0,421	0,494	0,451	0,440	0,413	0,440	0,289	0,121	0,198	0,163	0,166	0,169	0,092	0,146	0,079
E2	0,561	1,000	0,422	0,493	0,477	0,464	0,517	0,365	0,211	0,181	0,187	0,188	0,199	0,249	0,182	0,098	0,130
E3	0,421	0,422	1,000	0,544	0,349	0,297	0,288	0,333	0,228	0,239	0,174	0,360	0,140	0,287	0,122	0,299	0,250
E4	0,494	0,493	0,544	1,000	0,379	0,408	0,371	0,304	0,201	0,283	0,235	0,368	0,223	0,274	0,249	0,218	0,197
E5	0,451	0,477	0,349	0,379	1,000	0,535	0,605	0,481	0,250	0,150	0,214	0,122	0,268	0,206	0,154	0,035	0,248
E6	0,440	0,464	0,297	0,408	0,535	1,000	0,643	0,497	0,135	0,143	0,081	0,108	0,085	0,169	0,132	0,073	0,150
E7	0,413	0,517	0,288	0,371	0,605	0,643	1,000	0,486	0,171	0,070	0,097	0,048	0,126	0,186	0,096	0,032	0,134
E8	0,440	0,365	0,333	0,304	0,481	0,497	0,486	1,000	0,183	0,165	0,128	0,111	0,091	0,134	0,064	0,119	0,141
BO	0,289	0,211	0,228	0,201	0,250	0,135	0,171	0,183	1,000	0,242	0,176	0,150	0,224	0,220	0,226	0,189	0,290
C1	0,121	0,181	0,239	0,283	0,150	0,143	0,070	0,165	0,242	1,000	0,428	0,488	0,397	0,310	0,420	0,192	0,234
C2	0,198	0,187	0,174	0,235	0,214	0,081	0,097	0,128	0,176	0,428	1,000	0,388	0,331	0,330	0,306	0,148	0,244
C3	0,163	0,188	0,360	0,368	0,122	0,108	0,048	0,111	0,150	0,488	0,388	1,000	0,319	0,358	0,360	0,358	0,275
C4	0,166	0,199	0,140	0,223	0,268	0,085	0,126	0,091	0,224	0,397	0,331	0,319	1,000	0,317	0,287	0,111	0,283
C5	0,169	0,249	0,287	0,274	0,206	0,169	0,186	0,134	0,220	0,310	0,330	0,358	0,317	1,000	0,242	0,240	0,256
C6	0,092	0,182	0,122	0,249	0,154	0,132	0,096	0,064	0,226	0,420	0,306	0,360	0,287	0,242	1,000	0,347	0,253
C7	0,146	0,098	0,299	0,218	0,035	0,073	0,032	0,119	0,189	0,192	0,148	0,358	0,111	0,240	0,347	1,000	0,295
C8	0,079	0,130	0,250	0,197	0,248	0,150	0,134	0,141	0,290	0,234	0,244	0,275	0,283	0,256	0,253	0,295	1,000

4.3 Results of Structural Equation Modelling (SEM)

The SEM analysis provides the most important findings of the study (Figure 2). The direct effects of environmental scanning on business opportunity are weak (ME → BO = 0.056; IE → BO = –0.044). By contrast, indirect effects through CE practices are substantially stronger.

The strongest relationship identified in the model is the effect of Circular Resource Management on Business Opportunity (b = 0.437). This indicates that operational circular practices constitute the principal mechanism through which environmental knowledge is transformed into economic value. Sustainable Product Design also positively influences business opportunity, although its effect is weaker and more indirect.

Overall, the findings support the mediational role of CE practices and confirm that environmental scanning contributes to business opportunity primarily through organisational implementation mechanisms rather than through direct effects.

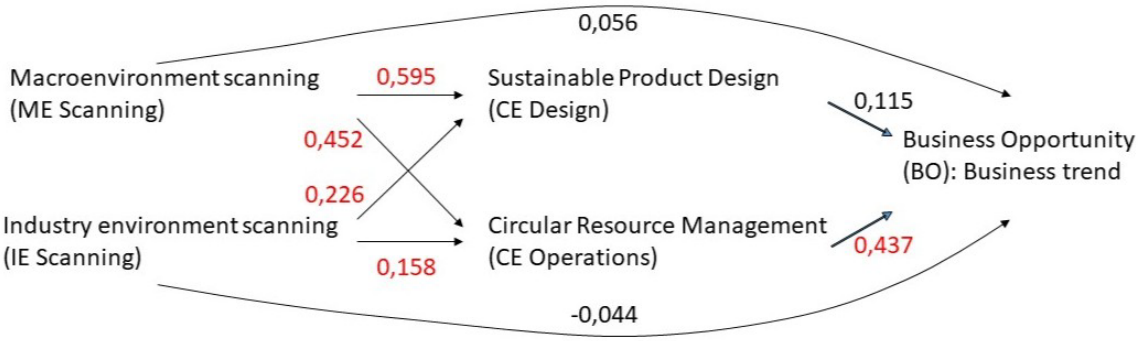


Figure 2: Structural model with standardized coefficients

5. Discussion

The aim of this study was to explain how knowledge gained through environmental scanning can be transformed into tangible business opportunities through the implementation of circular economy principles. The findings indicate that this relationship is complex and multi-stage. Neither more intensive scanning nor the mere adoption of circular practices automatically improves business performance. Instead, the results suggest a process of knowledge transformation: from selective acquisition of environmental information, through interpretation and organisational internalisation, to utilisation in project and operational activities. This interpretation places the findings at the intersection of dynamic capabilities theory, absorptive capacity, and the knowledge-based view, where competitive advantage depends not on possessing information itself, but on the

ability to integrate and translate it into value-creating actions (Teece, 2007; Cohen and Levinthal, 1990; Grant, 1996; Zirena-Bejarano et al., 2025; Agustí et al., 2022).

The results reveal clear selectivity in environmental scanning. Firms most frequently monitor technological and regulatory segments in the macro-environment, and customers and competitors in the industry environment, while socio-demographic factors and the natural environment receive less attention. Technological and regulatory signals are directly linked to innovation, productivity and compliance, whereas customer and competitor scanning supports adaptation to market dynamics. In contrast, socio-demographic and environmental signals are harder to translate into immediate business decisions because they are indirect and long-term. This supports the view that environmental scanning is a selective and interpretative process shaped by organisational cognition and existing knowledge structures (Daft and Weick, 1984; Choo, 1996; Helfat and Peteraf, 2015).

A similar selectivity appears in the implementation of circular economy practices. Firms more often adopt design-oriented practices, such as environmentally friendly materials and recycling-oriented design, together with less disruptive operational solutions like virtual prototyping and the use of external waste streams. The least frequent practice is the reuse of a firm's own production waste, which requires deeper integration of technological, process and organisational knowledge. From a knowledge-management perspective, circular design relies more on explicit knowledge, while operational circularity depends on tacit knowledge embedded in routines and organisational processes (Ranucci & Souder, 2015; Nonaka and Takeuchi, 1995). The findings therefore indicate that knowledge transformation into circular practices is gradual and asymmetric.

Another important finding is that environmental scanning alone does not significantly improve business development trends. Both macro- and industry-level scanning show weak direct effects on business opportunity, with the industry-level effect even negative. This confirms that knowledge itself does not create value. In dynamic capabilities theory, sensing is only the first stage; value emerges when organisations are able to seize opportunities and reconfigure resources accordingly (Teece, 2007; Schilke et al., 2018; Wilden & Gudergan, 2015; Amara et al., 2025). Environmental scanning therefore constitutes a source of knowledge, but not an independent source of value creation.

The importance of this distinction becomes clear in the analysis of indirect effects. The strongest relationship in the model is between Circular Resource Management and Business Opportunity, while indirect paths from scanning to business outcomes through circular practices—especially operational ones—are substantially stronger than direct effects. This indicates that circular economy practices are not secondary contextual variables but central mechanisms transforming knowledge into value. Environmental information gains economic significance only when translated into changes in resource use, operational processes and organisational routines. This interpretation is consistent with the knowledge-based view and prior research emphasising that circular practices contribute to performance only when integrated into organisational value-creation processes (Grant, 1996; Centobelli et al., 2020; Magnano et al., 2024; Khan et al., 2022).

A particularly important distinction emerges between circular design and operational circular practices. Although both dimensions positively influence business opportunity, the operational dimension is considerably stronger. Circular design primarily prepares the organisation for future opportunities by supporting compliance and long-term adaptability. Operational practices, however, directly influence efficiency, costs and resource utilisation, translating more rapidly into visible business outcomes. In this sense, circular design can be interpreted as "capability enabling", whereas operational circularity is "opportunity realising".

The comparison of extreme configurations provides additional insight. Firms characterised by low socio-demographic scanning and limited reuse of internal waste report substantially lower levels of positive business trends than firms combining intensive customer scanning with the use of environmentally friendly materials. This confirms that the co-occurrence of intensive scanning and circular implementation supports stronger business dynamics. However, some firms in the "weak" configuration still achieve positive results, suggesting that opportunities may also emerge through intuition, managerial experience or favourable market conditions. According to organisational learning theory, opportunity recognition may initially rely on intuition before becoming institutionalised within organisational routines (Crossan et al., 1999; Pidduck & Clark, 2025). Conversely, some firms with intensive scanning and strong circular implementation still report negative trends, indicating an implementation gap between recognising opportunities and effectively exploiting them.

The distinction between macro- and industry-level environments is equally significant. Macro-environmental scanning shows stronger relationships with business outcomes than industry-level scanning, suggesting that

systemic knowledge concerning regulation, technology and environmental trends has greater transformative potential than knowledge about current competitors or customers. The macro-environment generates exploratory knowledge capable of reshaping business models, whereas the industry environment more often reinforces adaptation and imitation.

Overall, the findings support viewing the model as a structured process of knowledge transformation. Organisations first selectively acquire environmental knowledge, then interpret it through existing competencies and business models, and finally translate it into project and operational activities. Only when these stages are successfully connected does environmental knowledge become a sustainable business opportunity. In this context, the circular economy is not merely a response to environmental pressures, but a key mechanism linking environmental knowledge with strategic and economic outcomes through operational reconfiguration and opportunity capture.

6. Conclusion

This study examined whether circular economy practices mediate the relationship between environmental scanning and business opportunity. The findings show that environmental scanning alone does not directly generate business value. Instead, its influence is realised through organisational capabilities that translate environmental knowledge into operational and strategic activities.

The study makes three main contributions. First, it integrates environmental scanning and circular economy research within a single dynamic capabilities framework. Second, it demonstrates that CE practices mediate the relationship between environmental scanning and business opportunity. Third, it shows that different CE dimensions generate different value creation mechanisms, with Circular Resource Management exerting the strongest effect on business outcomes.

From a practical perspective, the results suggest that firms should treat environmental scanning as a starting point for capability development rather than as an isolated information activity. Managers should invest in operational circular capabilities, cross-functional coordination and resource reconfiguration processes enabling the practical use of environmental knowledge. Particular attention should be paid to resource circulation practices, as these provide the strongest link between environmental information and economic value.

The study has several limitations. First, the use of perceptual measures may introduce subjective bias. Second, the cross-sectional nature of the data limits the ability to infer causality. Third, the research was conducted in a single country, which may affect the generalisability of the findings.

Future research could explore longitudinal designs to better capture dynamic relationships over time, as well as examine additional mediating mechanisms linking environmental scanning with business performance. Further studies could also investigate sector-specific differences and extend the analysis to different institutional contexts.

Ethics Declaration: The study complied with institutional ethical standards. Participation was voluntary and anonymous. No personal or sensitive data were collected. Because the data concerned organizational and technological aspects, formal ethics committee approval was not required.

AI Declaration: ChatGPT was used to support the search for scientific literature and to edit and format the bibliography according to Harvard style. All sources used were independently reviewed and critically used by the author, who takes full responsibility for the reliability, accuracy, and originality of the content.

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Can Universities Forge Organizational Readiness for AI Adoption? Evidence from Meta-analysis

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Abstract: Nowadays, universities eagerly aim for artificial intelligence (AI), yet empirical evidence remains fragmented across different levels of analysis, AI system types, and implementation contexts, blurring cumulative conclusions. Empirical models remain limited, lacking big picture that could give complex understanding of how implementation processes really work out in modern universities. This study aims to identify determinants of organizational readiness for AI adoption in higher education via meta-analysis and consolidate existing predictors into semantic blocks. A systematic search of literature yielded 28 empirical HE studies using PLS-SEM. Following PRISMA, predictors were coded into three levels and random-effects meta-analysis was conducted in R; pooled effects with confidence intervals were estimated and heterogeneity assessed using Q, I^2, and τ^2. Twelve out of fourteen observed predictors showed statistically significant positive effects on AI adoption. The strongest effect is shown by individual determinants, which confirms the behavioural logic of technology adoption models in which intention (ES = 0.907; $p < 0.001$) is the closest proximal predictor of the actual introduction of AI in HE. Cognitive predictors such as perceived usefulness and perceived ease of use also show comparable sustained effects, which confirms the importance of evaluating individual, cognitive-behavioural characteristics of personnel when implementing AI in HE processes The importance of capability-oriented factors was highlighted with AI literacy and self-efficacy, showing the importance of professional development programs for teachers to adopt AI successfully. Institutional determinants, such as social influence and competitive pressure have also shown significant results, indicating the importance of the external regulatory environment for universities. Organizational determinants also provided significant results. High heterogeneity for organizational readiness ($I^2 = 0.84$) indicated variation by context, AI solution type, and operationalization, supporting readiness as a dynamic capability. Given conceptual fragmentation and inconsistent modelling roles, future studies should standardize readiness measurement and test contingent and mediating mechanisms in HE AI implementation.

Keywords: AI adoption, Artificial intelligence, Higher education, Organizational readiness

1. Introduction

Artificial intelligence (AI) has rapidly moved from being a peripheral technological innovation to becoming a strategic issue for higher education institutions worldwide (Gordienko & Bagrationi, 2024). Universities are increasingly expected not only to experiment with AI tools, but also to integrate them into teaching, learning, research, administration, student support, and decision-making processes (Shwedeh, 2024). This shift is driven by several concurrent pressures: the digital transformation of educational systems, growing societal expectations for innovation, competition for students and resources, and the emergence of generative AI applications that have made AI visible and accessible to academic communities on an unprecedented scale (Michel-Villarreal et al., 2023; Wang et al., 2021). As a result, AI adoption in higher education has become a multidimensional organizational challenge that requires universities to align technological opportunities with human capabilities, institutional routines, and strategic priorities (George & Wooden, 2023).

At the same time, despite the rapidly expanding literature on AI in higher education, cumulative empirical understanding remains limited. Existing studies differ substantially in what they treat as the focal outcome, the level of analysis they prioritize, and the conceptual role assigned to readiness-related constructs (Acosta-Enriquez et al., 2024; Michel-Villarreal et al., 2023). Some studies focus on individual acceptance of AI by faculty members or students, emphasizing cognitive predictors such as perceived usefulness and perceived ease of use in line with the logic of technology acceptance models (Davis, 1989; Venkatesh et al., 2003). Other studies examine organizational conditions, such as managerial support, resource availability, IT infrastructure, or strategic alignment, while still others highlight institutional pressures, including social norms, professional expectations, or competitive dynamics (Shata & Hartley, 2025). Therefore, the field has developed as a fragmented set of parallel explanations rather than as an integrated body of evidence capable of explaining how AI adoption unfolds in universities as complex organizations.

This gap is further reinforced by conceptual ambiguity. In prior studies, readiness is operationalized inconsistently: some authors define it as a shared psychological state or perception of readiness for change, whereas others conceptualize it as a broader organizational capability, a resource-based condition, or a multidimensional construct that combines structural, cognitive, cultural, and strategic elements (Lokuge et al., 2019; Weiner, 2020). In AI-related research, this inconsistency becomes even more visible, as readiness is used

in different ways across empirical models and sectors, often without a stable measurement logic or common conceptual boundary (Hradecky et al., 2022; Muhyi et al., 2025). In some models, readiness appears as a direct predictor of AI adoption; in others, it functions more as a background enabling condition that shapes the feasibility of implementation; and in still others, it is implicitly treated as an intervening mechanism linking environmental pressures, organizational arrangements, and implementation outcomes (Hradecky et al., 2022; Lokuge et al., 2019). Such inconsistency complicates cumulative comparison across studies and makes it difficult to determine whether readiness should be interpreted as a relatively stable organizational attribute, a dynamic capability, or a context-dependent configuration of preconditions for change (Lokuge et al., 2019; Weiner, 2020). Consequently, although readiness is intuitively central to AI-related transformation in universities and other organizations, its empirical status remains insufficiently theorized and weakly synthesized in the literature (Acosta-Enriquez et al., 2024; Hradecky et al., 2022).

This article addresses that problem by asking whether universities can forge organizational readiness for AI adoption and, more broadly, which determinants of AI adoption in higher education are supported by cumulative empirical evidence. The formulation “forge organizational readiness” is important here. It implies that readiness should not be treated as a naturally given state or as a static checklist of available resources. Rather, it may be understood as something that universities actively develop through managerial action, capability training, technological alignment, and responses to external pressures. This view is especially relevant for higher education institutions, where innovation often depends on gradual coalition-building, professional legitimacy, and the coordination of decentralized actors.

2. Methodology

The collection and synthesis of empirical data for meta-analysis in this study was organized in such a way as to ensure maximum completeness of coverage of relevant literature and at the same time maintain methodological comparability of the included studies. The selection of publications was carried out sequentially and included several stages, reflected in the research design (see Figure 1).

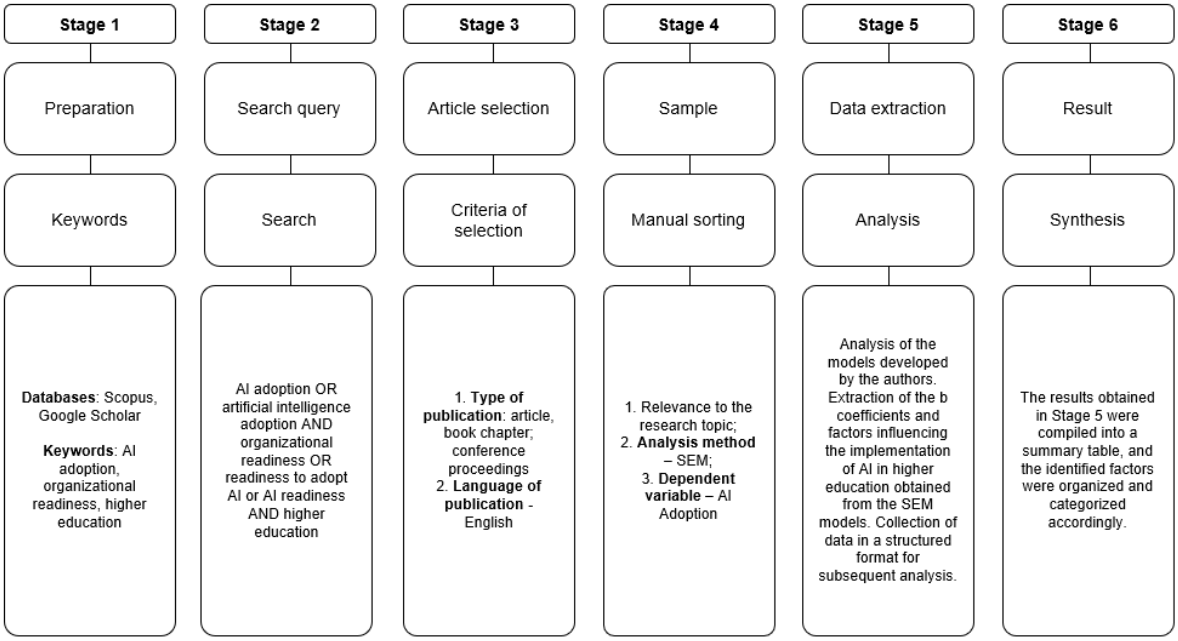


Figure 1: Meta-analysis guideline

The meta-analysis procedure was organized in accordance with PRISMA principles, focused on transparency and reproducibility of systematic reviews and meta-analytical generalizations. In dissertation logic, this means that the stages of search, exclusion, deduplication, selection by inclusion criteria, and final inclusion of research were recorded as consistent and verifiable procedures, rather than as an "expert selection" of sources (Moher et al., 2009). The search for publications was carried out in the international scientific databases Scopus, Web of Science, Google Scholar and Dimensions, which minimized the risk of incomplete coverage due to differences in the indexing of journals and thematic collections. Searching in various databases is advisable in research on digital transformation and the introduction of AI, since relevant empirical works are often distributed across

different disciplinary domains (information systems, management, organizational psychology, education) and can be presented in different types of publications. Consequently, the use of multiple databases increases the likelihood of identifying full-fledged empirical results and reduces the risk of systematic exclusion of significant works (Ewald et al., 2022).

The criteria for inclusion in the meta-analysis were set based on the task of ensuring methodological uniformity of the quantitative effects to be aggregated. At this stage, an advanced search was used using combinations of keywords reflecting three semantic cores: (1) AI and AI tools, (2) readiness to change, organizational readiness and technology adoption, and (3) the context of higher education organizations.

The set of predictors included in the meta-analysis was structured according to the multilevel logic of the theories of technology adoption and organizational change and reflected three classes of factors of different nature. First, the individual characteristics of the staff were highlighted, reflecting the cognitive-evaluative and competence-based basis of AI adoption: the expected usefulness of AI, the expected ease of use of AI, AI literacy and self-efficacy. These variables correspond to a stable tradition of behavioural models, where the assessment of usefulness and ease/effort acts as proximal predictors of the intention and use of technology, and competence resources enhance the ability to learn new tools and reduce subjective barriers to acceptance. Secondly, organizational conditions reflecting the resource and management security of the implementation were assigned to a separate block: resources, management support, organizational readiness for the implementation of AI and IT consistency.

Meta-analytical processing was performed in the R environment using the metafor package and in MS Excel for auxiliary calculations and verification of intermediate results. The choice of the statistical aggregation model was made in favor of the random-effects model, which methodologically corresponds to the nature of the field under study.

Inter-study variability was assessed using the Q, I2, and t2 statistics, which are generally accepted indicators of heterogeneity in modern meta-analysis methodology. The Q statistic is used to test the null hypothesis of homogeneity of effects, that is, that the observed variability can only be explained by sampling error. The I2 index is interpreted as the proportion of the total variability of the observed effects, due not to random error, but to real heterogeneity between studies. Thus, it allows us to assess how well the results of individual works are consistent or, on the contrary, differ significantly. Finally, t2 reflects an estimate of the variance of true effects between studies and is used as a parameter in the random effects model; its value is important for understanding the scale of the intercontext variability of the predictor's influence. The use of this set of metrics complies with methodological standards for assessing heterogeneity and provides a correct basis for interpreting the sustainability of results for each factor (Higgins & Thompson, 2002)

3. Results

Table 1: Consolidated results for meta-analysis

Variavle	n	sample	ES	SE	p-value	z-value	LCI	UCI	Q total	I^2	tau^2	Decision
Behavioral intention to adopt AI	3	1186	0.907	0.104	0.000	8.744	0.703	1.11	0.805	0	0	Supported
Compatibility	2	1012	0.223	0.116	0.055	1.915	-0.005	0.451	11.546	0.913	0.025	Not supported
Complexity	2	1319	0.04	0.117	0.734	0.34	-0.189	0.268	73.778	0.977	0.04	Not supported
Effort expectancy	2	633	0.148	0.032	0.000	4.625	0.085	0.211	0.88	0	0	Supported
AI Literacy	2	674	0.319	0.088	0.000	3.615	0.146	0.493	8.893	0.888	0.014	Supported
Competitive pressure	2	1012	0.101	0.012	0.000	8.227	0.077	0.125	0.78	0	0	Supported
Organizational readiness	3	967	0.172	0.044	0.000	3.896	0.086	0.259	12.772	0.84	0.004	Supported
Perceived ease of use	6	1968	0.221	0.061	0.000	3.607	0.101	0.34	102.672	0.914	0.016	Supported
Perceived usefullness	6	1866	0.226	0.055	0.000	4.118	0.119	0.334	28.952	0.785	0.012	Supported
Resources	2	1012	0.123	0.02	0.000	6.114	0.084	0.163	0.026	0	0	Supported
AI strategic alignment	2	1012	0.106	0.026	0.000	4.115	0.056	0.157	0.128	0	0	Supported
Self-efficacy	2	598	0.319	0.088	0.000	3.615	0.146	0.493	8.893	0.888	0.014	Supported
Social influence	3	620	0.308	0.11	0.005	2.793	0.092	0.525	13.863	0.928	0.023	Supported
Management support	3	1412	0.204	0.06	0.001	3.406	0.087	0.322	14.272	0.89	0.01	Supported

The results of meta-analysis are presented in table 1. Most of the identified factors demonstrate statistically significant positive effects on the introduction of AI technologies (12 out of 14). The strongest effect is shown by *individual determinants*, which confirms the behavioral logic of technology adoption models in which intention (ES = 0.907; p <0.001) is the closest proximal predictor of the actual introduction of AI in HE. Cognitive predictors such as perceived usefulness (ES = 0.226; p <0.001) and perceived ease of use (ES = 0.221; p <0.001) also show comparable sustained effects, which confirms the importance of evaluating individual, cognitive-behavioral characteristics of personnel when implementing AI in HE processes. Along with them, an essential role is played by AI literacy (ES = 0.319; p <0.001) and self-efficacy (ES = 0.319; p <0.01), which reflect the readiness of employees not only to understand the principles of functioning of AI systems, but also to confidently integrate them into professional activities. *Institutional determinants* such as social influence (ES = 0.308; p <0.001) and

competitive pressure (ES = 0.101; p <0.001) indicate the importance of the external regulatory environment and the market context. *Organizational determinants* are also significant: management support (ES = 0.204; p <0.01), organizational readiness (ES = 0.172; p <0.001), resources (ES = 0.123; p <0.001) and AI strategic alignment (ES = 0.106; p <0.001). Collectively, these results indicate that the introduction of AI into HE processes is not so much of a technological, rather than an organizational process, which is determined by the maturity of management processes, the ability to make organizational changes, and the consistency of AI with the existing architecture of goals and solutions.

4. Discussion

The results of this meta-analysis show that AI adoption in higher education should be interpreted as a multilevel process shaped by individual, organizational, and institutional determinants rather than as a purely technological or user-level phenomenon (Tunkevichus, O., & Bagrationi, 2025). This finding is important because prior research on AI in higher education has often emphasized isolated predictors, specific AI tools, or single implementation settings, thereby limiting cumulative understanding of how adoption unfolds across universities as complex organizations (Michel-Villarreal et al., 2023). In this regard, the present study contributes to literature by empirically consolidating fragmented evidence and showing that the implementation of AI in universities depends on the joint action of cognitive, organizational, and environmental mechanisms rather than on one dominant explanatory block.

More specifically, the meta-analytic results support the idea that universities adopt AI not simply because technologies become available, but because relevant actors perceive them as useful, manageable, legitimate, and organizationally supportable (Davis, 1989; Venkatesh et al., 2003; Paul, 2020). Such a pattern is especially important in higher education, where implementation processes are embedded in professional autonomy, institutional regulation, and organizational complexity rather than in purely hierarchical decision-making structures (Wang et al., 2021; Michel-Villarreal et al., 2023). Accordingly, the findings suggest that AI adoption in higher education should be conceptualized not as a single act of acceptance, but as a layered process in which individual readiness, organizational support, and external pressure jointly shape the transition from intention to actual implementation (Venkatesh et al., 2003; Paul, 2020).

The strongest beta effect was observed for behavioral intention, which is fully consistent with the core proposition of behavioral technology adoption models that intention is the closest proximal predictor of actual use or implementation behavior (Venkatesh et al., 2003). This result indicates that even in the context of universities as creative organizations, where AI initiatives may be supported through infrastructure, pilot programs, or formal strategies, actual adoption still depends heavily on whether individuals form a concrete readiness to use AI in their professional practice. In other words, organizational initiatives do not automatically translate into implementation unless they are mediated by individual motivational commitment to adoption.

The significant effects of perceived usefulness and perceived ease of use further confirm that the explanatory logic of TAM and UTAUT remain highly relevant for AI adoption in higher education (Davis, 1989; Venkatesh et al., 2003). These results suggest that university staff are more likely to support and use AI when they believe that such tools can improve work outcomes and when the technology is not perceived as excessively difficult to understand or operate (Davis, 1989; Venkatesh et al., 2003; Wang et al., 2021). This is particularly important for universities because academic and administrative employees typically operate under high workload, fragmented time resources, and professional accountability, which makes the subjective balance between expected benefit and required effort especially salient (Wang et al., 2021; Michel-Villarreal et al., 2023). Therefore, the findings confirm that AI adoption in higher education still follows the rational-evaluative logic of technology acceptance, even though it unfolds in a more institutionally dense environment than many traditional IT contexts.

The significant positive effects of AI literacy and self-efficacy deepen this interpretation by showing that adoption depends not only on utility beliefs, but also on users' confidence and competence in working with AI-related tools which go in alignment with basic principles presented by Compeau & Higgins in 1995. This result is theoretically meaningful because it extends the classic utility-centered tradition of technology acceptance toward a more capability-based understanding of readiness (Venkatesh et al., 2003). In the context of higher education, this means that even when AI is perceived as useful, adoption may remain limited if employees do not feel capable of interpreting outputs, managing risks, or integrating AI into discipline-specific tasks (Wang et al., 2021; Michel-Villarreal et al., 2023). Thus, the meta-analysis supports the argument that universities need not to only build positive attitudes toward AI, but also to develop a competence base among staff to enable meaningful adoption (Paul, 2020).

A second important result is that organizational variables also demonstrate significant positive effects, including management support, resources, organizational readiness, and AI strategic alignment. This pattern shows that AI adoption in universities cannot be fully explained by user perceptions alone and must also be treated as an organizational implementation process requiring coordination, legitimization, and infrastructural support (Liang et al., 2007; Paul, 2020). The significance of management support is especially consistent with prior research showing that leadership involvement helps legitimize technological change, reduce uncertainty, allocate resources, and remove barriers to implementation (Liang et al., 2007). In the case of AI, where concerns about ethics, data quality, responsibility, and changing work practices are particularly pronounced, visible managerial support may be even more important than in conventional IT adoption contexts (Michel-Villarreal et al., 2023).

The positive role of resources likewise confirms that the feasibility of AI adoption depends on the availability of financial, technical, temporal, and human capacities within the organization rather than on attitudes alone. In higher education, this includes not only access to digital tools and infrastructure, but also the institutional capacity to support training, experimentation, technical integration, and governance procedures around data and AI use (Wang et al., 2021; Michel-Villarreal et al., 2023). The significance of AI strategic alignment further suggests that implementation becomes more likely when AI initiatives are perceived as compatible with existing organizational systems, priorities, and digital architecture rather than as isolated or symbolic experiments (Henderson & Venkatraman, 1993). Together, these findings indicate that universities need organizational coherence around AI, not merely local enthusiasm for individual tools (Paul, 2020).

Most importantly, organizational readiness itself showed a statistically significant positive effect, which confirms that readiness is not merely a rhetorical or background notion, but an empirically meaningful determinant of AI adoption in higher education (Paul, 2020). At the same time, the very high heterogeneity observed for organizational readiness suggests that this construct does not operate in a stable or uniform way across studies. This likely reflects substantial variation in how readiness is conceptualized and measured, with some studies treating it as a broad organizational capability, others as a resource-related condition, and still others as a managerial or psychological preparedness factor (Paul, 2020; Tunkevichus & Bagrationi, 2025). Therefore, the present findings support the interpretation of organizational readiness as a dynamic and context-sensitive capability rather than a single fixed organizational attribute (Paul, 2020).

The significance of social influence and competitive pressure shows that AI adoption in higher education is also shaped by institutional and environmental mechanisms, not only by internal organizational factors (Horani et al., 2023). Social influence captures the normative dimension of adoption: individuals are more likely to support or use AI when meaningful others, such as colleagues, leaders, or professional communities, consider such behavior appropriate or expected (Venkatesh et al., 2003). In universities, this mechanism is particularly plausible because academic work is embedded in professional norms, reputational expectations, and community-based judgments regarding legitimacy, quality, and acceptable practice (Bouter, 2024). Therefore, the meta-analytic significance of social influence indicates that AI adoption in higher education is not purely instrumental, but also socially mediated.

The significance of competitive pressure further supports the relevance of the external environment in shaping institutional responses to AI (Erdmann & Toro-Dupouy, 2025). Universities increasingly operate in competitive fields defined by rankings, student recruitment, research visibility, funding opportunities, and broader narratives of digital modernization (Wang et al., 2021; Michel-Villarreal et al., 2023). Under such conditions, AI may be adopted not only because it improves internal efficiency, but also because it signals innovativeness, relevance, and strategic responsiveness to change (Sánchez-Rodríguez et al., 2025). Thus, the results indicate that AI adoption in higher education should also be interpreted as a response to institutionalized expectations and competitive pressures in the broader environment (Tunkevichus & Bagrationi., 2025).

5. Conclusion

This study sets out to identify the determinants of AI adoption in higher education and to clarify the role of organizational readiness through a meta-analysis of empirical PLS-SEM studies. The results show that AI adoption in universities is shaped by a broad set of statistically significant determinants spanning individual, organizational, and institutional levels. The strongest effect was observed for behavioral intention, which confirms the continuing relevance of behavioral technology adoption models in explaining actual implementation outcomes (Ajzen, 1991; Venkatesh et al., 2003). At the same time, significant effects for perceived usefulness, perceived ease of use, AI literacy, self-efficacy, management support, resources, strategic

alignment, social influence, competitive pressure, and organizational readiness demonstrate that AI adoption in higher education cannot be reduced to intention alone (Agrawal, 2023).

The findings therefore support a multilevel interpretation of AI implementation in universities. AI adoption is simultaneously a behavioral process, an organizational change process, and an institutionally embedded response to environmental pressures (Venkatesh et al., 2003; Paul, 2020; Wang et al., 2021). Within this broader architecture, organizational readiness occupies an important but conceptually unstable position. Its statistically significant effect confirms that readiness matters empirically, yet its high heterogeneity indicates that the field still lacks a sufficiently standardized and consistent understanding of how readiness should be defined and measured across contexts (Higgins & Thompson, 2002; Paul, 2020; Tunkevichus & Bagrationi, 2025). For this reason, organizational readiness should be interpreted not as a fixed background state, but as a dynamic capability emerging from the interaction of cognitive, structural, managerial, and institutional conditions (Paul, 2020).

The study contributes to literature in three main ways. First, it consolidates fragmented empirical evidence on AI adoption in higher education and shows that the field is more cumulative than it appears when viewed through isolated studies alone (Wang et al., 2021). Second, it demonstrates that organizational readiness is a meaningful explanatory construct, while also revealing the extent of conceptual fragmentation surrounding it (Paul, 2020; Tunkevichus & Bagrationi, 2025). Third, it provides support for moving from a narrow "technology acceptance" lens toward a broader framework of organizational readiness for AI adoption in universities, which better captures the complexity of higher education institutions as implementation environments (Davis, 1989; Venkatesh et al., 2003; Michel-Villarreal et al., 2023).

From a practical standpoint, the results imply that universities can forge readiness for AI adoption, but only through coordinated multilevel action. Successful implementation requires not only useful and accessible technologies, but also staff capability-building, managerial support, resource allocation, alignment with institutional systems, and sensitivity to the broader normative and competitive environment (Liang et al., 2007; Michel-Villarreal et al., 2023). Therefore, universities seeking to institutionalize AI should treat readiness not as a preliminary checklist, but as an ongoing process of organizational development and strategic adaptation (Paul, 2020).

At the same time, the study points to the need for further work. Future research should develop more standardized measures of organizational readiness, examine mediated and contingent mechanisms of AI implementation, and differentiate readiness across AI types, organizational forms, and national higher education systems (Paul, 2020; Michel-Villarreal et al., 2023; Tunkevichus & Bagrationi, 2025). Such work would strengthen the analytical precision of the readiness concept and improve the cumulative explanatory power of research on AI adoption in higher education.

Ethics Declaration: This study did not involve human participants, personal data collection, or experimental interventions and therefore did not require ethical clearance

AI Declaration: During the preparation of this paper, AI tools (specifically, ChatGPT 5.2. by OpenAI) were used to assist in language editing and improving the clarity and fluency of the text. The content generated by the AI was critically reviewed, edited, and integrated by the authors to ensure accuracy, originality, and academic integrity.

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The Value of Knowledge Management and Digital Innovation in Brand Communication for Generation Z

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Abstract: The development of digital technologies creates new opportunities for marketing communication while shaping the expectations of young consumers regarding how brands present their products, values, and innovative approaches. Generation Z represents one of the most active groups in the digital environment, and its consumer behaviour is closely connected with online content, interactivity, and the immediate availability of information. In this context, organisations increasingly need to understand the value of digital innovations in brand communication and how these innovations influence brand perception among young consumers. The value of knowledge management and digital innovations in brand communication with Generation Z lies in their ability to support a deeper understanding of young audiences and to transform this knowledge into authentic, interactive, and personalised digital communication. Insights derived from these interactions can represent an important source of organisational knowledge that may be utilised within knowledge management processes, particularly in identifying and applying insights about consumer behaviour when designing more effective marketing communication strategies. The aim of this paper is to examine the value of digital innovations in brand communication from the perspective of Generation Z. The study focuses on identifying which elements of digital communication are perceived as valuable by young users and how these elements influence their engagement, trust in brands, and overall perception of marketing communication. The research also considers the communication of ecological and sustainability values of brands in the digital environment, which has become an increasingly important component of contemporary marketing strategies. The empirical part of the study is based on a quantitative questionnaire survey conducted among respondents from Generation Z. The analysis focuses on selected aspects of digital communication, particularly preferred online content formats, factors influencing attention to digital advertising, and the perception of innovative elements in marketing communication. The methodological approach applies gap analysis to identify differences between the expected value of digital innovations from the perspective of Generation Z and their actual perception in brand communication. The findings highlight the importance of innovative communication elements that enhance user engagement and strengthen brand credibility in the digital environment. The identified gaps between expectations and perceived communication practices provide organisations with valuable insights for the more effective use of digital innovations in marketing communication. These insights may contribute to knowledge management practices by supporting organisations in better understanding the needs and expectations of Generation Z.

Keywords: Knowledge management, Digital innovation, Generation Z, Marketing communication, Sustainable brand communication

1. Introduction

In an environment characterized by continuous technological advancement, organisations must continuously adapt their processes, tools, and communication strategies to emerging digital trends. The development of digital technologies has transformed interactions between organisations and customers, enabling more efficient, personalised, and data-driven communication (Murár et al., 2024). Digital innovations have shifted organisations from traditional one-way communication toward interactive approaches that support continuous consumer engagement and generate large volumes of data for strategic decision-making and customer relationship management (Asbeetah et al., 2025; Al-Husain, 2025). In such an innovative environment, knowledge management is closely linked to digital innovation and communication, as digital technologies enable the creation, capture, storage, sharing, and application of knowledge within organisations. Tools such as cloud platforms, collaborative systems, artificial intelligence, and analytics improve information accessibility, support organizational learning, and facilitate the generation of data-driven insights. Communication plays a key role in transferring knowledge among individuals, teams, and communities of practice, thereby supporting experience sharing, coordination, and the diffusion of innovation. The literature emphasizes that successful knowledge management depends not only on technological infrastructure but also on organizational culture, processes, and the ability to integrate human knowledge with information and communication technologies (Choi et al., 2024; Stan et al., 2025). A major manifestation of digital transformation is brand communication. Technologies such as artificial intelligence, programmatic advertising, social media, and interactive digital tools provide new opportunities to understand customer needs, personalize communication, and enhance customer experience (Kovács et al., 2024; Daiva et al., 2025). At the same time, information overload and growing skepticism toward commercial content have increased demands for credibility, transparency, and authenticity. These challenges

are particularly relevant when communicating with Generation Z, one of the most digitally connected consumer groups. As digital natives, they extensively use online platforms for information acquisition, social interaction, and purchasing decisions (D'Acunto et al., 2025). Their preferences are characterized by a strong orientation toward visual, interactive, and personalised content, while emphasizing authenticity, transparency, and corporate social responsibility (Dašić, 2023; Kovács et al., 2024). Understanding their perceptions of digital communication therefore represents a valuable source of knowledge for organisations seeking to improve marketing communication effectiveness. From a knowledge management perspective, digital communication serves as a mechanism for acquiring and utilizing insights derived from customer interactions (Sánchez et al., 2022). Digital platforms provide information about customer preferences, behaviour, and expectations that can be transformed into actionable knowledge supporting communication strategies and organizational performance (Alavi et al., 2024; Yang et al., 2025). However, the effectiveness of this process depends not only on technological capabilities but also on the credibility, clarity, and relevance of communicated information. Despite the growing importance of digital innovation in marketing communication, limited attention has been devoted to how Generation Z perceives these innovations in relation to trust, communication effectiveness, and knowledge management processes (Alavi et al., 2024). Furthermore, identifying discrepancies between consumer expectations and their actual perceptions of digital brand communication may help organisations improve communication strategies and strengthen relationships with digitally oriented customers. The aim of this paper is to analyze the value of digital innovations in brand communication from the perspective of Generation Z and examine their significance within knowledge management processes. Particular attention is devoted to identifying differences between consumer expectations and perceived levels of digital communication through gap analysis.

The study addresses the following research question:

RQ1: What gaps exist between Generation Z's expectations of digital brand communication and their actual perceptions of communication performance, and how can these gaps be interpreted from a knowledge management perspective?

2. Theoretical Background

Digital innovations have become an important subject of contemporary research in marketing communication and knowledge management. From a knowledge management perspective, they not only transform communication processes but also support the acquisition, processing, and utilisation of insights derived from digital interactions (Asbeetah et al., 2025; Al-Husain, 2025). In marketing communication, this development is reflected in the shift from traditional one-way communication toward an interactive and data-driven environment characterised by continuous information exchange between brands and consumers (Kovács et al., 2024; Dašić, 2023). Digital technologies such as artificial intelligence, programmatic advertising, generative AI, and augmented reality enable more precise communication targeting, greater content personalisation, and more effective customer engagement (Daiva et al., 2025; Gündüzyeli, 2026; Murár et al., 2024). These technologies provide organisations with new opportunities to analyse customer data, improve customer experiences, and respond more effectively to changing market demands (Komarova et al., 2021; Dašić, 2023). Despite challenges related to expertise, resources, and increasing customer expectations, digitalisation has become a valuable source of customer knowledge and an important driver of competitive advantage (Komarova et al., 2021; Murár et al., 2024). Generation Z represents one of the most significant user groups of digital technologies and an important target audience for marketing communication. As digital natives, they extensively use online platforms for information acquisition, communication, and interactions with brands (Dašić, 2023; Kovács et al., 2024). Social media have become their primary source of information and a key space for building relationships with brands (D'Acunto et al., 2025). They prefer visual, interactive, and personalised content, while short-form videos and influencer marketing significantly shape their attitudes and purchasing decisions (Kovács et al., 2024; Rezníčková & Zaušková, 2019; Shankar et al., 2021; Giannattasio et al., 2024). At the same time, Generation Z is characterised by selective attention and a more critical evaluation of marketing communication. Due to information overload, authenticity, transparency, and trustworthiness have become increasingly important, with users paying attention primarily to content they perceive as relevant and valuable (Dašić, 2023; Gündüzyeli, 2026). Their sensitivity to environmental and ethical issues communicated by brands is also growing (Kovács et al., 2024; Runtukahu et al., 2025). These characteristics increase the importance of knowledge management in digital environments (Sánchez et al., 2022). Organisations face growing volumes of data generated through digital interactions, and the ability to transform these data into actionable knowledge has become essential for effective communication and customer relationship building (Yang et al., 2025; Alavi et al., 2024). The concepts of data, information, and knowledge represent fundamental levels of knowledge

processing. Data consist of raw facts, information emerges when data are organised and contextualised, and knowledge represents interpreted information applicable to decision-making and problem-solving. This understanding is based on the DIKW model, in which each level builds upon the previous one and contributes to more effective decision-making (Choi et al., 2024). However, data collection alone creates little value unless transformed into actionable knowledge (Choi et al., 2024). Knowledge management encompasses processes related to the creation, acquisition, sharing, storage, and application of knowledge to enhance organisational performance (Sánchez et al., 2022). Unlike information management, it also incorporates human interpretation, context, and experience, which convert information into meaningful insights (Stan et al., 2025). Modern technologies, including artificial intelligence and advanced analytics, enable organisations to process large volumes of data, identify customer behaviour patterns, and generate insights that support decision-making and marketing communication optimisation (Alavi et al., 2024; Yang et al., 2023; Liu et al., 2024; Yin et al., 2024; Gündüzyeli, 2026). In digital brand communication, knowledge management serves as a link between data, technology, and strategic decision-making. It enables organisations to transform data from digital interactions into information about customer preferences and subsequently into knowledge that supports more effective communication strategies. The systematic use of such insights contributes to communication personalisation, trust building, and the development of long-term customer relationships (Daiva et al., 2025; Sánchez et al., 2022).

3. Methodology

The empirical part of the study was conducted through a quantitative survey using a structured questionnaire. The aim of the research was to analyse Generation Z's perceptions of digital innovations in brand marketing communication and to identify their impact on consumer engagement, trust, and decision-making. To address the research question formulated in the introductory section of the paper, the empirical study was designed as an exploratory investigation focused on identifying attitudes, preferences, and differences in perceptions of digital communication among Generation Z respondents. Participants were selected using a convenience sampling method based on accessibility within the academic environment. Data collection was conducted over a one-month period between October and November 2025. Data were gathered through an online questionnaire created using Google Forms. The questionnaire was distributed primarily among undergraduate and graduate students of marketing communication through electronic communication and digital channels. The research sample consisted of 348 respondents belonging to Generation Z. Women represented 72.6% (n = 253) of the sample, while men accounted for 27.4% (n = 95). Respondents were aged between 18 and 27 years. Participation in the study was voluntary and anonymous. The questionnaire contained closed-ended questions, primarily using a five-point Likert scale (1–5), as well as multiple-choice questions focused on digital behaviour, content preferences, and marketing communication. The questions were grouped into four main areas: (1) perceptions of digital brand communication, (2) perceptions of digital innovations and their benefits, (3) trust, transparency, and perceptions of greenwashing in digital communication, and (4) preferences regarding content, communication formats, and digital platforms. The collected data were exported from Google Forms and processed using Microsoft Excel. The analysis included the calculation of frequencies, percentages, and mean values for individual questionnaire items. It was complemented by an interpretive approach aimed at identifying patterns and differences in respondents' perceptions of digital communication. The analytical procedure also included the application of gap analysis, which enabled the identification of discrepancies between Generation Z's expectations and their actual perceptions of brand digital communication. Expectations were derived from the declared importance of selected factors, such as transparency, innovativeness, and information accessibility, whereas perceptions were based on respondents' evaluations of current brand communication practices. Given the study's focus on knowledge management, the identified gaps were interpreted through three key knowledge management dimensions. The credibility of communicated information was interpreted as a knowledge credibility issue, the clarity and transmission of information as a knowledge transfer issue, and the influence of communication on consumer decision-making as a knowledge utilisation issue. This approach enabled the findings to be interpreted not only from a marketing perspective but also from a knowledge management perspective. The reliability of the measurement scales was assessed using Cronbach's alpha coefficient. This indicator was applied to evaluate the internal consistency of the measurement scales and to verify the reliability of the research instrument. Cronbach's alpha was calculated for the digital communication, digital innovation, and trust scales, each composed of multiple questionnaire items. Values above 0.70 are generally considered indicators of good reliability, while values close to 0.60 may be acceptable in exploratory research. The digital communication scale demonstrated moderate internal consistency (α = 0.69), whereas the digital innovation scale showed good reliability (α = 0.75). The trust-related items did not form a reliable scale (α = 0.30) and were therefore analysed separately. The results of the gap analysis provided

the basis for interpreting the identified differences between respondents' expectations and their actual perceptions of brand digital communication. The selected methodological approach thus enabled the identification of areas in which digital communication activities fail to meet Generation Z's expectations while simultaneously interpreting these gaps from a knowledge management perspective.

4. Results

The results suggest that the digital environment represents a natural space for the daily interactions of Generation Z. The high level of social media content consumption (4.59) confirms that digital platforms play a dominant role not only in entertainment but also in the acquisition and processing of information. Digital brand communication is perceived as a standard and expected form of communication (4.11) and, according to respondents, contributes to a better understanding of brands (4.01). However, the influence of digital communication on purchasing decisions remains lower (3.48), indicating that the availability of information does not automatically translate into decision-making support. The clarity of communication also received a moderate evaluation (3.53), suggesting that the effectiveness of information transfer may be limited despite the high level of digital engagement (Figure 1). This finding highlights a gap between the availability of information and its effective utilisation in consumer decision-making, representing an important challenge from a knowledge management perspective.

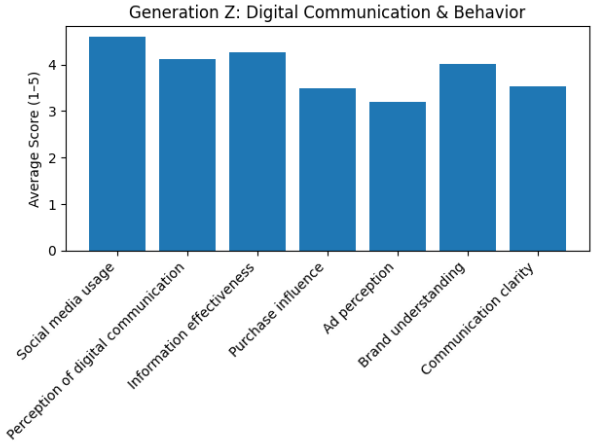


Figure 1: Digital Communication and Behavior of Generation Z

Digital innovations were evaluated positively, particularly regarding their ability to attract attention and increase engagement. Respondents indicated that innovative campaigns are more likely to capture their interest (4.02) and emphasized the importance of interactive and technologically advanced communication approaches. Digital innovations were also perceived as moderately supporting purchase decisions (3.59). However, their contribution to trust remained relatively limited (3.68), suggesting that technological sophistication alone is insufficient to build credibility. These findings indicate that Generation Z expects not only innovation but also authenticity, relevance, and meaningful communication content (Figure 2). The results further suggest that technological innovativeness alone does not constitute a source of competitive advantage unless it is accompanied by credible content and effective knowledge transfer.

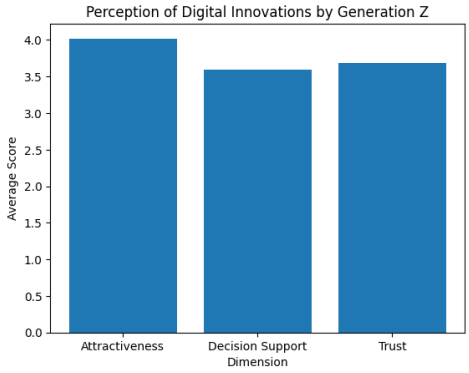


Figure 2: Perceived Impact of Digital Innovations on Generation Z

Trust emerged as one of the most problematic areas of digital brand communication. Although respondents clearly agreed that transparent communication increases trust (4.01), their actual trust in information communicated by brands online remained substantially lower (2.85). This discrepancy reflects a high level of scepticism toward brand communication and suggests that transparency alone may not be sufficient to build credibility. The situation is further intensified by the strong perception of greenwashing (4.38), indicating that respondents frequently question the credibility of environmental and sustainability claims communicated by brands (Figure 3). This finding points to the existence of a significant knowledge credibility problem, as recipients of information question not only the claims themselves but also the sources of the communicated information. The results also reveal a paradox of digital communication. Despite high levels of exposure to digital content and intensive use of social media, trust in communicated information remains low. This suggests that greater digital exposure does not necessarily lead to higher levels of trust but may instead be associated with a more critical evaluation of communicated claims and increased sensitivity to manifestations of greenwashing.

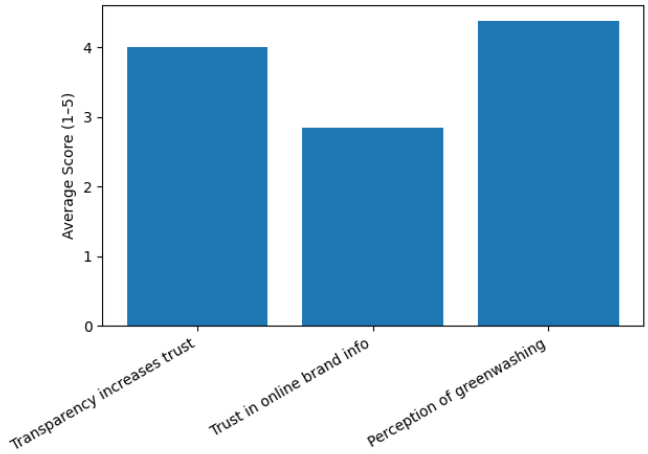


Figure 3: Perceived Trust and Skepticism in Digital Brand Communication among Generation Z

The analysis of content preferences revealed a strong orientation toward entertaining content (74.06%), while educational content accounted for 17.58% of responses. Regarding campaign formats, educational content (40.3%) and short-form videos (33.4%) achieved the highest levels of preference. These findings suggest that information is communicated most effectively when combined with engaging and accessible formats. Influencer marketing accounted for only a limited share of preferences (4.6%), which may indicate a growing critical attitude toward influencer-driven communication. The low preference for influencer marketing suggests that, in digital brand communication, Generation Z does not attach decisive importance to the popularity of the communicator but rather to the credibility and verifiability of the communicated information. This finding supports the assumption that source credibility represents an important factor in the acceptance of digitally communicated knowledge. Regarding digital platforms, YouTube (51.9%) and TikTok (24.1%) remain the dominant channels through which Generation Z consumes content and processes information (Figure 4).

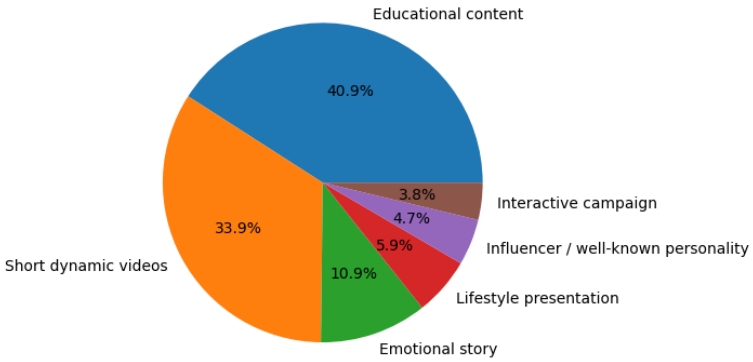


Figure 4: Preferred Campaign Formats among Respondents

The results were subsequently interpreted through gap analysis (Table 1), which enabled the identification of discrepancies between Generation Z's expectations and their actual perceptions of brand digital communication.

Table 1: Gap Analysis of Generation Z Perceptions of Digital Brand Communication

Finding	Mean Score	Interpretation	Knowledge Gap Category
Importance of transparency	4.01	Transparency is considered important for trust building	Knowledge Credibility Gap
Trust in brands online	2.85	Trust in digital brand communication remains low	Knowledge Credibility Gap
Perception of greenwashing	4.38	Sustainability claims are frequently questioned	Knowledge Credibility Gap
Clarity of digital communication	3.53	Communication is not always perceived as sufficiently clear	Knowledge Transfer Gap
Influence on decision-making	3.48	Information does not strongly influence purchasing decisions	Knowledge Utilisation Gap

The credibility gap is further reinforced by the strong perception of greenwashing (4.38). Respondents frequently questioned the authenticity of environmental and sustainability claims communicated by brands. This finding suggests that Generation Z is highly sensitive to inconsistencies between communicated values and actual organisational behaviour. Consequently, communication efforts focused on transparency do not automatically lead to greater trust if authenticity is perceived as questionable. A second gap was identified in the area of communication clarity. Although respondents generally viewed digital communication positively, the clarity of communication received only a moderate rating (3.53). This indicates that information may be available and accessible but is not always communicated in a sufficiently clear and meaningful way. The findings therefore point to limitations in the effectiveness of information transfer within digital brand communication. The third identified gap concerns the influence of digital communication on decision-making processes. Despite the high frequency of digital content consumption and the positive perception of digital communication, its impact on purchase decisions remained only moderate (3.48). The results suggest a gap between the cognitive and behavioural effects of digital communication. While digital communication contributes to a better understanding of brands and increases information availability, its ability to directly influence purchasing decisions remains limited. This indicates that knowledge transfer does not automatically result in its practical utilisation in consumer decision-making. The identified gaps confirm that the most significant shortcomings of digital brand communication relate to trust building, perceived authenticity of communicated information, communication clarity, and the ability to influence consumer decisions. These areas represent key challenges for organisations communicating with Generation Z in the digital environment. The contribution of this study lies not in identifying Generation Z's preferences themselves, which have been examined in previous research, but in interpreting the identified gaps through a knowledge management perspective. The findings indicate that the challenges of digital brand communication cannot be explained solely by content-related or technological factors but also by deficiencies in knowledge credibility, knowledge transfer, and knowledge utilisation within the communication process. The application of gap analysis in conjunction with these concepts extends existing knowledge of digital communication and provides a basis for further academic discussion on the role of knowledge management in marketing communication. The findings answer the research question by suggesting that the most significant discrepancies between expectations and perceptions occur in the areas of knowledge credibility, knowledge transfer, and knowledge utilisation within digital brand communication. The results further indicate that the greatest challenge of digital brand communication is not the lack of digital tools or innovative formats, but the ability to transform communicated information into credible and actionable knowledge. From a knowledge management perspective, effective digital communication therefore requires not only technological innovation but also trust, clarity, and practical value for the target audience.

5. Discussion

The findings confirmed that digital communication represents a natural way for Generation Z to obtain information and interact with brands. The high level of social media use and the positive perception of digital communication indicate that digital platforms play a significant role in shaping attitudes and consumer behaviour. This finding is consistent with previous studies highlighting the dominant position of digital media in the everyday lives of Generation Z (Kovács et al., 2024; Dašić, 2023). The results also suggest that digital

innovations increase the attractiveness of communication and enhance brands' ability to capture users' attention. Respondents particularly valued interactive and innovative communication elements, confirming the importance of personalisation and technological innovation in fostering customer engagement (Daiva et al., 2025; Gündüzyeli, 2026). However, technological sophistication alone does not guarantee higher levels of trust. A key finding is the discrepancy between respondents' expectations and their actual perceptions of digital brand communication. Although transparency was considered an important prerequisite for trust, overall trust in brand-communicated information remained relatively low. Combined with the strong perception of greenwashing, this finding highlights the importance of authenticity and communication consistency. The application of gap analysis revealed the most significant discrepancies in the areas of information credibility, transparency, and the ability of communication to support consumer decision-making. The findings suggest that organisations should focus not only on technological innovation but also on the quality and credibility of communicated information. From a knowledge management perspective, the identified gaps point to limitations in knowledge credibility, knowledge transfer, and knowledge utilisation. Organisations should therefore ensure that acquired insights are communicated in a manner that is credible, understandable, and relevant to users. The results further confirm the strategic importance of knowledge management in brand communication with Generation Z. As a generation characterised by intensive online interaction, constant access to information, and expectations of authentic and personalised communication, Generation Z requires organisations not only to communicate through digital channels but also to systematically acquire, analyse, and utilise knowledge about customer preferences, behaviours, and values. Digital innovations such as analytics tools, personalisation systems, social media, and artificial intelligence facilitate this process by transforming data into actionable knowledge. The value of knowledge management lies in its ability to convert data and feedback into communication decisions that enhance relevance, credibility, and audience engagement. The findings indicate that the availability of data and technology alone is insufficient. Organisations must also be able to understand and effectively apply acquired insights, as the ability to integrate knowledge with digital innovations is essential for building trust and long-term relationships with Generation Z. From a practical perspective, organisations targeting Generation Z should combine digital innovation with authentic, transparent, and personalised communication. The long-term value of digital innovations lies not only in increasing user engagement but also in supporting the creation, transfer, and utilisation of knowledge between organisations and their customers. The ability to transform data from digital interactions into actionable insights represents an important prerequisite for building trust, brand relevance, and long-term customer loyalty.

6. Conclusion

The aim of this study was to analyse the value of digital innovations in brand communication from the perspective of Generation Z and to examine their role in knowledge management processes. The findings confirm that digital innovations are an important component of contemporary marketing communication, particularly in enhancing user engagement and improving access to information. Generation Z perceives digital communication as a natural form of interaction and prefers interactive, visual, and personalised content. The results also indicate that digital innovations do not automatically increase trust or significantly influence purchasing decisions. The study identified notable gaps between respondents' expectations and their perceptions of brand communication, particularly regarding transparency, credibility, and authenticity. These findings highlight the importance of communication quality and its ability to create value for users. The main contribution of the study lies in the application of gap analysis, which revealed shortcomings in knowledge credibility, knowledge transfer, and knowledge utilisation. The findings provide organisations with practical insights for developing more effective digital communication strategies and better aligning communication with the expectations of Generation Z. From a knowledge management perspective, the study emphasises the importance of transforming data from digital interactions into actionable insights that support decision-making and customer relationships. The effectiveness of digital innovations therefore depends not only on technology but also on an organisation's ability to create, transfer, and utilise relevant knowledge. The study is limited by the use of a convenience sample from an academic environment, which restricts the generalisability of the findings. Nevertheless, it integrates digital innovation, brand communication, and knowledge management into a single analytical framework and offers practical implications for organisations operating in digital environments. Future research could compare different generations or countries and further examine the impact of emerging technologies, including generative artificial intelligence, on communication and knowledge management processes.

Acknowledgements

This paper was elaborated within a national research project supported by the Grant Agency of the Ministry of Education, Research, Development, and Youth of the Slovak Republic and the Slovak Academy of Sciences (VEGA) No. 1/0304/24 titled 'The Impact and Value of Digitalization of Innovations of Products Marketing Communication for Generations of Ecological Users'.

Ethics Declaration: The research presented in this paper was conducted using an anonymous questionnaire survey. Participation in the study was voluntary, and respondents provided informed consent for the processing of their data. No personally identifiable data were collected. Therefore, no formal ethical approval was required.

AI Declaration: Artificial intelligence tools were used in the development of this paper solely to assist with language translation and editing. All outputs generated by AI were critically reviewed, revised, and adapted by the author to ensure accuracy, originality, and academic integrity.

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Why SMEs Don't Use Academic Research: The Knowledge-to-Action Gap

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Abstract: Small and medium-sized enterprises (SMEs) often express baseline trust in academic research, yet report limited ability to translate research outputs into actionable decisions and routines. To address this phenomenon, this study examines a) the mechanisms that create a gap between trust in academic research and practical use, b) how SMEs move from accessing research to making sense of it and applying it in practice—and where this "research to action" process most commonly breaks down—and c) how differences in absorptive capacity and related routines explain variation in research utilization. Empirically, we draw on semi-structured interview data collected by the NOKKA project in southeastern Finland, comprising 23 SME representatives. The empirical analysis is grounded in three complementary perspectives. First, absorptive capacity explains firm-level differences in recognizing, assimilating, and exploiting external knowledge, offering a capability-based indicator of why some SMEs can convert research insights into practice more readily than others. Second, knowledge transfer stickiness provides a barrier-focused perspective on why knowledge—even when valued—tends to "stick" and fail to transfer into routines, highlighting frictions such as ambiguity and recipient-side constraints. Third, research utilization clarifies what "using research" can mean in practice (e.g., instrumental vs. conceptual use), while evidence-based management explains why and how research insights should be translated into actionable managerial practices to narrow the research–practice gap. Interview evidence indicates that SMEs typically rely on fast, familiar information channels, experience uncertainty and opportunity costs when assessing relevance and comprehensibility, and most frequently struggle at the point of converting insights into implementable actions. We further observe meaningful variation in "research literacy" and routines, suggesting different absorptive-capacity profiles across firms. This paper derives actionable guidance for designing low-barrier support that helps SMEs (i) find relevant research efficiently, (ii) reduce sensemaking costs, and (iii) operationalize evidence through case-based and action-oriented translation artefacts and facilitation.

Keywords: University-industry collaboration, Small and medium-sized enterprises, Research utilization

1. Introduction

University–industry collaboration (UIC) has become increasingly important as firms operate under persistent pressure to adapt and renew themselves. Small and medium-sized enterprises (SMEs) in particular face a demanding combination of rapid technological change alongside shifting market expectations, geopolitical uncertainty, and financial constraints. In such conditions, the ability to identify, absorb, and apply new information and practically usable knowledge becomes a central requirement for maintaining competitiveness. Universities represent a prominent and widely recognized source of such knowledge, offering research-based insights that can, in principle, support firms' learning, decision-making, and renewal.

UIC has been examined from multiple perspectives, such as the Triple Helix (and subsequent) model (Etzkowitz and Leydesdorff 2000, Cai and Etzkowitz 2020, El-Ferik and Al-Naser 2021, Tereschenko et al. 2024), which highlights the structures and interplay among universities, industry, and government. Later on, the attention has shifted from structural framing to a more processual and capacity-based framing (Mura, Di Flauro, and Fratocchi 2025), highlighting the barriers for knowledge-to-action, such as knowledge ambiguity, low absorptive capacity, and institutional cognitive differences (de Wit-de Vries et al 2018).

The success of collaboration efforts often hinges on acquired trust (Darabi, Saunders, and Clark 2021), and while SMEs may express baseline trust in university-produced knowledge and often regard academic research as credible (Rantala et al 2025), this trust does not automatically translate into systematic use. Barends et al. (2017) suggest that although SME managers may report positive attitudes toward evidence-based practice, they also report major barriers, such as a lack of time and limited understanding of scientific research to its uptake and implementation, suggesting that favourable attitudes do not automatically translate into systematic use. Personal experience and established practices can also affect the uptake of research evidence, as Rousseau (2006) suggests. Additionally, de Wit-de Vries et al (2018) argue that fear of opportunistic behaviour may limit the collaboration even further. Thus, we can identify a noticeable knowledge-to-action gap: knowledge that is accessed and even valued may still fail to translate into concrete decisions, routines, or implementable practices.

This paper addresses that gap by focusing on the research-to-action chain and by identifying where frictions most commonly emerge along the path from research access to practical application. Empirically, the study draws on thematic interview material collected from 23 SME representatives in southeastern Finland, providing a grounded basis for examining how research-based knowledge is encountered, interpreted, and (not) translated into action in organizational settings.

2. Theoretical Foundation and Research Questions

The knowledge-to-action process involves multiple steps for success. Therefore, the gap within it is unlikely to be explained solely by attitudes or processes. To address this gap, this study formulates three distinct research questions to clarify the drivers behind the observed disconnect between knowledge and action.

First, RQ1 focuses on explanation by asking which mechanisms and barriers create the disconnect between SMEs' baseline trust in academic research and their limited practical use of research outputs. The aim is to move beyond a generic "lack of use" claim and specify what prevents trusted knowledge from translating into implementable actions and organizational routines. Survey evidence suggests that SMEs may value research produced by academic institutions, indicating that university-produced research is often perceived as credible in principle (Rantala et al 2025). At the same time, research on SME–university collaboration shows that this trust is not unconditional: SMEs place importance on selecting academic partners they can access and understand, influencing how credible and useful the university partner is perceived to be in delivering the knowledge the firm seeks (Johnston 2022, Darabi, Saunders and Clark 2021). In addition, studies of SME-university collaborations emphasize that trust is initiated and developed through factors such as networking and referrals (Darubi, Saunders, and Clark 2021) and that, in a general setting, trust evolves as SMEs form judgments about their counterparts' competence and integrity (Schoorman, Mayer and Davis 2007). Taken together, these insights suggest that the relevant problem is not only whether SMEs trust academic knowledge as such, but also whether they trust that it can generate practical value under the constraints of everyday managerial work. Therefore, we formulate our first research question as

RQ1: What are the central mechanisms and barriers that weaken SMEs' trust in the practical usefulness of academic research, even when the research itself is considered credible?

Second, translating academic research into day-to-day managerial action is not a single decision but a process that unfolds through multiple steps. In SME settings, this translation problem is especially salient because firms may value university-produced research, yet still struggle to convert it into implementable practices. The core phenomenon addressed by RQ2 is therefore the "results-to-action" pathway: how research moves from being available to becoming actionable inside the firm.

The translation challenge is best examined by separating sensemaking from implementation. Sensemaking refers to how managers interpret research and connect it to their own context so that it becomes meaningful enough to guide action (Weick, Sutcliffe and Obstfeld 2005, Maitilis and Christianson 2014). This step is often difficult in university–industry settings because differences in goals and knowledge bases can create ambiguity and absorption problems (de Wit-de Vries et al., 2018), making it hard to interpret the findings in the firm's specific situation. However, even when SMEs succeed in making sense of the research, they may still fail to use it in practice. The knowledge transfer literature notes that partners often face difficulties with the application of knowledge, even when strong scientific evidence is provided (de Wit-de Vries et al 2019, Rynes, Giluk and Brown 2007, Lawler 2007), indicating that the bottleneck may occur after interpretation, when insights need to be converted into routines, decisions, or concrete interventions. This suggests that a limited understanding of the applicability process of scientific research is perceived as a major barrier to uptake and implementation, thereby preventing action even when the underlying message is understood. Therefore, we propose the following research question

RQ2: How do SMEs move beyond accessing academic research to making sense of it and applying it in practice, and where does this "results to action" process most commonly break down?

While RQ1 identifies the mechanisms that weaken SMEs' trust in the practical usefulness of academic research, and RQ2 examines where the research-to-action chain most commonly breaks down, they do not yet explain why some firms are more successful than others in exploiting research-based knowledge. To address this remaining gap, we turn to the concept of absorptive capacity, commonly understood as a firm's ability to recognize the value of external knowledge, assimilate it, and apply it to commercial ends (Cohen and Levinthal 1990).

In the SME context, absorptive capacity is especially consequential because firms typically operate under significant resource constraints. Limited time, scarce specialized personnel, and restricted internal R&D capacity or knowledge management processes reduce the ability to systematically search for, interpret, and utilize external knowledge (Johnston 2020, Warren 2025). At the same time, absorptive capacity is not solely an internal attribute. Prior research on university–industry knowledge transfer shows that communication, experience, and the use of intermediaries can facilitate knowledge absorption and application (de Wit-de Vries 2019), allowing SMEs to access complementary and diverse expertise that would otherwise remain beyond their reach (Benhayoun-Sadafiyine et al 2020). Finally, absorptive capacity is shaped by organizational conditions inside the firm. Research on organizational antecedents shows that coordination mechanisms, participation in decision-making, and socialization capabilities influence firms' ability to create value from external knowledge (Jansen, van den Bosch and Volberda 2005), while weak knowledge-oriented leadership and underdeveloped organizational capabilities can suppress firms' innovativeness by limiting their ability to assess and use external knowledge effectively (Ćirović et al 2026). These insights suggest that differences in the utilization of academic research are also reflected by the variation in SMEs' absorptive capacity and the routines through which it is enacted. We therefore propose the following third research question:

RQ3: How do SMEs' absorptive capacity and related routines explain differences in the utilization of academic research?

3. Empirical Part

The empirical material for this study was collected as part of the NOKKA research project during the winter of 2025–2026, with a focus on understanding how SMEs utilize academic research in their operations. The interview material consists of 23 interviews with SME founders or CEOs in southeastern Finland and was collected using a semi-structured interview template covering themes such as knowledge acquisition practices, attitudes towards academic research, competencies in translating academic output, and possible intermediaries in the process. During the interviews, the interviewer could expand on a theme and ask follow-up questions when needed. All interviews were conducted via Microsoft Teams with transcription enabled. In addition, the interviewers had the option to make their own notes, which were added to the individual transcripts.

The interview material was analysed using a theoretically informed thematic analysis (Brown and Clarke 2006). The transcripts were first read repeatedly to become familiar with the material, after which segments semantically related to the research questions were coded. Because the analysis was guided by the three research questions and their underlying concepts, the coding was not fully inductive but rather directed, with prior literature and the research questions providing the starting point to the categories, as Hsieh and Shannon (2005) suggest. The resulting codes were then compared across interviews and grouped into higher-order themes that captured recurrent mechanisms, process breakdowns, and capability differences. The quotations reported in the empirical section were selected as illustrative evidence of these broader themes, not as standalone anecdotes, so that individual excerpts are interpreted in relation to the full dataset and the cross-case analytical patterns identified during coding

3.1 Research Question 1

Regarding RQ1, the interviews suggest that SMEs differentiate between trust in the credibility of academic research and confidence in its practical usefulness. The main barriers do not concern whether research is "true," but whether it can be converted into context-relevant action with acceptable effort.

First, the most prominent trust barrier is a translation gap between research and applicability. SMEs commonly accept academic work as credible, yet struggle to see a clear pathway from results to concrete next steps. This is captured in interview wording such as: "Nice, but how does this help us?" and the recurring demand for a bridge between research and action: "How do we turn this into action?" Presenting explicit use cases is seen as one tool for closing this gap: "The biggest obstacle is putting it into practice… it would help if there was already a case or example of what this means in practice and how to apply it."

Second, time pressure amplifies "relevance risk" and reduces perceived usefulness. SMEs describe limited time as the binding constraint, which makes engagement with research a calculated risk. One respondent frames the barrier as "purely about time use", and another specifies the downside of low relevance as "wasted time… away from other work, meaning lost money." Similar accounts in the interview summaries describe day-to-day work as leaving little room for deeper engagement with research.

Third, academic jargon and formatting can obscure applicability and increase interpretation costs. Several interviews note that academic terminology requires extra concentration because it is unfamiliar, even when the underlying topic is relevant. Translation tools can reduce language friction, but do not remove the need to "decode" academic structure into practical implications. Having said that, the data does show some variation: some respondents report that jargon is "not usually a problem," especially when they already rely on translation tools and have more established routines for engaging research.

Multiple interviews indicate that SMEs rely on fast, familiar channels (newsletters, blogs, and networks) for actionable knowledge, while academic databases are rarely part of day-to-day problem solving. In the transcribed discussion, one respondent describes staying current as a personal responsibility through "following industry people, news, and mailing lists", and notes using "YouTube bloggers who go through headlines and results". The same respondent also frames operational problem-solving as happening elsewhere: "practical problems are usually solved via Google". Consistently, the interview summaries describe Google and organizational websites as natural starting points, implying that scholarly repositories are perceived as a poor fit for "in-the-flow" work.

At the same time, practical trust increases when research arrives already curated and formatted for use. One respondent explicitly reports that useful research information is "already filtered and written in plain language" through professional associations and regular communications, reducing the effort required to extract actionable implications. This suggests that intermediaries and ecosystem actors can strengthen trust in usefulness by embedding research in SMEs' practical context and presenting it in an action-oriented form. RQ1 results can be generalized as follows:

- SMEs generally trust the credibility of academic research, but not automatically its practical usefulness
- The main barriers are a translation gap from research to practice, time pressure, relevance risk, and the extra effort caused by academic jargon and formatting.
- In practice, SMEs rely on fast, familiar, and curated channels rather than academic databases

3.2 Research Question 2

RQ2 examines how SMEs move from merely encountering research to (a) making sense of it in their own organizational context and (b) converting that understanding into implementable actions, routines, or decisions. Across the interview material, this progression is best described as a two-step translation process with substantial variation in individual and firm-level sensemaking capacity, followed by a recurring bottleneck at the point of operationalization.

For the most part, the respondents describe academic texts as requiring additional effort due to unfamiliar terminology and structure. For example, one interviewee notes that engaging academic reports "requires concentration" because terminology is often unfamiliar, while language can add friction even though translation tools help. This variability matters because SMEs frame engagement as a cost–benefit decision: when firms have internal competence, use translation tools, or rely on already-processed inputs, the perceived sensemaking cost decreases.

However, even when meaning is understood, application commonly fails because the "how-to" layer is missing. "The biggest obstacle is putting it into practice," and that it would help to have "a case or example of what this means in practice and how to apply it." This emphasis aligns with accounts in which research is seen as interesting but not sufficiently anchored in operational terms (e.g., outcomes tied to sales or revenue) to justify the implementation effort.

Finally, interviews highlight a second, reinforcing barrier: implementation requires time and routine change under resource scarcity, which creates uncertainty about whether the insight will "pay off" in the firm's context. This is expressed as opportunity cost—for instance, one respondent frames non-relevance as "wasted time… away from other work, meaning lost money". Taken together, RQ2 results indicate that breakdowns happen between understanding and doing, unless research is accompanied by concrete translation artefacts (cases, examples, or stepwise guidance) that reduce perceived implementation risk. RQ2 findings can best be summarized as follows:

- The research-to-action process is best understood as a two-step translation process: first, SMEs must make sense of research, and second, they must convert that understanding into action.

- The dominant bottleneck lies after sensemaking: research may be understood, but the application fails because the practical "how-to" layer is missing.
- Implementation is further constrained by resource scarcity, routine change, and uncertainty about payoff, which can also weaken future willingness to engage with research.

3.3 Research Question 3

Regarding RQ3, the interviews suggest that differences in SMEs' use of academic research can be explained by variation in absorptive-capacity profiles and related routines, rather than by simple differences in attitudes toward science. The material points to three recurring profiles. High-AC SMEs engage with research relatively actively and systematically. In these firms, research use appears to be part of continuous development, as illustrated by cases where firms "read research weekly" across domains such as IT, economics, industry, AI, and management.

Medium-AC SMEs, by contrast, engage research more indirectly and reactively: knowledge use is typically triggered by newsletters, media, networks, or other intermediaries rather than by direct use of academic channels. They follow news "from own informal network, with which I stay in regular contact, receiving information on practices across different fields—offering collective support and perspectives on challenges and successes." This suggests both that this profile outsources the research sensemaking to other parties, but that there is also a collective component on display, where practical value for the research is created together with industry peers.

Finally, low-AC SMEs are characterized by weak routines for research acquisition and use, not because research is considered untrustworthy, but because it is perceived as insufficiently practical under everyday operating constraints. This is reflected in statements such as "time goes into keeping the projects running" and "time for searching and utilizing [research] is very limited." Overall, the key variation in absorptive capacity seems to lie in routines: higher-AC firms possess either internal sensemaking capacity or access to capable intermediaries, whereas lower-AC firms remain dependent on practice-native information channels and struggle to connect research to action. A breakdown of RQ3 findings can be found below:

- Differences in research utilization are best explained by variation in absorptive-capacity routines, not by simple pro- or anti-research attitudes.
- High-AC SMEs use research actively and systematically, medium-AC SMEs rely on mediated and reactive access through networks and intermediaries, and low-AC SMEs have weak routines and see research as too impractical for everyday operations.
- Overall, the key variation lies in whether firms have the routines and capabilities needed to acquire, interpret, and exploit external knowledge directly or through capable intermediaries.

4. Conclusions and Recommendations

This study explains why SMEs may trust academic research in principle yet still fail to use it systematically in practice. The findings suggest that the core problem is not credibility, but the difficulty of translating research into context-relevant, low-effort action, consistent with prior work showing that firms may value research while still facing major barriers to implementation (Barends et al. 2017; de Wit-de Vries 2019).

The findings connect the three research questions into a single process explanation. RQ1 shows that practical trust weakens when research is perceived as costly to interpret and difficult to translate. RQ2 shows that the main breakdown occurs not primarily at access or interpretation, but after sensemaking. This aligns with prior knowledge transfer research showing that ambiguity, absorption problems, and difficulties in applying knowledge often prevent successful transfer even when valuable knowledge is available (de Wit-de Vries 2019).

These mechanisms also appear mutually reinforcing. Disappointment in sensemaking or implementation can feed back into future trust judgments, linking RQ2 back to RQ1. If an SME invests effort in interpreting academic output but fails to derive practical value, later encounters may be approached with lower expectations and greater scepticism. Low practical use can therefore become self-reinforcing: unsuccessful translation attempts reduce willingness to engage and inhibit the development of routines that would make later engagement easier. This interpretation is compatible with earlier work suggesting that trust in UIC settings is shaped not only by perceptions of competence and integrity, but also by prior interactions and reciprocal experiences that reinforce willingness to cooperate (Cohen and Levinthal 1990; Darabi, Saunders and Clark 2021).

RQ3 provides a firm-level explanation for why this process unfolds differently across SMEs, as variation in research utilization is best explained by differences in absorptive capacity routines. SMEs differ in their ability to acquire, assimilate, and exploit external knowledge, and these differences appear in recurring high-, medium-, and low-AC profiles. This is partly aligned with Benhayoun-Sadafiyne et al. (2020), who show that SMEs' absorptive-capacity practices vary in focus and intensity depending on context, and with work emphasizing that organizational antecedents of absorptive capacity—such as coordination mechanisms, socialization, and knowledge-oriented internal capabilities—shape whether firms can create value from external knowledge (Jansen, van den Bosch and Volberda 2005). Taken together, the findings suggest that the SME knowledge-to-action gap is a layered problem: firms must first assess whether research appears usable, then make sense of it in context, and finally convert interpreted insights into action. Whether they succeed depends heavily on absorptive-capacity routines and the availability of translation support.

4.1 Theoretical Contribution

Theoretically, the study contributes by integrating three perspectives that are often treated separately: practical trust in research, research-to-action translation, and absorptive capacity. Existing literature has identified these elements individually—trust as a relational condition of collaboration (Darabi, Saunders and Clark (2021), knowledge transfer barriers as sources of ambiguity and application failure (de Wit-de Wries et al 2019), and absorptive capacity as a firm-level capability for processing external knowledge (Zahra and George 2002). This study shows that, in the SME context, these should be understood as sequentially rather than as isolated themes. This integrated account extends the knowledge-to-action discussion beyond the generic claim that SMEs "do not use research" by specifying how credibility, sensemaking, and capability interact over time.

Additionally, this study sharpens the distinction between trust in research and trust in the usefulness of research. Much UIC literature emphasizes trust as a precondition for collaboration, yet the present findings suggest that, the more relevant problem is not distrust in science per se but distrust in the usefulness of science. This moves the discussion closer to the research utilization and evidence-based management literature, where the challenge is not simply awareness of evidence but its operational relevance and translatability. By linking this distinction to a feedback loop between failed sensemaking and future trust, the study also offers a more dynamic interpretation of how trust may erode through repeated, but disappointing, attempts to use academic knowledge.

Finally, the study contributes to absorptive capacity research by showing that, in the context of academic research use by SMEs, the decisive variation lies less in abstract openness to knowledge than in the presence or absence of routines that support repeated acquisition, interpretation, and application. This finding supports the view that absorptive capacity is enacted through concrete organizational mechanisms rather than existing as a static firm trait. In the SME setting, it also highlights the relevance of mediated and networked forms of absorptive capacity, where external actors and intermediaries partly substitute for missing in-house capabilities.

4.2 Practical Contribution for UIC

From a UIC perspective, the practical implication is clear: if universities want SMEs to use research more systematically, they should not assume that credibility is sufficient. The main challenge is to increase the usability of research outputs. This means presenting findings in a form that reduces interpretation costs and shortens the path from results to application. This implication is consistent with prior UIC and knowledge transfer literature, which emphasizes the importance of intermediaries, communication, and practical contextualization in overcoming ambiguity and application barriers.

A second implication is that UIC initiatives should be designed not only to transfer knowledge, but also to build absorptive-capacity routines inside SMEs. This means supporting firms in developing repeated practices for identifying relevant research, interpreting it in context, and linking it to decisions and routines. For high-AC firms, this may require direct access to advanced research outputs and dialogue with academic experts. For medium-AC firms, intermediated and peer-supported formats may be more effective, such as curated briefings, translated research summaries, and network-based discussion. For low-AC firms, the priority may be to lower entry barriers by embedding academic insights into very concrete, problem-centered formats that fit operational realities.

Third, the findings suggest that universities and intermediary actors should take the risk of negative cumulative experiences seriously. If SMEs repeatedly encounter research in forms that are difficult to interpret and impossible to operationalize, they may gradually disengage from academic knowledge channels altogether.

UIC practice should therefore aim not merely at contact creation, but at creating early experiences of practical success. In this sense, successful UIC may depend less on persuading SMEs that academic research is valuable, and more on demonstrating that it can be translated into workable action under the time and resource constraints of small firms.

Ethics Statement: Ethical clearance was not required in this research. All necessary permissions for research were obtained at the time of interviews, and the data used in the analysis was anonymized.

AI Declaration: Generative Artificial Intelligence tools were used in the generation of this paper in the following way: 1) Proofreading and grammatical errors (Grammarly), 2) Refining the overall tone of the text and checking for inconsistencies (Microsoft Copilot GPT-5.4, Gemini 2.5). All ideas and content originate from the author.

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Environmental Knowledge Management from the Perspective of Young Employees: An Economic Sector Comparison

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Abstract: Currently, degradation of the natural environment led many companies to consider implementation of more sustainable practices. In the academic literature, environmental knowledge required and acquired by employees, moreover, is often considered part of knowledge management, with a growing number of researches focusing on Environmental Knowledge Management (EKM). In practice, however, EKM in firms from different sectors vary and interventions are sometimes lacking. The research objective of the current paper is to examine selected elements of the EKM in enterprises operating in different economic sectors. Three research questions connected with EKM functioning were thus enquired through a structured questionnaire, sent electronically to employees, using non-random, convenience sampling. Therefore, statistical analysis of the 297 collected questionnaires stressed a high relevance of environmental protection without differentiation between economic sectors, while the EKM assessment of employees varies between firms from different sectors. The evaluation of EKM, moreover, does not align with the relevance of environmental protection according to most of the employees, signalling – based on motivation expectancy theory – a moderate dissatisfaction with the functioning of EKM among young employees and the existence of an intensification potential of unused environmental protection policies in companies interested. These findings confirm that there is potential among staff to implement a more effective EKM system, yet in practice companies are not making use of it.

Keywords: Environmental knowledge management, Environment, Employees, Economic sector, Environment protection, Expectancy theory of motivation

1. Introduction

Current climate change and the prevailing consumer trends are encouraging companies to reduce the negative environmental impact of their operations. Upcoming regulatory changes and increasing public awareness of environmental issues are more compelling arguments for integrating EKM into the strategy and daily functioning of companies at all levels. Activity in this area offers the opportunity to build a competitive advantage, as well as to implement eco-innovations and sustainable practices. Combining industrial ecology with knowledge management (KM) tools and concepts leads to the creation of an EKM system (Wernick, 2003). Implementing this system and making it available to employees at all levels of the organisation enables them to achieve an appropriate level of environmental awareness and make environmentally sound decisions regardless of their position (Huang and Shis, 2009). Companies using EKM-based management can increase resource productivity and reduce waste generation. Environmental knowledge encompasses what employees know about natural environment protection, what raises their concern in connection to it, and their responsibility for environmental protection. Those elements then seem perfectly in line with the overall principles of sustainable development both at whole economy and single organization level (Frick et al., 2004). As market-oriented enterprises play the most significant role in generating negative environmental impacts, monitoring and improving their performance in this regard should therefore be a strategic priority (Wang et al., 2023). Despite the growing importance of environmental protection within companies, research to date has mainly focused on organisational strategies, manufacturing and production technologies, and the views of senior management. The opinions and perceptions of front-line staff on this issue have been analyzed much less frequently. This issue seems particularly important given the entry of generation Z into the labour market. The members of this group are characterised by high environmental awareness and high employer expectations.

2. Literature Review

KM within a company and knowledge utilisation are crucial for the achievement of organisation objectives. Knowledge base and its dissemination constitute, in fact, the foundation of an organisation's competitive advantage (Muscatello, 2003). During the progressive process of continuous improvement of business strategies, knowledge has become a valuable resource that determines competitiveness and fosters the creation of an innovative environment (Yusof et al. 2012; Lee and Lee, 2023). Since knowledge within an organisation is, by its very nature, dispersed, KM systems must integrate it from various sources (Mahmood et al., 2023). One of organisations main tasks is then to develop, disseminate, and utilise knowledge (Zhang 2024).

The characteristics of a KM system relate to principles such as: employee-centredness, treating employees as the primary resource for creating, accumulating, and applying knowledge, and increasing the effectiveness of activities through employee initiative (Edwards, 2022).

KM is one of the most important and strategic areas within organizations in the process of implementing and maintaining sustainable development (Hassanzadeh et al., 2023). A company's focus on KM in the context of sustainable practices determines its position as a responsible entity fulfilling its obligations regarding natural environment respect (Chopra et al. 2021). In this context, KM has emerged as an additional tool available to companies and supporting the implementation of sustainable development practices (Chang et al. 2018). Internal knowledge sharing is crucial to promote training and continuous improvement in EKM within companies, while employees' trainings are considered one of the key factors influencing their competencies (Tongsamsi and Tongsamsi, 2015). This process provides them with the knowledge, skills, and competencies necessary for the organisation to face new and changing requirements (Wedchayanon, 2009). Insufficient knowledge by employees leads to failure to achieve company objectives. The role and importance of training in the process of acquiring environmental knowledge are confirmed by the research of Moraes et al. (2019), which was carried out in the financial sector and confirms the impact of training on ecoefficiency in banking.

Further research on EKM was conducted by Goh et al. (2012), focusing on the environmental performance of companies in Malaysia, pointing out that socialization, externalization, and internalisation play a very significant role in employee engagement and EKM effectiveness. These research conclusions, moreover, stress the importance of further discussion on KM and potential initiatives concerning practices and mentoring, that will involve experts (Goh et al., 2012). Huang and Shish (2009) research based on metallurgical industry analysis stressed that information flow among employees has a significant impact on EKM. Based on a case study analysis, they pointed out that in particular this can take place through an institutionalised process, relaying on the creation, collection, sharing, utilisation, and internalisation of environmental knowledge. Based on such a study, continuous KM improvements have led to a reduction in water consumption and atmospheric emissions in the metallurgical sector (Huang and Shish, 2009). In turn, research by Scuotto et al. (2024), based on the touristic sector as an example, showed that behavioural intent and personality have a significant influence on attitudes towards environmental issues. These authors, furthermore, argue for the need to enforce and promote EKM in that sector (Scuotto et al. 2024).

Research conducted by Kabaja (2025) in the food service industry revealed that both training and the EKM system are lacking. Furthermore, there was a lack of commitment from the supervisors and the employees expected greater initiative and motivation from the management. The employees of this study reported that their companies could be more environmentally friendly, but the issue was not considered the most relevant (Kabaja, 2025). Meanwhile, Belijić et al. (2013) drew attention to good practices in the food and beverage industry. The research revealed that companies in this sector are highly aware of KM, although none of them has yet developed a specific KM policy or strategy.

Despite the growing number of studies dedicated to EKM, there are still relevant gaps to fill in the literature. The existing analyses, indeed, generally focus on single economic sectors (e.g., tourism, food services or finance), often hindering comparisons with other ones since each research uses a different scale and measurement method, or focuses on different geographical areas.

Furthermore, many studies address mainly the organisational or managerial level, overlooking the individual perspective of frontline workers. Yet, very often, workers are those who actually determine environmental outcomes, having an impact on environment through the many relevant decisions they take day by day. They, moreover, shape the organisational climate in which environmental protection and KM take place, influencing organisational culture practical application and its effects on firm functioning. When conducting EKM research, it is also important to take into account the general level of environmental awareness within the populations under study. An analysis of the findings of Piekarski et al. (2016) conducted in Poland demonstrates that environmental awareness is influenced by numerous variables. For example, people living in rural areas pay greater attention to issues of water or forest pollution (Piekarski et al., 2016). This confirms the existing and well-documented relationship in the literature between environmental awareness and the level of industrialization and urbanization of the respondent's place of residence. Therefore, the effectiveness of ECM practices may depend not only on organisational practices, but also on employees. Consequently, the effectiveness, suitability, and acceptance of environmental knowledge may vary among employees and depend on them.

Basing on expectancy theory of motivation and the associated motivational system effectiveness evaluation methodology (Lawler and Porter, 1967; Nadler and Lawler, 1977; 1989; 2007), moreover, the main factor that can affect employee behaviour and commitment to various goals and objectives is subjective worker expectations about potential outcomes of actions carried out in a given organisational context. These expectations are in turn affected by the subjective internal and intrinsic assessment by employees of a given value, the relevance of a goal, or the aim. As was originally done in the aforementioned studies, then current research assumes that each person differs from another in terms of needs, values, and behaviour in a given situation, while the same person reacts differently to various situations arising in the workplace, rationally making decisions about his or her own behaviour based on its expected outcomes. Therefore, a survey among employees of companies from various sectors was conducted, focusing in particular on young workers from generation Z in the early stages of their career. Based on data from the Polish Statistic Office, in 2024 generation Z employees - eg individuals born after 1995 (Różańska-Bińczyk, 2022) – constituted, indeed, between 15 and 16 % of the workers employed in the country, representing a relevant part of the workforce. As stressed by Różańska-Bińczyk (2022), in addition, in Poland generation Z respondents tend to evaluate highly environmental protection and ecology as a social goal in general and take into account such aspects as firm reputation for engaging in eco-friendly practices upon selecting their employer. In terms of motivation, then, this can be considered as a higher subjective value attributed to environment protection by generation Z employees. If, as emerges from data analysis, such workers highly praise interventions aimed at improving and extending environment protection, as per Kotter (1995) change implementation model, in turn, they can be considered as a very useful basin of potential change agents more willing than others to implement such policies and EKM strategies. According to Scuotto et al. (2024) – as well as based on more theoretical considerations based on the Holland (1997) person-environment fit model and the widespread use of personality questionnaires in worker selection – the prevalence of environmentally friendly values and attitudes among such types of employees can support the idea that they can be the loudest representatives of O'Connor's (1993) opponent style of behaviour to insufficient environmental protection practices. Moreover, exactly such factors can constitute a potential advantage for firms willing to implement or improve EKM policies and support the diffusion of eco-friendly practices. As a matter of fact, they can be able to use exactly such kind of workers attitude as a leverage to overcome the current status quo inertia, in the unfreezing and then refreezing phases of more eco-friendly policies implementation as per Lewin (1947) and Egan (1994) change models.

Although being partially an outcome of the focus on generation Z employees, finally, the high percentage of employees working for less than 5 years among the respondents can be considered a good proxy of the lower rank that the enquired workers have. It allows, thus, to assume the desired front-line workers' point of view in the analysis and to better assess the existence of unused potential for bottom-up environmental protection policies elaboration or the willingness of enquired category of employees to engage and adhere to more pervasive EKM top-down interventions.

Similarly to what happens with section A answers in the analysis of the Nadler and Lawler (1977; 1989; 2007) questionnaires, then the general relevance of personal environmental protection in the view of the respondents was first asked. As in section B of the aforementioned questionnaires, the respondents were then requested to provide their subjective assessment of various aspects of EKM functioning in the company in which they are employed. Therefore, it was assumed that precisely such subjective elements, arising from the interaction between, on the one hand, the actual measures taken as part of EKM within the company and, on the other, the personal preferences and evaluation of the situation by employees, can help to determine the desired direction of interventions aimed at improving EKM functioning in the companies considered and diagnose the eventual existence of unused potential for more extensive implementation of environmental policies.

In fact, the objective measures implemented within a given company were viewed merely as one of the factors influencing the actual functioning of the EKM within the company. These measures alone, however, would not allow providing an accurate assessment of the ultimate impact of the actions undertaken. They do not provide, in fact, sufficient information regarding the organisational context and climate in which EKM takes place. An analysis of the measures taken as part of EKM alone, as a matter of fact, would ultimately fail to take into account whether employees would be willing to increase their involvement in activities aimed at supporting environmental protection and if they are sufficiently motivated to do so without the need for additional incentives or the use of other persuasion and dissuasion means at the company end. Meanwhile, as any change implementation in firm operation practices and even more so in the case of overall strategic goals and policies

reshaping, improving or implementing from zero EKM in a given firm would need strong commitment from management and the highest possible support among employees to minimalize resistance to change and improve the chances of success of such undertakings. Assessing the existence of attitudes supportive to EKM improvements and environmental protection practices among employees seems then a crucial aspect to consider, before even starting to conceive an actual EKM improvement policy and plan the actual kind of interventions needed.

According to the authors, the presented considerations thus justify the need for cross-sectional research, encompassing studies across various sectors and focusing on generation Z frontline staff and their subjective assessment of both environmental protection relevance as a corporate objective and actual EKM functioning according to them. This approach then provides an opportunity to examine the practical aspects of EKM and compare them between sectors.

The purpose of the study is therefore to examine the selected elements of the EKM system in companies from different economic sectors. Based on the literature review presented and the signalized importance of environmental protection in companies and generation Z employees, the following research questions have then been formulated:

RQ1 – Environment protection relevance differs significantly according to employees of firm operating in different economic sectors?

RQ2 – EKM evaluation differs significantly per sector basing on employees opinions?

RQ3 – The personal evaluation of selected elements of company EKM according to workers is aligned with the environment protection relevance for the same employee?

3. Methodology

Quantitative research methods were used to achieve the objective of the study and answer research questions. The tool used in the study was a questionnaire distributed to respondents via the Internet in an online format. Convenience sampling was used. The questionnaire was structured and based on a review of the literature. It consisted of two parts: a demographic section and a substantive section. In the first section, respondents provided information regarding: gender, age, length of service, and sector in which the firm hiring them operates. In the second part, the questions were developed based on an analysis of previous research results described in the review of the literature. The study population consists of company employees. Given the exploratory and diagnostic nature of the study, it was deemed that a sample size of 300 respondents would be sufficient at this stage – Tab. 1.

Before the study began, a pilot test was conducted in the presence of the interviewer, to refine the questionnaire and to check whether the questions and the format were suitable for the respondents. The findings from this stage were used to make iterative improvements, ultimately resulting in a finalized and refined version of the questionnaire, collected and distributed electronically via a Google form. To achieve the objective of the study and answer the research questions, the final questionnaire was organized into four sections, allowing one to assess, respectively:

- environmental protection relevance for the employee – two questions,
- the availability and quality of training and support regarding environmental protection knowledge in employee firm – four questions,
- access to knowledge about environmental protection in worker company – three questions,
- the perceived commitment of the company representatives to environmental protection according to the employee – two questions.

In total, the research questionnaire comprised 11 substantive questions and 4 classification questions.

Analogously to what happens in the case of Nadler and Lawler (1977; 1989; 2007) questionnaires analysis[1], moreover, four synthetic indexes where constructed, e.g.:

[1]Where, considering the difference among section A and B answers as in the case SI4, motivational system effectiveness is usually analyzed: - per worker basing on averages of different answers concerning independent motivational factors, - per factor averaging the answers of whatever number of workers taken into account in the inquiry, - overall considering the average of all answers for each of the factors and all the respondents, as was done in the case of SI1, SI2 and SI4 (Cf. Krawczyk-Sołtys, 2009; Mikuła, 1998).

1. SI1 – An index averaging the two answers from the section a. concerning environmental protection relevance
2. SI2 – An intermediate instrumental index grouping together the answers to two questions from the section b.
3. SI3 – An index averaging the aforementioned SI2 together with the remainder of the answers from section b., as well as all answers to questions from section c. and d., which can, thus, be conceived as a general measure of the overall EKM evaluation according to the employee,
4. SI4 – An index calculated as the difference of SI3 and SI1 (e.g.: SI4 = SI3 – SI1) measuring the alignment of firm EKM functioning according to the employees with environment protection relevance according to the same employee.

The distribution of the online questionnaire allowed to obtain a rich and diverse data set which – after excluding three questionnaires due to the inability to align the answers of the respondents with the final sector classification adopted for the subsequent analysis – is characterised by the structure of the classification variables reported in Tab. 1.

Table 1: Sample and raw-data features

Grouping variables	Categories	Structure indicator (%)
Gender	Female	41.75
	Male	55.89
	Others	0.34
	Refusal	2.02
Age	18-22	73.40
	23-26	21.55
	27-35	4.04
	36-45	1.01
Length of employment	up 2 years	65.66
	2-4 years	27.27
	5-8 years	5.05
	over 8 years	2.02
Sectors	Agriculture and food industry	5.39
	Manufacturing	20.54
	Education	5.05
	Constructions	1.68
	Gastronomy, Hotels and Entertainment	23.23
	Finance, Banking and Insurances	5.05
	Transport and Logistic	16.16
	Health, Cosmetics and Sport	4.71
	Commerce and e-Commerce	16.50
	Administration	1.68

The majority of the sample consisted of men (55.89%) and individuals of generation Z aged 18–22 (73.4%) and 23-26 (21.55%), who had been in employment for less than two years (65.66%) or 2-4 years (27.27%). The data were first pre-processed and then analysed using IBM SPSS software, specifically employing nonparametric K-group testing based on the Kruskal-Wallis test to account for the data ordinal and noncontinuous nature, as well as on descriptive statistics analysis.

3.1 Data-preprocessing and Analysis

First, to reduce the number of pairwise comparisons, initial raw data concerning sectors in which the firm employing the respondent is operating were regrouped, so that:

- Other Services category joins together Education, Administration, Health, Cosmetics and Sport, as well as Finance, Banking and Insurances initial sectors,
- Manufacturing and Constructions were joint in a single Industrial Production & Construction category – Tab. 2.

Table 2: Sectors used for group comparison in SPSS

Sectors classification		
Id number in SPSS	Sector name	Frequency
1	Food production & Agriculture	16
2	Industrial Production & Constructions	66
3	Gastronomy, Hotels & Entertainment	69
4	Transport & Logistic	48
5	Commerce & E-commerce	49
6	Other Services	49

To be able to address the research question RQ1, then, the synthetic index SI1 was elaborated, averaging the answers to section a. questions. It's worth signalizing, then, that among the respondents there is not a significant (at a 0.05 level) differentiation per Industry of such an index basing on Kruskal-Wallis test – Tab. 3 and Fig. 1.

Table 3: SI1 and Environment Protection Relevance not significant differentiation among industries

SI1 test Statistics[a,b]	
Kruskal-Wallis H	3.517
Df	5
Asymp. Sig.	.621
a. Kruskal Wallis Test, b. Grouping Variable: Industries	

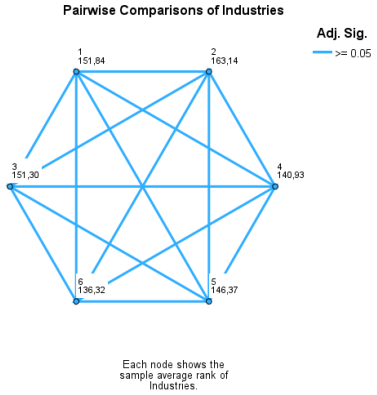


Figure 1: SI1 and Environment Protection Relevance pairwise comparison of Industries

Moreover, the overall distribution of the index supports a high value attributed by the respondents to Environment Protection overall (e.g. the theoretical mean value is 3.835, while the mode is 4.0 on a ten-mark ordinal 1 to 5 scale, with a visible higher frequency of 4.0; 5.0 and 4.5 values and the consequent right-hand skewness of the distribution – Tab. 4 and Fig. 2), confirming Różańska-Bińczyk (2022) results.

Table 4: SI1 and Environment Protection Relevance descriptive statistics

SI1 Descriptive Statistics				
N	Mean	Std. Deviation	Minimum	Maximum
297	3.835	.9460	1.0	5.0

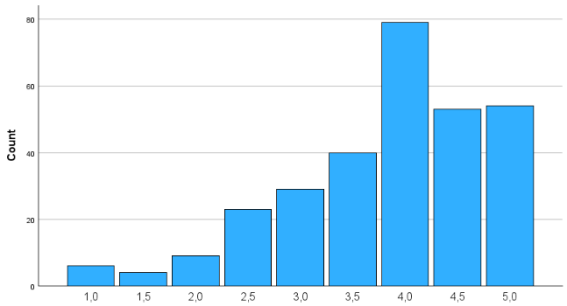


Figure 2: SI1 and Environment Protection Relevance distribution

To address RQ2, it seemed worth, then, considering and discussing in detail the information concerning EKM Evaluation according to employees, which was possible to analyse based on the answers to section b., c. and d. of the questionnaire. As to be able to elaborate the SI3 overall EKM evaluation synthetic index on a scale comparable to SI1, however, an instrumental SI2 index had to be created. The answers to two of the questions from section b., indeed, were initially conceived on a scale from 1 to 3 and had to be regrouped together to obtain an index concerning the EKM Policy adopted by the respondent firm measured on a scale from 1 to 5 – Tab. 5.

Table 5: SI2 EKM Policy construction

Training realization and environment defence responsible person		
Ordinal number in SPSS	Kind of EKM policy	Frequency
1	No training and no or unidentified responsible	212
2	Partial training and no or unidentified responsible	34
3	Dedicated training, but no or unidentified responsible and identifiable responsible, but no training	23
4	Identified responsible and partial training	18
5	Identified responsible and dedicated training	10

Similarly, since the answers to the other two questions from section b. were initially provided on a 1 to 6 scale, yet in both cases values of 5 and 6 were the less frequent, those twos last kind of answers got collapsed in a single category, allowing the rearrangement of the answers on a 1 to 5 ordinal scale comparable with the rest of the answers from questions from other sections of the questionnaire and SI1.

It has to be pointed out, then, that, while not each of the questions in section b., c., and d. of the questionnaire is significantly differentiated across industries, based on Kurskal-Wallis test results, at least one of the indicators is different among at least one and in some cases even two or three different pairs of industries in each of the aforementioned sections of the questionnaire and areas of EKM functioning considered. The overall synthetic index SI3 concerning overall EKM Evaluation obtained considering all the different aspects asked at once, furthermore, is still significantly different in the industry of Industrial Production and Constructions compared to the Other Services one in general – Tab. 6. While the realized disaggregated analysis of the data in different areas has been omitted here and will be published in a separate paper for matter of space, it seems worth, thus, discussing the general differences emerging on an overall scale among sectors, when general EKM evaluation by employees is considered.

Such a synthetic index, indeed, can be considered as a general indicator of how EKM in place in their firm is evaluated according to workers perception and – after answers to questions from section b. rearrangement – it is an average of 11 different answers measured on a 1 to 5 ordinal scale and comparable with the formerly discussed S1 synthetic index concerning Environment Protection Relevance according to a given employee.

Table 6: SI3 and EKM Evaluation significant differentiation among Industries

SI3 test Statistics[a,b]	
Kruskal-Wallis H	14.253
Df	5
Asymp. Sig.	.014
a. Kruskal Wallis Test, b. Grouping Variable: Industries	

It, moreover, differs significantly among the Industrial Production & Construction sector and the Other Services one (Tab. 7), which, based on Mean Ranks analysis (Fig. 3), is characterized by a lower level of satisfaction of the workers employed in firms from such industry in terms of overall EKM evaluation.

Table 7: SI3 and EKM Evaluation pairwise comparison among Industries

Pairwise Comparisons of the distribution of variable SI3 among industries					
Industries	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.[a]
6-5	13.480	17.331	.778	.437	1.000
6-3	17.709	16.026	1.105	.269	1.000
6-4	34.951	17.421	2.006	.045	.672
6-2	51.650	16.176	3.193	.001	.021
6-1	53.503	24.700	2.166	.030	.455
5-3	4.230	16.026	.264	.792	1.000
5-4	21.472	17.421	1.233	.218	1.000
5-2	38.170	16.176	2.360	.018	.274
5-1	40.024	24.700	1.620	.105	1.000
3-4	-17.242	16.123	-1.069	.285	1.000
3-2	33.941	14.770	2.298	.022	.323
3-1	35.794	23.802	1.504	.133	1.000
4-2	16.699	16.273	1.026	.305	1.000
4-1	18.552	24.763	.749	.454	1.000
2-1	1.853	23.904	.078	.938	1.000
Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .050.					
a. Significance values have been adjusted by the Bonferroni correction for multiple tests.					

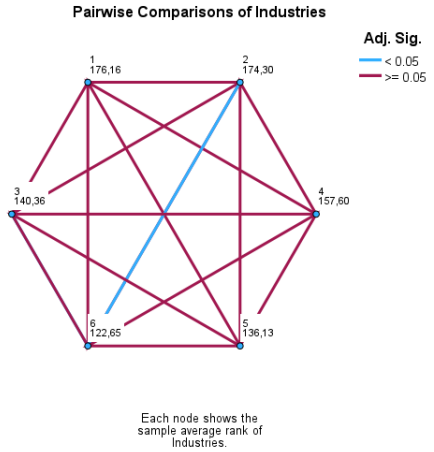


Figure 3: SI3 and EKM Evaluation pairwise comparison and significant Mean Ranks Differentiation among Industries

Considering RQ3, moreover, it is worth pointing out that SI4 index allows to measure the difference among the two formerly elaborated synthetic ones concerning respectively overall EKM Evaluation according to a given respondent (e.g. SI3) and the Relevance of Environment Protection for him (e.g.: SI1) is not significantly differentiated per sector.

Table 8: The not significant differentiation of SI4 and EKM Evaluation to Environment Protection Relevance alignment among Industries according to workers

SI4 Test Statistics[a,b]	
Kruskal-Wallis H	4.644
Df	5
Asymp. Sig.	.461
a. Kruskal Wallis Test; b. Grouping Variable: Industries	

However, SI4 is characterized by a negative mean (eg -1.33 in a range of possible levels from -4.0 to +4.0 of the index value) and a distribution tested as not normal and evidently skewed toward the left range, signalling - based on its own construction and the similar interpretation of negative results of Nadler and Lawler

questionnaire analysis (Krawczyk-Sołtys, 2009) – the fact that the respondents consider their own employers overall EKM slightly lacking in comparison to how important Environment Protection is for them personally.

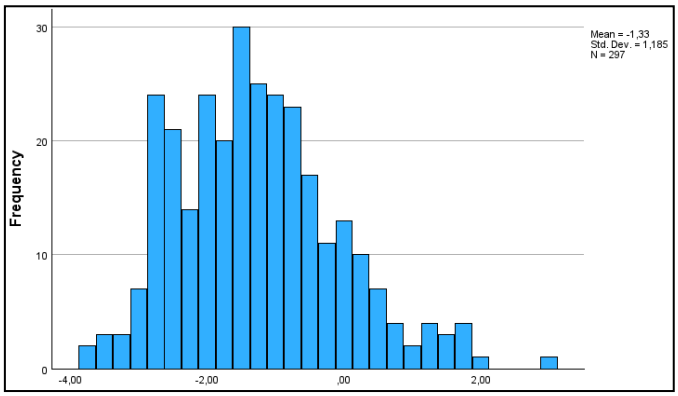


Figure 4: The negative and left-hand skewed distribution of SI4, EKM Evaluation to Environment Protection Relevance alignment index

The results then support the idea that it can be worth considering the improvement proposals provided by the employees and the disaggregated indexes per sector in different aforementioned areas of EKM functioning, which was possible to obtain based on the same questionnaire, in further research, delving more in depth into the matter of the possible ways in which analysed firms could increase the alignment of their EKM system with their own employees' expectations.

4. Conclusions

The current study points out that the workers in the question generation Z consider highly relevant environmental protection and that there is no significant differentiation of this aspect based on the sector in which the companies hiring them are operating. Therefore, such a result seems to rule out the possibility that the eventual inefficacy of the policies implemented by firms and aimed at improving the protection of the environment can be due to a lack of interest in this purpose in the interest of those employees. The inquired employees, moreover, evaluate the functioning of the elements analyzed of the EKM system in their own company differently depending on the sector in which the firm operates. In particular, workers from Other Services sector tend to evaluate worse their own firm EKM functioning in comparison to workers from Industrial Production and Construction sector. EKM system improvements and its better alignment with employees' expectations can thus be more urgent in the analysis that operate in the Other Services sector. EKM evaluations to Environmental Protection relevance alignment do not differ significantly per sector, yet, in most of the cases, a lack of alignment of those two factors is worth noticing. Current research signals, in fact, a general enquired employees' dissatisfaction with EKM system functioning in analysed companies. As a result, increasing the level of alignment among EKM perceived functioning and workers expectations, as well as improvements of EKM activities, strategies, and policies, can be useful and worth undertaking in most of the companies surveyed. Finally, the results show the existence of a, at the moment, not yet fully utilized, potential for intensifying and improving environment protection policies, independently from the activities already undertaken in the vast majority of the companies enquired and in all of the considered economic sectors. Considering that the majority of employees inquired were generation Z individuals, moreover, it seems possible to signal that focusing on such workers can be particularly fruitful for firms considering EKM system implementation, willing to improve the one already currently in place, or even aiming more in general to increase their commitment to environmental protection.

The obtained results overlap with those achieved by other authors. Similar indications of the high level of employees' and generation Z individuals' awareness and engagement as far as natural environment issues are concerned were already pointed out in Kabaja (2025) and Różańska-Bińczyk (2022). Beljić et al. (2013), as well, confirms similar results with respect to high-level environmental awareness among workers, although in this case managers instead of lower-level employees were considered. The results reported here are, moreover, not far from those achieved by Goh et al. (2012), who propose the increase of initiatives supporting the propagation of EKM assumptions in particular through additional mentoring and apprenticeships opportunities for workers, as well as motivating and encouraging them to share the knowledge they already possess.

A first limit of current research can be that the personal perception of environment protection relevance both according to workers and companies can abruptly change due to external shocks and under the effect of factors behind the direct control of any of the parts considered, as, for example, the armed conflicts lasting in Middle-East at the moment (Lawler and Porter, 1967; Nadler and Lawler, 1977; 1989; 2007). Due to the very methodology used, moreover, while it is possible to assess whether a particular individual or group of individuals is satisfied with EKM functioning in a particular context, giving practical advises for a given firm analysed, the possibility to generalize the results to other firms or groups of employees is limited. Only an actual analysis of the current situation in place in a given company can as a matter of fact confirm or negate that an unexploited potential as the one emerging in the case of employees and firms enquired actually exists. The very fact that it was actually possible to find common trends among generation Z workers taken into account can, however, support the idea that, although with caution, some kind of generalization of presented results can be attempted. Other limitations of this study include the use of convenience sampling, which should be borne in mind when analysing these results. However, as a final methodological consideration, it is worth mentioning that the use of a similarly constructed and structured questionnaire, as well as the analysis of obtained results based on analogous methods, can, according to the authors, be useful to assess the possibility or the need to take more measures to improve the functioning of EKM. As a matter of fact, according to them, it can be effectively used both in the case of a wider set of companies taken into account in academic researches realized by scholars, as well as at the single firm level, directly by interested managers and stakeholders, recurring to a similar method to evaluate the opportunity to improve or implement EKM in their own company and identify categories of employees on which the firm can rely to improve environmental protection practices.

Acknowledgement

The publication presents the result of the Project no 062/ZJO/2026/POT financed from the subsidy granted to the Krakow University of Economics.

Ethics Declaration: According to the law in force in the country where the survey was conducted, consent was not required. All respondents voluntarily participated in the survey.

AI Declaration: The Writefull program was used to proofread the English text.

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New Trends Towards AI, Agility and Maturity in Learning Organisations: A Scoping Review

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Abstract: Technology adoption plays a central role in the success of organisations, where organisational maturity can only be achieved based on learning organisation principles and agile teams for cross-functional collaboration. These constructs are seldom examined in tandem, and are more often approached as separate aspects in the complex adaptive systems in today's organisations. Recent AI developments necessitate a re-evaluation of how learning organisations are optimised in digitally transformed environments. Knowledge management (KM) has evolved into a strategic enabler of organisational learning and adaptive capacity. This paper reports on findings of a scoping review that explored trends in organisational maturity, conceptualised as the extent to which organisations institutionalise continuous learning, reflective practice, and knowledge integration across systems, culture, and leadership. Databases Google Scholar, Scopus, Web of Science and ProQuest Central were searched and sources published from 2009 to 2025 were selected for thematic analysis. Using the PRISMA-ScR reporting guidelines and Covidence for data extraction, 37 articles were selected and analysed to identify trends and gaps in research. Findings indicate that sustainable competitive advantage emerges when organisational maturity, AI integration, and continuous learning are aligned to support anticipatory, evidence-based decision-making in complex environments.

Keywords: Agile organisations, Learning organisations, Organisational maturity, AI in learning organisations, Complex adaptive systems, Competitive advantage

1. Introduction

KM has evolved from a document-centric function to a strategic enabler of excellence in organisations (Sorenko, 2021, Rehman, 2025) where organisational learning and adaptive capacity cannot be negated. Learning organisations can be conceptualised as complex adaptive systems (CAS) characterised by continuous interaction, feedback, and evolution. Within this context, KM processes enable organisational learning through dynamic knowledge creation and sharing (Nonaka & Takeuchi, 1995). The integration of artificial intelligence enhances these processes by strengthening feedback loops, enabling real-time decision-making, and supporting adaptive capacity, thereby advancing organisational maturity Studying learning organisations, as a part of KM, as explained by Senge (1990), and later by authors including Shih-Wei et al (2020), Titihalawa et al. (2025) and others, focus on the continuous, adaptive, and generative learning to sustain performance. This offers organisations the means to support and nurture learning at individual, team, and systemic levels Employees could collectively enhance their capability to create desired results. on how technology and the level of its adoption play a cardinal role in and levels of maturity in organisations, in general. In a constantly and disruptively technological world these constructs should not be studies and implemented in isolation, and with considering organisational maturity and agility (Lu, 2024; Steegh, Van De Voorde & Paauwe, 2025). Agility is the capability to quickly adjust to changes, such as currently being experienced by AI developments, and these strategies aim to sustain competitive advantages (Ehiorobo, 2020). However, organisational agility can only be achieved through KM practitioners and their ability to recognise and respond to changes and challenges (Devarakonda, 2019; Munteanu et al., 2020). Agile teams and organisations, organisational maturity, and learning organisations share key features that enhance organisational effectiveness and adaptability. Steegh, Van De Voorde and Paauwe (2025) add that cross sectional collaboration and hierarchical differentiation in agile teams lead to shared leadership, where team reflexivity and feedback add to its effectiveness. Agile organisations focus on quick responsiveness through iterative processes.

In addition, organisational maturity reflects a company's ability to evolve its practices and processes within the complexities posed by disruptive technologies such as AI innovations (Ross, 2019). Organisations that may have reached maturity before these disruptions, are now faced with a new wave of developments to stay abreast of the maturity curve. Recent AI innovations and developments necessitate a re-evaluation of what must be considered in optimising learning organisations.

2. Background

Technology and the level of its adoption and implementation plays a cardinal role in learning organisations and levels of maturity in organisations, in general. Yet, these constructs are often studied in isolation. Recent AI innovations and developments necessitate a further re-evaluation of factors to considered in optimising learning

organisations. Drawing on principles of organisational learning, this paper reports on a scoping review as explained by Tricco et al., (2018), of recent trends looking at organisational maturity, seen as the extent to which organisations institutionalise continuous learning, reflective practice, and knowledge integration across levels. Does it reflect the depth of collective learning embedded in systems, culture, and leadership practices in a digitally changed world? How can mature organisations cultivate learning cultures characterised by psychological safety, feedback loops, cross-functional collaboration, and mechanisms for converting tacit knowledge into shared organisational memory? In this context, KM is not merely the storage of information but a dynamic process of knowledge creation as explained by Nonaka, sense-making, and strategic alignment. The value of AI may still be unexplored, while it enhances this learning ecosystem by augmenting organisational foresight and forecasting capability. Organisational maturity refers to the degree to which an organisation has developed structured processes, governance, technology and knowledge systems, leadership capacity, whilst subscribing to a learning culture. As complex systems, organisational maturity and forecasting depend on an organisation's ability to systematically use knowledge, data, and learning processes to anticipate and shape future outcomes rather than merely react to them. More advanced AI applications, including scenario modelling, pattern recognition across weak signals, and knowledge graph integration, enable double-loop learning by revealing structural inefficiencies and hidden assumptions embedded in organisational data. When integrated within reflective governance frameworks, AI can even contribute to triple-loop learning by informing strategic reorientation and policy redesign. However, the effectiveness of AI-driven forecasting depends on organisational learning maturity. Without strong feedback mechanisms, ethical reflexivity, and knowledge-sharing norms, AI risks reinforcing existing biases and silos. How do recent studies approach the understandings of learning-oriented organisations to position AI as a cognitive partner within a socio-technical system to capitalise on collective intelligence, and adaptive strategy? The paper argues that AI-enabled forecasting represents not merely technological advancement but an extension of organisational learning capability. Utilising the PRISMA Scoping Review Extension (PRISMA-ScR) (Tricco et al., 2018) as reporting guideline and the Covidence tool for data extraction, a total of 57 articles were analysed, and qualitative data were extracted were thematically coded and analysed further. Based on the findings of the scoping review, this paper explores existing trends, assumptions and governance structures, to see how organisational maturity is viewed. Some studies argue that agile organisations link better to the concept of both learning organisations and organisational maturity. Findings are that sustainable competitive advantage emerges when organisational maturity, AI integration, and continuous learning are aligned to support anticipatory, evidence-based decision-making in complex environments. Studies further advocate the need for a shift in approaches where long-term prediction accuracy must reconsider a more agile and adaptive approach towards better foresight and rapid learning.

Though KM studies in technology adoption, maturity and agility of organisations always underpinned the aims and efforts of learning organisations, recent AI developments and innovations beg new answers and asks: (1) how can organisations continue to cultivate learning cultures to maintain maturity levels amidst the demands and possibilities arising from AI innovation? The value of AI may still be unexplored (Vinning et al. , 2025), while it enhances this learning ecosystem by augmenting organisational foresight and forecasting capability. This paper looks at research published around these issues.

3. Research Design

Guided by the PRISMA Extension for Scoping Reviews protocol (PRISMA-ScR), (see Tricco et al., 2018; Page et al, 2020), this scoping review explored the role that AI. It examined the current trends, gaps, as well as reported best practices in recent reported studies. The selected databases provided 57 hits and qualitative thematic analysis was used to identify themes observed in current research.

3.1 The Search Strategy

Peer-reviewed articles and book chapters in English, published between 2019 and 2025, were considered for inclusion in this study. The following constructs were used to filter the results: (1) Learning organisations; (2) Agile organisations and discussion including AI impacting change (3) Maturity in organisations including changes of digital transformation. Based on the recent escalation AI and GenAI developments (as reported by Floridi, 2019 and others), the study is limited to research reported during the last seven years at the time of this study.

The search strategy covers learning organisations in the pursuit of agility and maturity in terms of AI incorporation. The study does not consider organisation learning, which for the purpose of this study is considered to be the ongoing processes through which organisations acquire, share, and apply knowledge from experiences, while a learning organisation is the structural and cultural model where business organisations set out to instil continuous, adaptive, and generative learning to improve performance. (Senge, 1990). For the latter,

employees collectively enhance their capability to create desired results. It is built on five core disciplines: systems thinking, personal mastery, mental models, shared vision, and team learning.

The databases included in this study are Google Scholar, Scopus and ProQuest. Databases were queried from January 2025 to May 2025. A combination of the following keywords was used: “artificial Intelligence”, “digital transformation”, “AI transformation”, “learning organisations”, “agility”, “agile organisations”, “complex systems”, “adaptive complex systems” and “organisational maturity” as systematically as possible within the search functionality and capabilities of each website. Search terms used included: Learning organisations AND complex adaptive systems OR CAS; agility OR agile organisations OR agile teams AND learning organisations AND Organisational maturity; AI OR AI application AND learning organisations.

3.2 The Selection of Sources of Evidence

These results of each search were filtered according to document type, publication date, and then further refined to look for aspects such as Information or research ethics. A data log of the search strategies and complete results, with links, were recorded in Excel. This study focuses mainly on businesses as learning organisations being a subset of KM. As educational institutions approach this topic differently, studies primary focusing on AI in education, teaching and learning were excluded.

3.3 Inclusion and Exclusion Criteria

Studies included in the literature search met the following inclusion and exclusion criteria:

Inclusion criteria: Reported studies focusing on business organisations and learning organisations. Studies reported in full-text, peer-reviewed journal articles and conference papers between 2019 and 2025, covering concepts of in the titles, abstracts, or keywords were identified and included. Only studies in English were considered and selected.

Exclusion criteria: Studies not in learning organisations or industries. Non-peer reviewed sources were excluded. The following document types were excluded: books, book chapters, grey literature, articles with abstracts only, patents, and reports, and duplicate studies found in the databases. Studies in other languages that are not English were excluded. Studies on organisational learning without focussing on learning organisations where excluded.

3.4 Knowledge Synthesis

The PRISMA extension for scoping reviews (PRISMA-ScR) was published in 2018, and an updated checklist of 20 essential reporting items was revised in 2021 (Page et al., 2021). This scoping review synthesizes evidence selected to assess the extent of literature covered on this topic. This study indicates whether further research in terms of recommending systematic reviews of the literature are feasible. The PRISMA-ScR flowchart presented in Figure 1 explains the identification, screening, inclusion/exclusion, and extraction for this scoping review. It outlines each step taken, which enhances not only the transparency, but also the reproducibility and rigour of the review process followed.

The review included searches in ProQuest (n=667); Scopus (n=14); Web of Science (n=36) and Google Scholar (n=857), totalling 1574, records included in the initial abstract screening. Twenty-six (26) duplicate records were removed. Of the 1078 studies screened, based on their titles and abstracts, 454 were excluded as they did not meet the inclusion criteria, leaving 624 studies. Full-text reviews followed, and 26 studies were excluded. Reasons included: Reason 1: wrong outcomes (n=11), Reason 2: wrong population (n=1), Reason 3: no full-text available (6), and Reason 4: wrong publication type (n=1). Once the full-text screening was completed, 57 studies were included for extraction. The studies were exported an Excel spreadsheet and thematically data analysed.

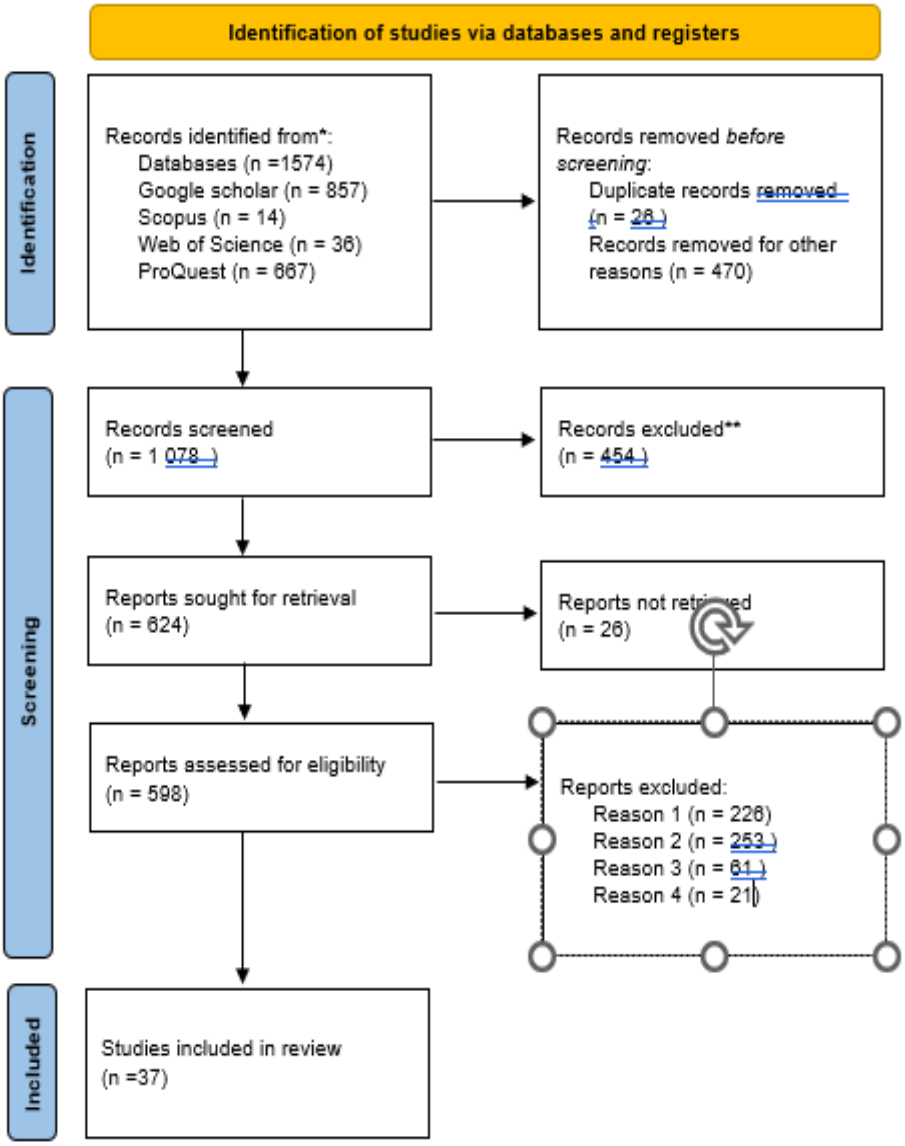


Figure 1: PRISMA 2020 Flow Chart

4. Presentation and Discussion of Findings

In Table 1, the different research methods used in the studies analysed are summarised. Industries in these studies ranged from hotels, marketing to supply chain organisations. Countries where this research originated include Poland, China, USA, Germany, Norway, Portugal

4.1 Trends, Themes and Gaps Identified

Although this study can report on an exponential increase in research from 2019 to date, selected studies report a general gap on the topic and add that there remains a paucity in literature, particularly addressing topics of AI as relating to maturity models (Ellefsen, 2019).

Table 1: Summary of Search Results

Research Method	Trends and Gaps	Themes	Authors
• Multiple case studies • Systematic reviews • Critical reviews • Surveys	1. AI readiness models 2. Leadership mindsets 3. AI maturity	**LO, KM & CAS**	Korecki (2023); Nault & Ruhi (2024); Nimmi, Vilone & Jagathyraj (2022); Rahman, Dzunur'aini, & Nur'aini (2022); Taherdoost & Madanchian (2023); Usmani, & Priyadarshini (2025); Riaz, Morgan & Kimberley (2023);
		OA, leadership and LO	Steegh, Van De Voorde and Paauwe (2025); Olan et al., 2022); Row & Brook (2022); Shafiabady et al., (2023); Titihalawa (2025); Armanious & Padgett (2021); Ehiorobo (2020); Eliane & Scafuto, (2022); Kucharska (2025); Ratajczak, (2023); .
		AI in LO, Performance	Li, K. C., & Wong, B. T. M. (2023); Majeed & Ravindran (2026); Li & Wong (2023); Morandini e. al., (2023); Ranjan et al., (2024); Reichl & Gruenbichle (2023);
		AI readiness, digital transformation and OM	Cardoso E, and Su X. (2022); Chandrakasan et al., (2023), (2023Lichtenhaler (2025); Anna (2025); Ellefsen(2019); Felemban, Sohail, & Ruikar (2024); Alavi, Leidner, & Mousavi. (2024); Lech & Werbinska-Wojciechowska Sylwia; Mielcarek, et al., (2025); Reichl & Gruenbichler (2023); Robertson (2022); Sadiq (2021); Usmani & Priyadarshini (2025); Vining (2025);

Studies (Shih-Wei et al., 2020; Titihalawa et al., 2025; Alavi, Leidner, & Mousavi, 2024) confirm that KM as a discipline has evolved into a field where the systematic creation, sharing, application, and governance of organisational knowledge is transitioning. Rooted in the seminal work of Peter Senge, learning organisations are characterised by systems thinking, shared vision, and collective learning practices that enable organisations to respond proactively to environmental change, where AI is now part of technological transformation. Learning organisations amidst these developments are dependent on systems that are adaptive, and responsive to rapid technological change, exhibiting properties such as self-organisation, co-evolution, and path dependency

4.2 Learning Organisations, Agility and Leadership

Boerma, De Laat and Vermeulen (2024) hail the benefit for organisations to pay attention to organisational agility in learning, as profound technological, occupational and societal changes are a constant. Learning as part of organisational agility however is an under researched area of attention. Agility and learning organisations form significant tangents where formal and informal learning can take place. (Boerma, De Laat and Vermeulen, 2024; Kucharska et al., 2025). Both learning organisations and agile organisations display the ability to be responsive to changes. Kucharska et al (2025) state that leaders with an agile mindset develop their competencies and tacit knowledge through continuous informal learning practices such as experiential learning, critical thinking, feedback, mentoring, and supportive organizational cultures that foster agility and adaptability (Kucharska, 2025). Chandrakasan et al.,(2025) lament that the lack of the appropriate leadership styles to prosper observed in a Malaysian study is causing many organisations

4.3 How AI Strengthens Learning Organisations

Lichtenthaler (2025) states that AI management focusses mostly on consists of the strategies, processes, practices, activities, and tools, for achieving consistent access and using AI intelligence for better performance and forecasting. AI innovations enable organisations to capture, analyse, and leverage organisational knowledge at scale. By automating routine tasks and providing data-driven insights, AI allows employees to focus on higher-value learning and strategic thinking. This creates a feedback loop where organisations continuously improve their practices based on AI-generated intelligence, directly supporting the learning organisation model.

4.4 Factors Associated with AI Weaknesses

The findings of this scoping review are affirmed by a later study of Litvinenko (2026) stating that there are weaknesses in applying and utilising AI in organisations for learning. Currently barriers caused by context blindness, bias, and the black-box nature of AI, overreliance and cognitive deskilling, limited cross-domain

transfer, and psychological or power-related barriers to codification and sharing – factors that can weaken AI's benefits if unmanage. Alavi, Leidner and Mousavi (2024) note that particularly GenAI has the propensity to reduce human interaction and socialisation. This may exclude more junior staff from learning**.**

4.5 AI's Role in Advancing Organisational Maturity

Studies (Ellefsen et al., 2019) state that there are many instances where organisations fall behind with digital transformation and organisational maturity as so far AI is concerned. Organisations that are AI-mature significantly outperform early-stage AI implementers, but many companies struggle to advance from AI pilots to enterprise-wide AI adoption. AI maturity involves developing organizational capabilities to effectively implement, manage, and scale AI solutions.

4.6 Accelerating Agile Practices with AI

Shafiyabadi et al.; (2023) state that AI should be employed to predict organisational agility and responsiveness. This would enable agile teams to move faster while maintaining quality. AI tools accelerate agile methodologies by automating code generation, backlog management, testing, and other iterative processes. AI tools used include Machine Learning (ML) methods e.g., Support Vector Machine (SVM), Decision Trees (DT), and K-Nearest Neighbours (KNN).

4.7 New Maturity Models

Usmani et al., (2025) questions India's readiness to reap the benefits of incorporation AI effectively, and state that there is a paucity of proven and updated models and frameworks to guide organisations. One of the few alternative models of maturity that addresses AI is offered by Lichtenhaler (2025), describing thee 6 levels of existing transformation in organisations:

- *Level 0: Isolated Ignorance* – AI is ignored;
- *Level 1: Initial Intent* – Preliminary experimentation with AI technology; .
- *Level 2: Independent Initiative* – Multiple, uncoordinated AI activities focused on efficiency;
- *Level 3: Interactive Implementation* – Coordinated AI usage integrated with human intelligence;
- *Level 4: Interdependent Innovation* – Strategy, combined with innovation;
- *Level 5: Integrated Intelligence* – Seamless, sustainable AI-human collaboration and learning.

However, most studies analysed for AI-readiness as part of learning organisation strategies and technological maturity, has yet to be realised.

5. Conclusion

The findings of this scoping review indicate that organisational maturity, organisational agility, and AI adoption should not be approached as separate organisational factors. These are interdependent constructs within contemporary learning organisations. Learning organisations function as complex adaptive systems in which knowledge creation, sharing, and continuous learning are enabled through dynamic interactions, feedback mechanisms, and adaptation. Within this environment, AI increasingly serves as a critical enabler of organisational learning by strengthening KM processes, supporting real-time decision-making, and enhancing adaptive capacity. At the same time, agile organisational practices provide the much-needed flexibility and responsiveness required to navigate rapidly changing technological faced by organisations today. All while organisational maturity provides the structures, capabilities, and governance mechanisms necessary to institutionalise learning and innovation. Collectively, these constructs share common foundations, including continuous improvement, collaboration, knowledge sharing, strategic alignment, and adaptive leadership. Lichtenhaler, (2025) further underpins the risk of ignoring the importance of AI adoption in learning organisations. While Shih-Wei and Lamb (2020) add and remind that older models of maturity can no longer answer to the demands of new developments, and AI-maturity models require urgent attention The findings further suggest that organisations are beginning to assess AI maturity and develop pathways towards enterprise-wide AI integration, although adoption remains uneven and relatively slow.

New trends that this study was able to identify are that there are efforts to assess organisation's current AI maturity levels and develop a roadmap to advance from pilots to enterprise-wide integration, but that these are slow on the uptake. It is evident that AI integration could potentially strengthen organisational agility by equipping employees and managers with real-time insights, predictive analytics, and intelligent decision-support capabilities. In turn, responsiveness and adaptability will improve. There is a need for deeper studies and full-scale systematic literature reviews on the intersection of the practicalities of agility, maturity and the changing

landscape of learning organisations. In particular, leadership styles have been identified as a concern and a gap requiring further empirical research to enhance new skills to manage AI-driven decision-making.

This study concludes by highlighting the need for further research to examine the intersection of organisational maturity, agility, and AI-enabled learning in a more integrated manner. To this end, attention should be given to emerging leadership capabilities, governance models, and organisational competencies required to support AI-driven decision-making and sustainable organisational learning. Understanding these relationships will be essential for developing organisations that are resilient, innovative, and capable of thriving in increasingly complex and technology-mediated environments.

Ethics Declaration: This study used secondary data and no ethical clearance was required.

AI Declaration: For this research, the grammar assistant software tool Grammarly was used for editing purposes.

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Knowledge Management in Times of Uncertainty: Barriers and Opportunities in Graduate Education

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Abstract: In Higher Education Institutions (HEIs), graduate education is essential in the socialization, production, and transfer of knowledge and innovations for society. In this sense, graduate programs contribute to a knowledge society by training future researchers in collaboration with experts in a knowledge area, innovating in research with them, sharing these innovations through formal and informal practices, and ensuring learning through systematic reviews and discussions with research networks. These knowledge management (KM) dynamics can be hindered by a turbulent environment in which social, economic, political, and cultural demands call for changes to current KM practices. This paper examined two leading graduate research programs in the northwestern region of Mexico that underwent several changes in their institutional structures and scientific practices due to environmental shifts. We analyzed 1) the challenges faced by these programs from a public university in Mexico due to changes in policies, 2) how they managed to generate knowledge, and 3) what opportunities emerged during this period. Documentary analysis was conducted as a case study using a qualitative approach, which helped us conduct an in-depth analysis and understand the KM strategies adopted in both contexts. We sought participation from program directors and scholars who met certain leadership criteria. This study highlights that political change was both a barrier and an opportunity for knowledge production, as it imposed budget cuts on science but also introduced new perspectives that enabled wider impact in knowledge transfer. Nevertheless, the KM strategies that emerged from the pandemic, such as diversifying funding sources and adapting certain scientific practices, were solutions for advancing science, quality education, and research on social retribution.

Keywords: Educational innovation, Higher education, Knowledge management, Policy education, Research collaboration, Science and technology

1. Introduction

Knowledge has become an essential component for economic and social development (Mijangos and Manzo, 2012). Contemporary organizations recognize this as a corporate asset and a competitive advantage due to its capacity to innovate; consequently, they have adopted Knowledge Management (KM) practices to improve decision-making (Davenport and Prusak, 1998; García and Gómez, 2015).

In this context, Higher Education Institutions (HEIs) also contribute to knowledge society by managing knowledge through substantial activities such as teaching, training highly skilled human capital, and producing, applying, and transferring new knowledge (Jiménez, Cornelio and Vera, 2017). These institutions are increasingly integrating their research efforts and innovations with community needs to foster social and economic development (Tassone *et al.*, 2018; González, Rodríguez and González, 2021). Most of the above-mentioned occur within graduate programs, where students socialize, learn scientific values, traditions, and technical skills, and produce original knowledge to advance in it (Campanario, 1999; Ben-David, 2017).

It is important to note that a turbulent environment can impede KM dynamics. For example, situational factors like the geographical location of organizations (Minakata, 2009), financial or political pressures (Jiménez, Cornelio and Vera, 2017), or, in smaller spheres (as in organizational culture), factors such as beliefs, values, and practices may affect KM management processes (Cabrera, Romo and Rodríguez, 2025). In this regard, Nonaka and Takeuchi (1995, pp. 49–50) observe that:

> *"Organizations deal with uncertain environments not merely through passive adaptation, but through active interaction […] The organization that wishes to cope dynamically with the changing environment needs to be one that creates information and knowledge, not merely processes them efficiently. Furthermore, the organizational members must not be passive but must rather be active agents of innovation."*

Nevertheless, all organizations (including graduate programs) are complex due to the convergence of rules, formal structures, subjectivities, and situational frameworks during the decision-making process (Vergara, 2010), and consequently in KM. Therefore, it is necessary to understand KM processes in educational institutions. However, research on KM in HEIs remains fragmented and lacks a comprehensive understanding;

moreover, the study of this field is predominantly concentrated in Europe or carried out primarily in the private sector (Ramjeawon and Rowley, 2018; Quarchioni, Paternostro and Trovarelli, 2022).

Previous literature has described KM as a process where knowledge is acquired, created, shared, or applied to generate innovations or improvements (Bueno-Broterson, Araya-Guzmán and Salazar-Concha, 2025). Other studies have analyzed various approaches to KM, including research, teaching, assessment, mentoring, training, and informal learning (Galgotia and Lakshmi, 2022; Syihabuddin *et al.*, 2025). Some researchers found that human resources, leadership, organizational culture, curriculum, technology, and quality assurance mechanisms are key enablers of KM (Galgotia and Lakshmi, 2022; Santos, Carvalho and Martins, 2024; Hussein, 2025). In addition, studies have identified challenges and barriers to KM (Ahmad *et al.*, 2017; Kassa and Ning, 2025). Finally, some research has examined the effects of KM on teaching, organizational performance, and organizational learning (Adeinat and Abdulfatah, 2019; Mohammadi and Faskhodi, 2022; Al-Sulami *et al.*, 2023).

Based on this review, the present study aimed to explore the barriers and opportunities to KM in two graduate programs at a public university in the northwestern region of Mexico. These underwent several changes in their institutional structure and scientific practices due to governmental and political changes and the effects of the COVID-19 pandemic. In this context, we analyzed 1) the challenges faced by these two graduate programs due to changes in policies, 2) how they managed to generate knowledge, and 3) what opportunities emerged during this period.

In the Latin-American context, KM research in HEIs is still in its embryonic stage. The existing literature focuses on the description and exploration of KM processes or enablers (Ríos, 2012; Avendaño and Flores, 2016; Jiménez, Cornelio and Vera, 2017; González, Rodríguez and González, 2021). To fill this gap in research, this study sheds light on how a learning organization faces a turbulent environment and engages in new learning processes.

2. Transformations of Institutional Organizations and Knowledge Management

Organizations have generated practices in response to the speed of social change and integration into a global context. In Mexico, innovation and market practices, such as entrepreneurship, internationalization, administrative and academic accreditations/certifications, or the commitment to create quality programs to compete in international rankings, point to heteronomous processes in universities, given that the government conditions funding and resources on the compliance of certain indicators (Acosta, 2019).

In this context, KM contributes to institutional efficiency and the construction of significant educational actions (Bueno-Broterson, Araya-Guzmán and Salazar-Concha, 2025); however, KM processes differ from one institute to another (Adeinat and Abdulfatah, 2019). In this regard, the theory of organizational knowledge creation (Nonaka and Takeuchi, 1995) analyses how organizations generate, create, and transfer knowledge internally, creating a cycle of learning in which individual and collective knowledge converge.

In changing environments, the new institutional (NI) theory has found an echo in educational researchers. DiMaggio and Powell (1991) and Meyer and Rowan (2006) note that it can respond to the complex framework presented by HEIs. They offer an alternative to answer how institutional arrangements form, mediate, or direct institutions. In other words, this theoretical approach focuses on how individuals and organizations innovate and contribute to change, without being constrained by organizational structures or their own activities (Scott, 2014).

In this regard, this study takes the NI perspective to observe the environmental pressures to change in educational organizations (their formal and administrative structure), the cultural context that surrounds them, and the rationalities of educational actors to achieve their personal interests, which could result in defying the shift, maintaining their old mindset in a new field, or 'changing their strategies to obtain rewards within the same set of rules of the game' (Powell and Dimaggio, 1991, p. 25). The organizational knowledge creation theory explores the knowledge practices and interactions among individuals that foster or hinder organizational learning.

3. Methods

We analyzed the cases of the graduate programs in 1) Physics and 2) Materials Science, both of the Universidad de Sonora (UNISON), one of the leading public institutions in postgraduate education and scientific research in the northwestern region of Mexico, in the state of Sonora. UNISON depends heavily on

federal policies and programs that have funded projects, strengthened its structure, and consolidated its postgraduate offerings. Such are the cases of these programs, both established in 1984. The Materials Science and Physics graduate programs were created to train people to consolidate teaching and research in their respective disciplines. The development of both programs relied on sponsorship from the Ministry of Science, Humanities, Technology, and Innovation (SECIHTY) and the Ministry of Public Education (SEP). These programs have cultivated networks, produced knowledge in high-impact journals, and fostered student mobility, among other activities that earned them recognition from SECIHTY as a high-quality program.

We carried out a case study. This approach was chosen for in-depth analysis and comprehension of events within their context (Stake, 1995; Yin, 2003). In this regard, the above-mentioned programs were chosen because of their departments' notable record of scientific production, collaboration, and internationalization. We conducted semi-structured interviews that explored interviewees' experiences with government research policies and the challenges and opportunities that have emerged recently. The study was approved by a committee of three experienced qualitative researchers at UNISON.

Participants were recruited through purposeful sampling. Since KM strategies are fostered from directive spheres, we sought the participation of program directors and scholars who followed certain leadership criteria: 1) a minimum of four years of experience in the graduate program, and 2) membership in the National System of Researchers (known by the acronym SNII in Spanish), a program endorsed by SECIHTY. The informants participated voluntarily. An invitation was sent via email, informing them of the study's purpose and that the data would be used confidentially and anonymously if they agreed to participate. We contacted the program directors for their approval, and after establishing a rapport, we connected with prospects and secured interviews with 14 participants (see Table 1).

Table 1: Characteristics of participants of the study

Participant	Gender	SNI Level	Academic Program
1	Female	2	Materials Science
2	Male	1	Materials Science
3	Male	2	Materials Science
4	Female	3	Materials Science
5	Female	2	Materials Science
6	Male	1	Materials Science
7	Female	2	Materials Science
8	Male	2	Physics
9	Male	3	Physics
10	Male	3	Physics
11	Male	2	Physics
12	Male	1	Physics
13	Male	1	Physics
14	Male	3	Physics

Once consent was obtained, the interviews were conducted in person and via videoconferencing platforms. In addition, an extensive document review was conducted to reconstruct events (including university development plans and regulations, staff resumes, and federal acts, among other documents). This explained the study's focus and validated the information obtained from the interviews (McMillan and Schumacher, 2001).

The data were analyzed using MAXQDA 22 qualitative analysis software. This aided in organizing the information and coding it for thematic analysis based on the study's areas of interest. The coding process was iterative and simultaneous with the analysis, following Saldaña's (2009) guidelines. The initial codes and categories followed the themes of the interview, based on the theoretical framework: a) Program's organization, b) Institutional context, c) Routines and transitions. We inductively added codes for subjects that were not anticipated.

We reviewed the initial codes, created new categories, refined them, and reduced them to explain the case. The final themes and codes were:

1. Program's dynamics and environment

- *Program institutionalization*
- *Disciplinary activities*
- *Bureaucratic dynamics*

2. Normative transitions

- *Heterogeneous reactions*
- *Decision-making*
- *Possible alternatives to change*

To better understand the dynamics of change and the KM process in the studied programs, we organized the results as follows: 1) Challenges faced during the transition period, and 2) Knowledge production in a new reality.

4. Results and Discussion

4.1 Challenges Faced During the Transition Period

Both programs have different dynamics and internal operational norms. However, they are subject to human resources training, thesis and dissertation supervision, scientific publication, and project dissemination, impacting both students' and professors' development. These were affected by policy changes, which led to trust dissolutions. Some of the changes were due to the onset of the COVID-19 pandemic, including the cancellation of student mobility scholarships.

In the interviews, some participants mentioned benefiting from funds without complications. In contrast, a considerable group had to multiply their efforts to get their research proposals approved. As noted by some participants: 'Project calls still exist; I don't see any impact. People say that SECIHTI doesn't support them, but there are financial limits (...) There's a budget, and not everyone can be funded' (Interviewee 14, Physics); 'Due to the pandemic, most resources were allocated to the health sector, and there began to be many restrictions on other projects. Even if the projects were submitted multiple times (...), nothing was obtained because resources were limited' (Interviewee 9, Physics).

This highlights how recent changes impacted academics. Meanwhile, the ones affected reduced their research and limited their overall internationalization practices. In addition to material and equipment purchases, the canceled funds supported international collaboration activities. Some have sought university financial support, but it is partial and restrictive, which generated dissatisfaction among the informants: 'The trusts were established as a strategy to ensure that funds allocated to projects weren't subject to annual budget fluctuations… It is difficult to incur expenses at the UNISON if an activity is conducted at the end of the fiscal year (Interviewee 3, Materials Science).

Regarding students, the university financed them through a *fee trust* funded by their tuition. After the new regulations, all graduate programs that intend to maintain SECIHTI's recognition must not charge tuition fees. Consequently, the funds are no longer available, which restricts access to the training required to complete their degree.

A concern for interviewees was the restriction on purchasing and maintaining laboratory equipment. Previously, those who benefited from programs could fund the purchase of materials or reagents. However, these can no longer cover new equipment or maintenance expenses, threatening work when it becomes outdated: 'The budget cuts affected us a lot. The equipment is becoming obsolete, and [it's] going out of service. We won't have anything to work with!' (Interviewee 13, Physics). We need to acquire new equipment, but SECIHTI is not supporting us (...) The university does not have the resources(...)' (Interviewee 1, Materials Science).

The findings show that the graduate programs studied consider all KM activities (acquisition, creation, sharing, and application of knowledge) regularly at both administrative and academic levels. However, in a changing context, these practices face barriers such as a lack of economic and technological resources, bureaucratic processes that impede innovation and progress, and institutional factors stemming from the university's new regulations. These results align with the challenges identified by Kassa and Ning (2025), who observed that

public institutions lack KM sustainability due to continuous changes in human resources and organizational structures. This difficults the implementation of a successful KM strategy in public universities.

4.2 Knowledge Production in a new Reality

There are strategies for continuing research in both programs. In experimental work, relationships within the country and abroad have enabled students and professors to process their data in other laboratories while communicating results virtually. Interviewee 1 from Physics said they usually 'send samples by courier or ask to deliver them when someone goes to another institution'. This practice is also shared among Materials Science researchers; however, collaborations between public institutions are at risk.

In our findings, both feed from the same funding and are affected by limited resources: *'We rely on collaboration with other* institutions (…). This way, we are overcoming resource constraints. However, this is temporary, because if the equipment does not have the proper maintenance and we don't purchase new ones, this will "blow" at some point' (Interviewee 9, Physics).

There are groups of professors, mainly in Materials Science, who, due to time and project limitations, choose to crowdfund. Interviewee 7 from this program declared 'Sometimes we buy things; sometimes the Department does. Equipment maintenance is expensive, and due to limited resources, we fundraise among professors to pay for repairs. We do it because we need that equipment´. These actions have become a common solution in the recent context.

Student mobility and conference participation have also undergone adjustments to ensure graduation requirements are met. In this regard, Interviewee 12 from Physics stated the following: 'I have sent [them] abroad, but everything has been covered through my SECIHTI project; that's why it has been easier to manage these activities.' Although academic activities have been limited to available funding, scheduling conflicts, travel arrangements, and time zone differences, media and technology have supported the continuity of academic plans during the transitional period.

Since both programs were created, they have relied mostly on government funds and continue to do so. External funding is uncommon among informants. In this regard, UNISON annual reports observe that most scientific projects rely on internal sources or SECIHTI's. This means there is resistance to exploring new forms of financing among research groups.

UNISON has promoted calls for projects funded by external organizations. Interviewees kept this in mind, but few reported acting on it. The Materials Science program stood out: 'We just submitted a research proposal to the faculty authorities (...) [Now] we seek funding from a European foundation' (Interviewee 5, Materials Science); 'Fortunately, I have not lacked SECIHTI projects, but I have also had collaborations with France (...) I also received financial support from an American society' (Interviewee 3, Materials Science).

Regarding the diversification of funding sources in both programs, some informants mentioned avoiding working with the industry. Interviewee 6, from Materials Science, noted: 'We're already working on our research, and to work with companies, you must dedicate exclusively to that'.

These insights present a series of KM enablers in graduate programs within a restrictive environment. All the informants stood out for their leadership, as they sought alternatives to certain limitations in their practices (ensuring the continuity of their projects through collaborations, crowdfunding, reallocating project funds, or changing the dynamics of academic activities). This mindset can be explained by a scientific culture that fosters communication and collaboration among researchers who share the same research line and interests (Campanario, 1999). This disciplinary factor fosters more KM enablers, such as the creation of communities of practice (in which individuals share expertise and learn from one another) and an organizational culture that may transcend academic boundaries and impact the program's administration. Santos, Carvalho, and Martins (2024) have already identified these enablers in the case of Portuguese private institutions; nevertheless, our findings offer a new perspective by explaining the dynamics of scientific communities and their impact on KM and graduate education.

5. Discussion

The organizational culture plays a pivotal role in the success and development of KM (Ahmad *et al.*, 2017). In this sense, individuals can motivate others to create/share/acquire/apply knowledge or limit organizational dynamics and the introduction of new rules (Kassa and Ning, 2025). Our study also presented the negative side

by showing a high dependence on public funding and a reluctance to seek external resources from industry or NGOs.

Resistance to change is a common barrier for KM. Li, Liu and Liu (2016) explain that resistance results from the individual's perception of greater loss, greater time and effort demands, and/or social pressures. Following Nonaka and Takeuchi's theory (1995), this reaction might delay or interrupt knowledge conversion within organizations since a reconfiguration of rules should lead to new knowledge and, therefore, to an internalization of practices.

Some informants in our study resisted changing their routines, regardless of alternatives for continuing academic research. For NI, this is common when a policy is enforced abruptly (Jelonek and Mazur, 2020; Sabzalieva, 2022). Bernasconi (2006) notes that adherence to old politics can generate conflicts in adapting to change. In our study, this is significant as both graduate programs were funded and developed under public policy programs. Therefore, their communities are used to these practices; thus, it is difficult for them to engage in new funding dynamics.

In our study, seeking collaboration with foundations, scientific societies, or other higher education institutions is an example of achieving this goal and an opportunity for KM to foster knowledge-based interorganizational collaborations. Some individuals in our study have managed to generate knowledge. From an institutionalist perspective, these adjustments can be explained as follows:

- An attempt to maintain scientific authority and rewards. According to Meyer and Rowan (2006), individuals choose to change their practices to restrictive institutional settings for their benefit. In this sense, the adaptation of UNISON members might be instrumental in keeping their economic incentives and social recognition.
- A logic of appropriateness in which, knowing their role within an institution, individuals take action to fulfill their institutional responsibilities and foster stability in the organization (Vergara, 1997). This would explain the researchers' willingness to crowdfund their projects.

Both explanations indicate that the studied programs are undergoing an adaptation process; however, to assess organizational stability and adaptation, individuals must adopt routines and shared beliefs regarding new rules (Vergara, 1997; March and Olsen, 2006). In this sense, some of the strategies mentioned might be emergent rather than transcendent.

An exception to superficial changes is the researchers' disposition to work and share information remotely. Beyond presenting restrictions, the pandemic contributed to innovations and continuity in both programs. This finding highlighted that changes are more invasive during a political transition than during a global crisis (Sabzalieva, 2022): during the pandemic, adapting to new practices was crucial for graduate programs to survive, while the political change threatened individuals' academic paths and beliefs.

6. Conclusions

This article contributed to the study of changes in public educational institutions in a developing country, their implications for KM, and how a learning organization can face a turbulent environment and engage in new learning processes. Although this study cannot generalize to all graduate programs, it highlights shared issues across similar contexts, prompting a recommendation for research into the challenges and opportunities, primarily in the Global South. It also contributes to an understanding of individual and subjective factors (such as values and beliefs) in KM processes, prompting educational managers and stakeholders to consider these drivers in decision-making. This approach would provide a more comprehensive overview to support the redefinition of public and university policies in the development of highly skilled human capital.

This trend may be transferable to other Global South contexts, specifically in Latin America, where research in most institutions still depends on public funding, and the articulation with the private sector is neither institutionally consolidated nor paired with the researcher's interests.

Acknowledgements

We want to acknowledge the technical and financial support of the Writing Lab, Institute for the Future of Education, Tecnológico de Monterrey, Mexico, in the production of this work.

Competing interests: The authors declare no competing interests.

Ethics declaration: The ethics approval was granted by a qualitative research committee designated by the Educational Innovation Program of the Interdisciplinary Faculty of Social Sciences at University of Sonora. This group of experts reviewed the methodology and interview protocol to ascertain whether the information sought would not compromise the confidentiality or the identity of the informants.

AI declaration: The authors used Grammarly Pro version to check the correct grammar of our original text, since our native language is not English but Spanish. The authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

Data availability statement: Data is not currently openly available to protect the interviewee's identity.

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Knowledge Management for Sustainable Multidimensional Wealth: Reframing the MSW Model

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Abstract: This paper interprets the RMS Model, translated as Multidimensional Sustainable Wealth (MSW) Model, through a functional knowledge management (KM) architecture in order to clarify how multidimensional organisational wealth depends on knowledge-related capabilities. The paper is derived from a doctoral study that designed an integral business management model aimed at fostering Sustainable Multidimensional Wealth (MSW) in firms. That study followed a predominantly qualitative and exploratory orientation grounded in theoretical inquiry, documentary analysis, and interpretive-inductive reasoning, and resulted in the MSW Model, structured around five categories, ten subcategories, and forty-four emerging themes. Rather than treating MSW as a KM framework in origin, this paper argues that a functional KM lens provides a useful analytical vocabulary for interpreting selected MSW subcategories. Recent literature increasingly portrays KM as a field concerned with knowledge creation, sharing, integration, application, governance, and continuity, while also linking it to organisational learning, ESG integration, sustainability, and intellectual capital. Building on this literature, the paper maps five MSW subcategories — Corporate Culture, Corporate Talent, Corporate Intelligence, Corporate Governance, and Corporate Legacy — onto core KM functions. This mapping is used to explain how knowledge-related capabilities can support organisational outcomes that go beyond operational efficiency and extend to broader forms of value creation. The paper makes three contributions. First, it specifies a functional KM architecture and uses it as an analytical device for examining the MSW Model. Second, it shows that selected MSW subcategories can be interpreted as organisational loci through which KM functions are enacted, coordinated, and sustained. Third, it argues that MSW extends current KM debates by linking knowledge-related capabilities to multidimensional organisational wealth, particularly through continuity, legacy, and long-term viability. In doing so, the paper positions MSW as a structured interpretive framework that connects KM with organisational design and sustainable business management. It also suggests a pathway for future empirical research on how organisations may align knowledge processes with broader human, functional, contextual, economic, and transcendent dimensions of wealth.

Keywords: Knowledge management, Sustainable business management, MSW model, Organisational design, Multidimensional wealth

1. Introduction

Knowledge management (KM) has moved beyond repositories, codification systems, and information-processing routines. Recent research increasingly portrays it as a strategic and interdisciplinary field connected with organisational learning, decision-making, innovation, sustainability, and long-term value creation (Edwards and Lönnqvist, 2023; Durst, Edvardsson and Foli, 2023). Organisations therefore need managerial logics able to address ESG pressures, cultural fragmentation, technological change, and value creation beyond purely financial outcomes (Broccardo et al, 2025; Su et al, 2025).

The contemporary KM literature remains somewhat fragmented. Some studies focus on systems and analytics, others on learning culture, human resource practices, and knowledge sharing, and others on sustainability, intellectual capital, or governance. Fewer contributions offer a conceptual architecture that integrates these perspectives into a broader management model.

This paper addresses that gap by using a KM lens to reinterpret the MSW Model, originally developed in a doctoral thesis on business management for Sustainable Multidimensional Wealth (Vega-Baez, 2025). Although the thesis did not present MSW as a KM model, its architecture contains several components that can be interpreted through a knowledge management lens.

The paper addresses the following question: how can the MSW Model be interpreted through a functional knowledge management architecture, and what theoretical and managerial insights emerge from mapping its subcategories onto core KM functions? The paper develops an analytical reinterpretation rather than an empirical validation.

The paper makes three contributions. First, it specifies a functional KM architecture composed of knowledge creation, sharing, integration, application, governance, and continuity. Second, it shows that five MSW

subcategories - Corporate Culture, Corporate Talent, Corporate Intelligence, Corporate Governance, and Corporate Legacy - can be interpreted as organisational loci through which these KM functions are enacted. Third, it argues that MSW extends KM debates by linking knowledge-related capabilities to multidimensional organisational wealth, continuity, and legacy.

The next section reviews recent literature on KM. The third explains the methodological positioning of the article. The fourth presents the MSW-KM mapping. The fifth discusses implications, limitations, and future research. The final section concludes.

2. Knowledge Management as an Integrative Organising Logic

Recent literature suggests that KM is best understood not merely as the management of information stocks, but as the orchestration of social, cognitive, strategic, and institutional processes that enable organisations to create, share, integrate, apply, govern, and preserve knowledge. Edwards and Lönnqvist (2023) call for a broadened research agenda, while Durst, Edvardsson and Foli (2023) show that KM research in SMEs increasingly spans leadership, strategy, culture, and capability development.

KM can also be approached through a functional architecture rather than as a generic umbrella concept. Recent work recurrently describes KM as a set of functions concerned with knowledge creation, sharing, integration or transfer, application, governance, and continuity over time (Edwards and Lönnqvist, 2023; Kowshik et al, 2025). This view preserves the conceptual autonomy of KM while making it compatible with adjacent domains such as learning, strategy, innovation, and sustainability (Khadir and Durst, 2025). In this paper, these functions are used to interpret MSW rather than to claim that MSW originated as a KM framework.

One important stream places social and cultural conditions at the centre of KM. Naqshbandi et al (2024) show that AMO-based HR practices and knowledge sharing contribute to a learning organisational culture. Meher et al (2025) link learning culture to organisational performance through KM and organisational intelligence, while Ahsan (2025) highlights the role of leadership in cultivating lifelong development. Together, these studies show that knowledge is shaped by values, routines, expectations, and leadership practices.

A second stream is particularly relevant because it links KM to ESG-related capabilities and sustainable performance. Recent studies show that KM contributes to sustainability by enabling collaboration, decision quality, strategic alignment, reporting capability, and the translation of environmental and social concerns into organisational action. This is visible in work connecting KM with ESG-oriented sustainability (Su et al, 2025), the integration of ESG practices into organisational strategy (Suciu et al, 2025), knowledge application for sustainable performance (Nguyen et al, 2025), green knowledge management and environmental culture (Baquero, 2025), and sustainability implementation through integration with other management domains (Broccardo et al, 2025). Related research on intellectual capital further suggests that ESG performance and competitive advantage increasingly depend on intangible and knowledge-based capabilities (Amitrano et al, 2025; Ahmad, Wu and Khattak, 2025).

A third stream relevant to this paper is the renewed interest in intellectual capital as a basis for value creation. Čabrilo, Užienė and Kianto (2025) argue that intellectual capital theory should evolve towards a more ecosystemic and socially responsive perspective. Likewise, Amitrano et al (2025) connect intellectual capital, ESG dimensions, and competitive advantage in SMEs, while Ahmad, Wu and Khattak (2025) show that green intellectual capital supports sustainability and sustainable business model innovation.

Recent ECKM contributions also reveal a strong interest in linking KM with adjacent managerial domains. Hidayat, Rosari and Sitalaksmi (2025) review knowledge-based HRM, Krawczyk (2025) examines KM in sustainability reporting, and Suciu et al (2025) address the role of KM in integrating ESG practices into organisational strategies.

Taken together, the literature suggests that KM is increasingly associated with organisational learning, culture, talent, sustainability, reporting, strategic alignment, and intellectual capital. Yet it still lacks sufficiently developed frameworks that bring these elements together into a unified management architecture. The MSW Model is relevant at this point because its multidimensional structure offers a way to organise these dispersed concerns into a coherent framework. The next section therefore interprets five MSW subcategories through a functional KM architecture centred on creation, sharing, integration, application, governance, and continuity.

3. Methodological Positioning and Analytical Scope

This article is a conceptual paper that develops an analytical reinterpretation of the MSW Model through a functional knowledge management (KM) lens. The MSW Model was originally proposed in a doctoral study entitled Diseño de un modelo de gestión empresarial para generar riqueza multidimensional sostenible (Vega-Baez, 2025). That study followed a qualitative and exploratory orientation based on theoretical inquiry, documentary analysis, and interpretive-inductive reasoning.

The present paper does not reproduce the doctoral thesis in abbreviated form, nor does it report new empirical findings. It does not draw on interviews, surveys, case studies, experiments, or intervention-based research conducted specifically for this article. Although the paper discusses managerial implications, it is not positioned as a Design Science study and does not claim to develop or validate an artefact.

Methodologically, the paper follows a theory-adaptation logic. It brings two conceptual domains into dialogue: the MSW Model as a framework for sustainable multidimensional wealth, and recent KM literature addressing knowledge creation, sharing, integration, application, governance, and continuity. The paper therefore operates as an analytical mapping exercise rather than as an empirical validation study.

The analysis proceeded in four steps. First, the core architecture of the MSW Model was identified from the doctoral thesis. Second, recent literature on KM, organisational learning, ESG and sustainability, and intellectual capital was reviewed. Third, five MSW subcategories were mapped onto core KM functions. Fourth, the implications of this mapping were discussed in theoretical and managerial terms.

This positioning preserves fidelity to the original logic of the MSW Model while allowing it to enter a new scholarly conversation in KM. The contribution lies not in prediction, causal testing, or artefact validation, but in conceptual clarification, theoretical integration, and the development of a structured interpretive framework for future empirical research.

4. Reframing the MSW Model Through a Functional Knowledge Management Architecture

4.1 MSW as a Multidimensional Management Architecture

The MSW Model was originally conceived as a response to the limitations of conventional business management models that privilege economic results and short-term efficiency. Its central proposition is that organisations should be designed to generate Sustainable Multidimensional Wealth across five major domains: economic, human, functional, contextual, and transcendent wealth (Vega-Baez, 2025). These domains are operationalised through ten subcategories, including Culture, Talent, Intelligence, Strategy, Governance, Ecology, Philanthropy, and Legacy.

From a KM perspective, the importance of this architecture lies in its refusal to isolate value creation in one dimension alone. Knowledge in organisations is not created or applied only to improve operational efficiency. It also shapes the quality of relationships, the formation of identity, the interpretation of environmental signals, the legitimacy of decisions, and the continuity of organisational meaning. In this sense, MSW can be interpreted as a multidimensional management framework whose selected subcategories are closely aligned with knowledge-related organisational capabilities.

This interpretation does not imply that every MSW component is reducible to KM. Rather, it means that KM provides a useful analytical vocabulary for understanding how the model's different dimensions interact. In particular, five subcategories create the strongest bridge between MSW and KM: Corporate Culture, Corporate Talent, Corporate Intelligence, Corporate Governance, and Corporate Legacy.

4.2 Mapping MSW onto a Functional KM Architecture

To make the paper's central argument more explicit, Table 1 maps five MSW subcategories onto a functional KM architecture. Rather than treating MSW as a KM framework in origin, the figure shows how key subcategories can be interpreted through six core KM functions: knowledge creation, knowledge sharing, knowledge integration, knowledge application, knowledge governance, and knowledge continuity.

Table 1: Interpreting the MSW Model Through a Functional Knowledge Management Architecture

MSW subcategories	Functional KM architecture	Organisational outcomes
Corporate Culture	Knowledge creation; Knowledge sharing; Knowledge continuity	Human wealth; Contextual wealth; Transcendent wealth
Corporate Talent	Knowledge creation; Knowledge sharing; Knowledge application	Human wealth; Functional wealth; Economic wealth
Corporate Intelligence	Knowledge integration; Knowledge application	Functional wealth; Economic wealth; Contextual wealth
Corporate Governance	Knowledge governance; Knowledge application; Knowledge continuity	Functional wealth; Contextual wealth; Long-term organisational viability
Corporate Legacy	Knowledge continuity; Knowledge sharing; Knowledge governance	Transcendent wealth; Contextual wealth; Long-term organisational viability

Table 1 maps five MSW subcategories onto six knowledge management functions and shows how these capabilities contribute to multidimensional organisational wealth and long-term viability, highlighting that the relationship between MSW and KM is one of analytical interpretation rather than conceptual substitution, since KM provides the vocabulary through which the organisational role of selected MSW subcategories can be clarified, and showing that knowledge-related capabilities contribute not only to operational efficiency but also to human, contextual, transcendent, and long-term outcomes.

4.3 Corporate Culture as a Condition for Knowledge Creation and Sharing

Recent literature consistently shows that organisational culture is not peripheral to KM; it is constitutive of it. Knowledge sharing, learning orientation, and collaborative sense-making depend on trust, norms, openness, and the willingness to engage in collective development (Naqshbandi et al, 2024; Meher et al, 2025). Within the MSW framework, Corporate Culture can therefore be interpreted as the social substrate that enables the movement from dispersed individual knowing to coordinated organisational learning.

Many KM initiatives fail not for technological reasons but because the organisation lacks a culture that supports knowledge exchange. In the MSW logic, culture contributes not only to human wealth but also to functional wealth through coordination, contextual wealth through stakeholder relationships, and transcendent wealth through shared meaning.

4.4 Corporate Talent as a Carrier of Tacit and Explicit Knowledge

A second key bridge is Corporate Talent. Knowledge does not exist apart from the people who embody, enact, adapt, and transmit it. Hidayat, Rosari and Sitalaksmi (2025) show that knowledge-based HRM has become an important research domain precisely because organisations must align people practices with knowledge creation and utilisation. Likewise, Ahsan (2025) highlights the role of leadership in fostering continuous development, while Naqshbandi et al (2024) connect HR practices with learning culture through knowledge sharing.

Within MSW, Corporate Talent can be interpreted as the organisational capacity to cultivate, mobilise, and renew human carriers of knowledge. This includes technical skills, interpretive capabilities, collaborative competence, commitment, and developmental readiness. From a KM perspective, talent is the medium through which tacit knowledge becomes socially useful and explicit knowledge becomes actionable.

This linkage is especially important because it prevents KM from being reduced to codified assets alone. Organisations generate long-term viability not only by documenting what they know, but by developing people who can reinterpret and apply knowledge under changing conditions. In this sense, talent is both a KM concern and a strategic management concern.

4.5 Corporate Intelligence as Knowledge Integration for Action

Corporate Intelligence is perhaps the most direct point of contact between MSW and KM. In the doctoral thesis, this subcategory refers to the organisation's capacity to observe, analyse, and understand internal and external realities in order to support strategic action (Vega-Baez, 2025). Interpreted through KM, Corporate Intelligence

represents the process by which fragmented information is transformed into insight that can guide decision-making.

This interpretation resonates strongly with contemporary research. Meher et al (2025) connect KM with organisational intelligence, while Nguyen et al (2025) show that knowledge application contributes to sustainable performance. The implication is that knowledge becomes valuable when it informs action. It is not enough to collect information; organisations must integrate it, interpret it, prioritise it, and use it to shape responses.

Within the MSW framework, Corporate Intelligence links knowledge to multiple wealth dimensions. It supports economic wealth through better strategic decisions, functional wealth through improved coordination, contextual wealth through greater environmental awareness, and transcendent wealth through more coherent long-term orientation. It thus exemplifies the paper's core argument that KM is a multidimensional organising logic.

4.6 Corporate Governance as the Legitimisation and Prioritisation of Knowledge

A further contribution of the MSW interpretation is the recognition that knowledge has to be governed. Corporate Governance is often treated separately from KM, yet recent research on sustainability and strategy increasingly suggests that governance structures determine how information is prioritised, whose knowledge counts, and how decisions are made accountable (Broccardo et al, 2025; Suciu et al, 2025; Krawczyk, 2025).

In the MSW framework, Corporate Governance can be interpreted as the institutional arrangement through which knowledge is legitimised, prioritised, and translated into coordinated action. Governance shapes decision rights, attention, accountability, and continuity. Without governance, knowledge may remain available yet underused, contested, or disconnected from strategic action.

This is especially relevant in sustainability-related contexts. ESG integration, sustainability reporting, and long-term organisational viability all require governance mechanisms that ensure knowledge is not treated as episodic input but as part of an ongoing architecture of responsibility and sense-making. Interpreted in this way, governance becomes a KM issue because it determines the organisational conditions under which knowledge can influence action at scale.

4.7 Corporate Legacy as Organisational Memory and Long-Term Purpose

The most distinctive contribution of the MSW framework to KM may lie in Corporate Legacy. Much KM research focuses on creation, sharing, application, and retention. MSW adds a broader concern with continuity of identity, memory, meaning, and long-term purpose. In this respect, it extends the conversation from knowledge assets to organisational memory and enduring significance.

This extension aligns with recent work in intellectual capital and sustainability that calls for broader and more socially grounded understandings of value creation (Čabrilo, Užienė and Kianto, 2025; Amitrano et al, 2025). Legacy invites organisations to ask not only what they know and how they use it, but what they preserve, transmit, and stand for over time. It therefore adds a temporal and normative layer to KM.

In practical terms, Corporate Legacy includes institutional memory, identity narratives, accumulated experience, and continuity of purpose across generations of leaders, teams, and stakeholders. From a KM perspective, it expands retention from a technical concern into a strategic and cultural concern. From an MSW perspective, it contributes especially to transcendent and contextual wealth and reinforces long-term continuity.

5. Discussion

5.1 Theoretical Implications

This paper makes three theoretical contributions to current KM debates. First, it shows how a functional KM architecture can be used to interpret a multidimensional management model by mapping five MSW subcategories onto core KM functions. Second, it extends the conversation from knowledge processes to multidimensional organisational wealth. Third, it foregrounds continuity and legacy as underdeveloped dimensions of organisational knowledge.

The paper also contributes to theory by connecting KM with broader organisational outcomes without collapsing KM into adjacent domains. The MSW interpretation suggests that knowledge-related capabilities contribute simultaneously to human, functional, contextual, economic, and transcendent forms of value.

Finally, the paper advances KM theory by foregrounding continuity and legacy. While KM literature often addresses retention, the MSW lens broadens this discussion towards organisational memory, continuity of meaning, identity preservation, and long-term purpose.

5.2 Managerial Implications

The proposed mapping also generates practical implications for managers and organisational designers. It suggests that organisations should not treat KM as a separate programme limited to repositories, documentation, or technology platforms. Instead, managers can examine how knowledge-related capabilities are distributed across domains such as culture, talent, intelligence, governance, and legacy.

The model can also inform concrete managerial decisions. At the level of Corporate Culture, it directs attention to the social conditions that enable knowledge sharing and learning. At the level of Corporate Talent, it highlights the need to invest in people as carriers of tacit and explicit knowledge. At the level of Corporate Intelligence, it supports the formalisation of sensing, interpretation, and knowledge integration processes. At the level of Corporate Governance, it points to decision structures that legitimise and coordinate knowledge use. At the level of Corporate Legacy, it encourages organisations to treat continuity, memory, and purpose as strategic concerns.

The paper therefore offers an interpretive framework that managers may use to identify gaps between intended value creation and actual knowledge-related capabilities. It can guide architecture-level reflection on which processes, structures, and developmental priorities are required to align knowledge with multidimensional value creation.

5.3 Limitations

These contributions should be interpreted in light of the paper's limitations. This article is conceptual and does not provide empirical testing of the proposed mapping. It does not report case studies, interviews, surveys, or intervention-based research conducted specifically for this paper. Its contribution lies in conceptual clarification, analytical mapping, and theory adaptation.

5.4 Future Research Agenda

The analysis enables four directions for future research. First, scholars may empirically examine whether the proposed mapping between MSW subcategories and KM functions is observable across different organisational contexts. Second, future research may test whether certain KM functions are more strongly associated with specific dimensions of multidimensional wealth. Third, comparative work may explore how the MSW-KM relationship varies across sectors. Fourth, longitudinal research may examine whether organisations with stronger capabilities in knowledge governance and continuity develop greater resilience and long-term viability over time.

6. Conclusion

This paper has argued that the MSW Model can be more clearly understood when interpreted through a functional knowledge management architecture. Rather than subordinating KM to sustainability, the paper shows that KM provides a useful analytical vocabulary for explaining how selected MSW subcategories support multidimensional organisational wealth.

The main value of this reinterpretation lies in its integrative power. MSW brings together concerns often studied separately - culture, people, intelligence, governance, continuity, and long-term purpose - and invites a more holistic and human-centred understanding of KM. Organisations need more than efficient information systems; they need architectures capable of aligning knowledge with meaning, coordination, responsibility, and multidimensional wealth.

MSW should therefore be understood not as a final answer, but as a theoretically grounded platform for future research and practical experimentation.

Ethics Declaration: Ethical clearance was not required for this study because of the nature of the research.

AI Declaration: The structural editing of this paper was carried out by the authors. As non-native speakers of English, they used ChatGPT and Grammarly for translation, stylistic editing, and orthotypographic editing. The authors are fully responsible for the final text.

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Development of a Human-centric Systemic Interdisciplinary Approach to Enterprise Content Management Institutionalisation

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Abstract: Enterprise Content Management (ECM) solutions are essential for organisations aiming to enhance efficiency, effectiveness, and productivity in their information management endeavours. It is widely accepted that ECM solutions must be fully institutionalised, yet full institutionalisation is globally problematic. Internationally, even technologically advanced countries struggle to implement and maintain sound information management practices enabled by ECM solutions. Human dimensions are arguably the primary contributing factor for the perceived lack of full institutionalisation of ECM solutions, necessitating a deep understanding of human behaviour during the implementation and institutionalisation phases. The study strives to focus on the effect of knowledge-sharing, learning, sensemaking, and organisational environments on human behaviour during ECM-institutionalisation. This study proposes a systemic interdisciplinary approach to understand human behaviour during ECM-institutionalisation and offers a comprehensive lens through which the complex interplay of human behaviour, processes, information, and technology can be examined. A literature review, results from a maturity assessment and change adoption survey as part of an ethnographic study provided findings indicating a multifaceted, dynamic system, leadership support and fostering a learning culture to be pivotal. Skilled change agents balancing autonomy and cooperation are vital. Digital literacy encompassing sociological awareness and emotional intelligence part of customised training lead to information behaviour change. By enhancing collaboration through interdisciplinary methods, this approach provides valuable insights into the human dimensions of change, facilitating more effective institutionalisation of ECM solution. This study contributes a robust approach for understanding and managing the human dimensions of ECM-institutionalisation and enhances collaboration by bridging boundaries between disciplines, fostering a deeper understanding of the human dimensions involved in ECM-institutionalisation. The findings have significant implications for future ECM projects, enabling organisations to navigate the complexities of change management more effectively.

Keywords: Organisational change management, Knowledge management, Organisational culture, Enterprise content management institutionalisation, Learning culture

1. Introduction

"An empowered organisation is one in which individuals have the knowledge, skill, desire, and opportunity to personally succeed in a way that leads to collective organisational success" (Covey, 2024). This quote underlines the difference between implementing and institutionalising an enterprise content management (ECM) solution. Successful implementation only guarantees partial institutionalisation due to the ongoing challenges of assimilation and routinisation due to the human dimension of what is required for full ECM-institutionalisation (Venter 2025). Institutionalisation is regarded as the full adoption, diffusion, and entrenchment of organisational practices by organisations (Beddewela, Anchor & Warin, 2021:2791), as a long-term integration between people, process, technology, and information, especially after project implementation. There is a strong indication that ICT institutionalisation is problematic because insufficient attention is paid to the human side of technology implementations (Schabenberger 2020). ECM implementations are undertaken as part of organisations' digital transformation journeys, to enhance or comply with a range of legislative requirements. Digital transformation necessitates changing an organisation's business model, infrastructure, and culture. Many managers have a somewhat outdated view of data and information, and struggle to encourage employees to think differently about information, their work, and their role in the organisation (Schabenberger, 2020).

Changed information behaviours cannot be enforced (Delaney and D'Agostino 2015). Instead, it is a long-term process in which employees must be regularly updated on the reasons for the change. Integrating new technology and information practices disrupts established work routines and relationships, frequently changing job roles, which can threaten job competency and security. Employees often resist change because of the uncertainty and insufficient understanding of the need for change (Delaney and D'Agostino 2015). Resistance is heightened by management's behaviour, but when actively supporting change while addressing employees' concerns, transition will proceed more smoothly. Visionary leadership is crucial for implementing and sustaining transformation towards changed behaviour (Delaney and D'Agostino 2015). Managers who abandon institutionalising the solution before it is fully realised undermine the process.

ECM solutions are critical for organisations aiming to enhance efficiency, effectiveness, and productivity. The full benefits of these solutions can only be realised if they are thoroughly institutionalised (Alshammari, Mokhtar and Abdulmanap, 2025). In an ethnographic study spanning ten years (Venter 2025) human dimensions were observed as the primary contributing factor for the perceived lack of full institutionalisation of ECM solutions, which triggered the need to understand human behaviour during ECM implementation and institutionalisation. The results was the conceptualisation of a systemic interdisciplinary approach based on the observations and data collected during the study. The focuses of the approach is on how interdisciplinary methods enhance collaboration and offers a comprehensive lens through which the complex interplay of human behaviour, processes, information, and technology can be examined.

2. Research Methods

Findings from the ethnographic research (2014-2024) are based on active on-site involvement, using an observation schedule during the implementation and ECM-institutionalisation between 2014-2018. Observation continued from 2018-2024 with complete anonymity and confidentiality as agreed in the ethics application. From these observations an intensive literature review to confirm the observed phenomenon is broader in application than the observed cases only. Ethnography implies that the researcher is part of the participants' daily lives to observe and interpret their individual and collective behaviour, establishing a trust relationship with the participants and intermingling with them as an integral part of the socio-cultural dynamics of the group (Whitehead 2005). Descriptively analysed questionnaires from two groups (n=108 and n=296) informed individual unstructured discussions, formal interviews, and collaborative interaction over the ten year period, resulting in rich transcripts for this conceptualisation. Evidence captured participants' shared culture developing over time, as well as their reactions to changes in their new reality post ECM-institutionalisation.

3. Conceptualising a Systemic Interdisciplinary Approach to ECM-institutionalisation

The human ecological context affect ECM-institutionalisation. Humans naturally form cultures and communities with implicit rules for behaviour, which are crucial for managing transitions and achieving transformation (Islam, Furuoka and Idris 2021). Recognising the complexity of human behaviour and the necessity of a holistic approach that integrates various disciplines supports the argument that understanding and managing these human dimensions is essential for successful ECM-institutionalisation (Schmitt et al, 2023*)*. This fits into the broader human ecological context by showcasing how individuals' interactions and behaviours are shaped by their environment. Figure 1 provides a 3-dimensional concept view of how the interdisciplinary approach developed from this ethnographic study (Venter 2025).

3.1 The Three-dimensional Conceptual View of the Organisation During ECM-institutionalisation

The ECM environment is complex due to how the systemic whole behaves, interacts, and responds differently to stimuli in its individual parts and facets (Lawrimore, 2004). In the context of this study, complexity refers explicitly to the behaviour of people interacting with the ECM solution.

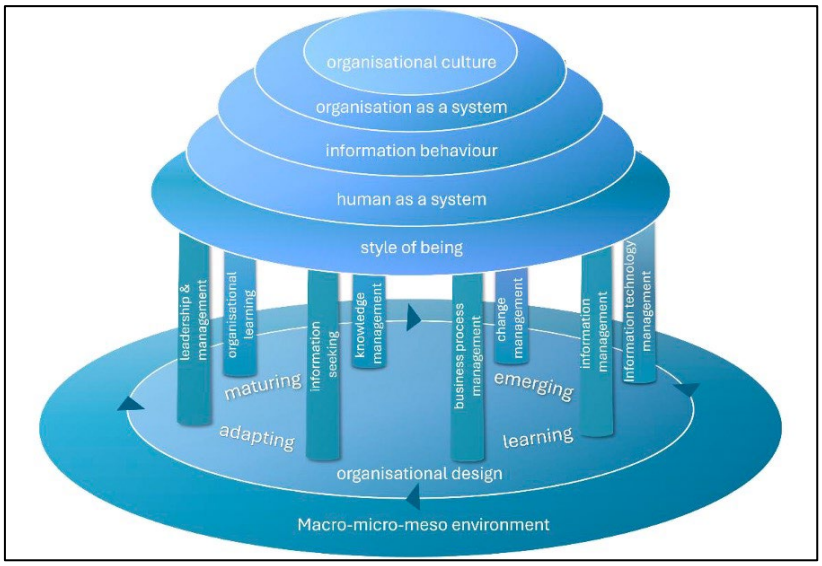


Figure 1: 3-Dimensional concept of Figure 2 (authors' own)

3.1.1 The macro-meso-micro environment

The macro-meso-micro environment describes an organisation's volatile and interactive nature with its environment (Dopfer, Foster and Potts 2004). This interaction is a complex system of emergent economic behaviour supported by a specific set of rules, structures, and processes. In the approach, "micro" refers to the internal carriers of organisational rules. "Macro" refers to the external forces that push the organisation to react to socio-economic and political changes. "Meso" refers to the interacting nature of the micro and macro environment using the exchange of knowledge about consumer/client/customer habits, behaviour and needs concerning environmental, socio-economic, and political changes (Dopfer et al., 2004:266-269).

The macro-environment manifests itself in the broader political, economic, societal, technological, legal, and ecological factors (PESTLE), that continuously fluctuate (Matovic, 2020:96-98). The meso environment manifests in "the connective structure of common knowledge". Building a network of alliances, suppliers, customers/clients/consumers, distribution channels, and emerging businesses is critical to any organisation's survival. Organisations depend on building a knowledge base of other organisations competing for the same consumer base to remain competitive (Dopfer et al., 2004:266-267). ECM solutions that are implemented and not fully institutionalised will affect the meso environment, which relies heavily on information availability. The micro environment manifests in developing organisational structures, resourcing the organisations, dividing labour, developing capabilities, setting rules for engagement with clients and consumers, building alliances, and finding outlets for products and services supported by the growth of knowledge about the industry within which the organisation operates (Swartz, 2021). The adaptability of the micro environment is specifically important after the global COVID-19 lockdowns forced organisations to rapidly adapt to remote working and virtual collaboration (Kniffin et al, 2021, Nadkarni and Prügl, 2021). Client observations (2020-2024), affected by the episodic nature of lockdown-induced virtual collaboration, did not necessarily institutionalise good information management practises or meaningful digital transformation. Episodic change is defined as infrequent, intentional organisational shifts (Weick and Quinn 1999), that occur when an organisation must swiftly adapt to external environmental shifts. Examples such as remote work, dismantled information silos, and digitised resources during lockdowns were short-term, aimed at specific problems, broad in scope, and often not fully implemented. After the change period, inertia sets in until a new problem necessitates intervention. While episodic change rarely leads to profound systemic shifts, it frequently occurs during enterprise-wide IT projects (Venter and Mearns 2025).

3.1.2 Organisational design

Continuous change tend to be long-term, ongoing, evolving, and cumulative (Weick and Quinn, 1999) and results from continuous learning, knowledge-sharing, improvisation, and innovative thinking. Continuous changes frequently uncover and resolve deep-rooted systemic problems that hamper organisational progress. Continuous change exists because the organisational leadership sanctions continuous learning towards adaptive, innovative work practices. The organisation as complex adaptive system requires design in which every part contributes to its well-being and survival, using continuous improvisation, innovation, and learning to emerge and evolve into a progressively mature organisation on which the structure of the organisation is built. Transformational change is required to function optimally in a digitally transformed society. Employees do not change their behaviour because management wants them to, they change because they know the consequences if they do not change. When people change, organisations change, enabled through understanding the bigger picture and a shared vision (Nadkarni and Prügl, 2021).

3.1.3 Pillars of the interdisciplinary approach

In Venter and Mearns (2025) pillars are identified as foundational to the interdisciplinary approach. *Information technology management* representing the relationship between people, process, technology and the end-user. *Business process management* enhancing business processes with feedback from knowledgeable participants. *Organisational change management* based on interaction with people to understand, embrace and adopt change in the work culture. *Information Management* to manage information sources at object level as strategic asset of the organisation. *Knowledge management* with collaborative learning, knowledge-sharing and sensemaking. *Organisational learning* as a normal part of how the organisation innovate. *Information-seeking* through search, find and act on information as learning enabler and decision support. *Leadership and management* and their role to inspire learning behaviour. Once the pillars were established as foundational to the complexity of the human ecological dimension of the interdisciplinary approach, several lenses through

which a focussed view on the human as integral part of the ECM-institutionalisation process were conceptualised.

3.1.4 The lenses that forms the telescopic view

The lenses in Figure 1 rests on the pillars to stabilise a telescopic view progressively focusing through each lens. Viewing the human through the first lens, *styles of being* positions the human as part of a dynamic system that interact with information, technology and peers through inherent *styles of being*. Change impact employees on multiple levels, emotionally, psychologically, and socially, creating a sense of discomfort, identifying what drives and motivates employees to adapt to change. It recognises that understanding and managing human behaviour is an ongoing process requiring continuous adaptation and support. Personality styles of dominance, influence, steadiness and compliance (abbreviated DiSC®) help determine behavioural styles, as the "primary emotions" and associated behaviour with combinations of emotions (DiSC® Profile 2021, Alshehri et al, 2018).

DiSC® profiling enables employees to understand themselves and empowers them to adjust their behaviour to work successfully in collaborative teams (Alshehri et al, 2018). Understanding employee personality and behavioural styles is critical for successful change and transition of the organisation to function optimally in a complex, evolving environment (Avey, Wernsing and Luthans 2008). Personality and behaviour affect communication between members of collaborative teams (Khuong et al, 2016). Better understanding of being human during an ICT implementation should equip leadership to focus on the well-being of the employees in relation to the work (Bellis et al, 2022), helps address resistance and improve the adoption of new practices.

3.1.5 The human as a system

Seeing the human as a system acknowledges the continuous, cyclical process of information-seeking, knowledge-sharing, sensemaking, learning, and innovation as an ongoing process (Gaston 2017:7). Human adaptability is vital in these interactions to foster a learning organisation and culture. Employees' information behaviour is complex, and the foundation for organisational information behaviour (Sammut-Bonnici 2015). Successful ECM-institutionalisation depends on recognising the value of information and addressing record-keeping responsibilities. Viewing information as a strategic resource, management and leadership must pay closer attention to the users' information behaviour as part of a system that values information as a strategic resource and asset. Monetary value of information should be reflected on the organisation's balance sheet, with an information management function that is adequately resourced and strategically positioned to ensure information user performance in record-keeping reflect the value of information beyond merely "admin" that needs to be done by somebody else. Employees' own information behaviour influences how other humans in the system handle information, through technology, via processes, in entrenched cultures, across organisational structures (Meshkati et al. 2016).

3.1.6 Information behaviour

A third lens focus on information behaviour. Problematic information behaviour often signals deeper systemic organisational issues. Through analysing information behaviour, management can identify and address underlying problems. Feedback from the observations during the ethnographic study highlighted that understanding and managing information behaviour is vital to overcoming systemic issues towards successful ECM-institutionalisation. Collectively information behaviour constitutes either an organisational strength or a weakness. When organisations better managed the human dimensions of information use, adaptation to change was observed to be more swift (Venter 2025). When employees' needs and behaviours are understood and supported, they are more likely to be engaged, motivated, and productive. Essentially, this ensures that technology and processes align with the human element, leading to a more harmonious, efficient, and successful ECM-institutionalisation.

Collective information behaviour brings into perspective often overlooked challenges such as practices inadvertently encouraging information hoarding. Efforts to create structure and discipline through compliance for the sake of ticking boxes instead of changing practices can lead to inconsistent information behaviour, failing to protect information as a strategic asset. Management and leadership must clearly articulate what and why they have expectations, upskilling themselves to be transformational leaders and identify transformational leaders among the employees (Ackerman and Anderson 2019:1-10). Employees with transformational leadership abilities must be empowered to lead the change at all levels of the organisation and work towards stability during the ECM implementation, beyond the project to anchor solutions in daily operations. Empowered employees proved themselves to use information optimally. Such employees will also be valuable role-players, especially within the current hype to integrate artificial intelligence (AI) into information solutions.

Employees should be upskilled with the necessary information-seeking, analysis and synthesis skills to function optimally in a digitally transforming environment.

3.1.7 Organisation as a system

Employees tend to anthropomorphise the concept of the organisation, viewing it as "persons" (Martin 2022). Like a "parent," the organisation bears responsibility for employee well-being and safety. The fourth lens highlights the organisation as a system, with the intricate interplay of people, processes, technology, and information within the broader ecosystem. The art of management lies in aligning all these components with the organisation's vision to achieve specific goals, ensure competitiveness and sustainability, through external pressures and internal dynamics. The organisation navigate multiple simultaneous changes, from episodic, to continuous, developmental, transitional, and transformational change in different contexts, simultaneously. Not all change can be treated the same and ideally transformational change is what the organisation aspires to in ECM-institutionalisation (Venter and Mearns 2025).

The technostress, information overload, barriers to ECM-institutionalisation and cognitive dissonance typical to modern organisations cause psychological strain on employees. To address these challenges, placing the human central in the organisation as system, support is required on multiple fronts. Mindfulness techniques help employees develop non-judgmental awareness of their thoughts and emotions, reducing stress and promoting mental clarity (Tenschert et al, 2024). Cognitive behavioural training help employees identify and challenge negative thought patterns, reducing cognitive dissonance and improving decision-making (Hristov, Camilli and Mechelli, 2022). Digital detox programs encourage regular breaks from digital devices to help alleviate technostress and improve overall well-being. Stress management techniques, relaxation exercises and time management skills, can be beneficial (Lehmann et al, 2021). Support systems through peer support groups or access to mental health professionals create safe spaces to discuss challenges and seek guidance (Jolly, Kong and Kim, 2020). Technology training to use new technologies effectively and increase confidence and competence (Beer and Mulder, 2020). Flexible work arrangements and remote work options support balance and reduce stress and regular check-ins with managers regarding workload and wellbeing is encouraged (Garr, 2022).

Wellness unit staff equipped to recognise and address technostress proactively, rather than waiting for employees to seek help, can help improve decision quality and mental workload management towards greater job satisfaction. This understanding was observed during the study to help improve the institutionalisation rate of ECM by addressing the root causes of resistance.

3.1.8 Organisational culture

Organisational complexity in an ever-evolving environment influences employees' information behaviour, in turn affects organisational information behaviour and the entire organisation significantly. From the multiplicity of lenses discussed, it is essential to recognise that we are dealing with a system (environment) within a system (organisation) within a system (people), utilising systems (processes and technology). Each system's components impact the subsequent system and results in the entire ecosystem's equilibrium to be disturbed (Paris 2018). Such ripples can leave the organisation in a state of disruption rather than transformation. Interactive learning behaviours need to lead to emergence and progress into maturity. Emergent change behaviour refers to complex systems working synergistically to create new realities. Employee resistance diminishes when employees are cognitively absorbed in the change process, their attention shifts from apprehension to active participation (Agarwal and Karahanna 2000). Emergence applies to how employees adapt to new realities in a changing environment and how the organisation sustains itself amid ever-changing stakeholder demands. ECM implementation can support and encourage emergence, but only if fully institutionalised. Organisational maturity depends on employees collectively adapting to changing circumstances for the organisation's benefit. They must be willing to adapt to changes and fully institutionalise technology. The organisational culture, is seen as a single eyepiece for the telescopic view, through which to focus on human behaviour during the ECM-institutionalisation.

Changing the view from the 3-dimensional Figure 1 to a 2-dimensional perspective (Figure 2) offers a perspective from the top with the eye piece of organisational culture at the centre. Each lens circles out but are adjustable to manage the systems towards alignment for ECM-institutionalisation.

3.2 Systemic Interdisciplinary Approach to Understanding Human Behaviour During ECM-institutionalisation

Figure 2 is viewed through the eye piece of organisational culture. The complex adaptive organisational system needs adjustment on multiple levels, in increments at different points in time to absorb and institutionalise the disruptiveness of the ECM solution as it touches on all information, all systems, all processes and all users. New behaviours to adapt to new working methods needs to be embraced in a learning and innovative workspace towards emergent behaviour. This process is not linear but continuously interacts with the ecosystem in perpetual motion. The lenses are continuously adjusted to focus on what is needed at any point in time to facilitate the adaptation.

Collaborative learning behaviours foster innovative thinking, interactive learning and perpetual adaptation to realities, maturing to changing circumstances. The goal of the systemic interdisciplinary approach is to understand human behaviour during ECM-institutionalisation and embed systemic change in an organisation to enable inside-out transformation rather than outside-in changes. Change that is deeply rooted in the organisation's core transforms it from within, rather than imposing changes on it. Integrating behavioural assessments into the systemic interdisciplinary approach allow organisations to better gauge the complex interactions between people, processes, technology, and information towards the kind of lasting, meaningful transformational change.

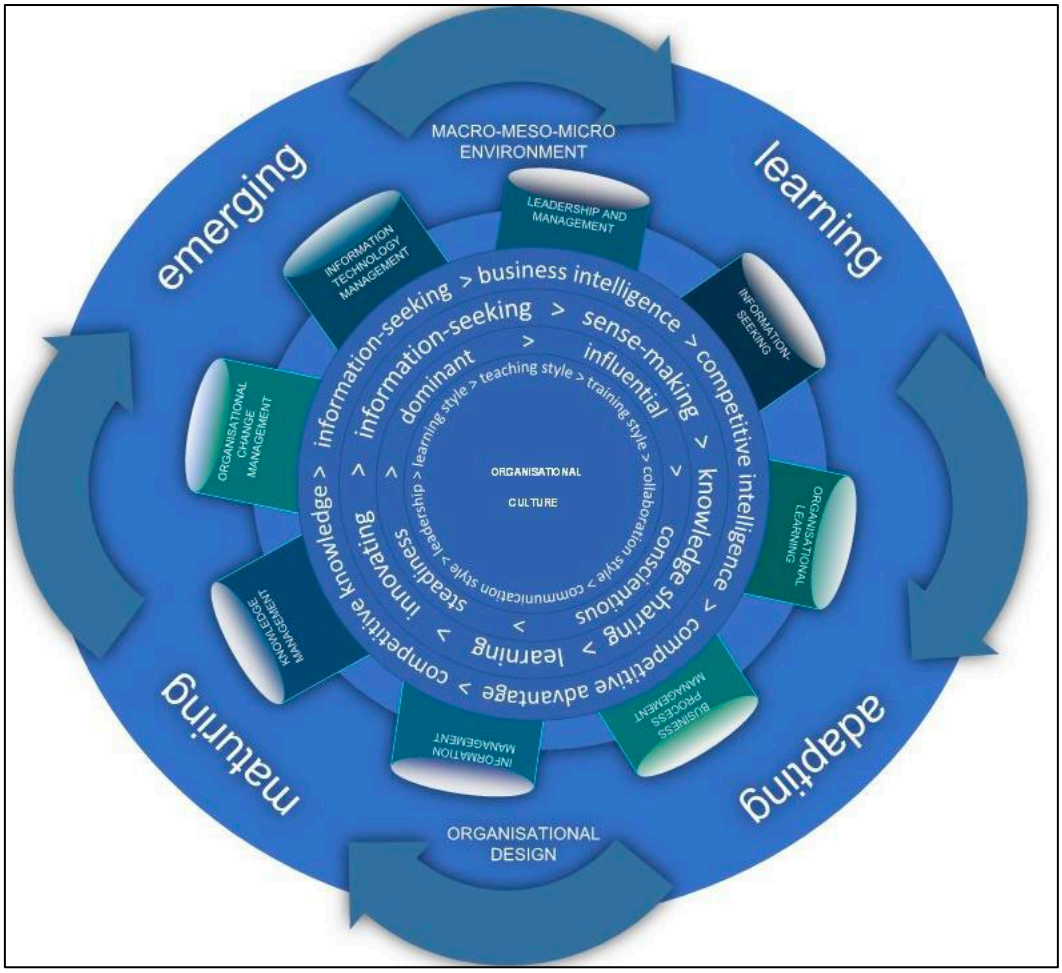


Figure 2: Systemic interdisciplinary approach to understanding human behaviour during ECM-institutionalisation (authors' own)

4. Positioning Knowledge Management as a driver in the interdisciplinary Human-centric Approach to ECM-institutionalisation

Having project change management activities as an add-on to an ECM implementation was observed to not necessarily ensure ECM-institutionalisation (Venter 2025). Such activities are short-term in nature and typically end with project sign-off, frequently leaving the organisation disrupted rather than transformed. ECM-institutionalisation requires transformation management as a strategic business function ensuring the change

becomes a part of the organisational culture. Transformation management often includes long-term monitoring, continuous improvement, and embedding new behaviours into daily operations, which is impossible if the change management activities are limited to the project duration. Transformation management is about re-inventing the organisation, not just about making superficial changes during ICT implementations.

The knowledge management function in the organisation is ideally positioned to accelerate the leadership required to support ECM-institutionalisation. Aligned to the interdisciplinary human centred approach of ECM-institutionalisation, knowledge management (KM) feeds off its multidisciplinary roots. Dalkir (2023) identifies organisational science, cognitive science, linguistics, information technologies, information and library science, among others, as a blend of expertise not previously seen, in which the human is at the centre driving towards organisational change. This perfectly mirrors the requirements that were observed during the ten-year ethnographic study.

Using the systemic interdisciplinary approach to understanding human behaviour during ECM-institutionalisation driven through the KM function as accelerator and leadership driver will assist with digital transformation, implementing and institutionalising ECM as part of the broader digital transformation journey. KM can support in managing the cultural change and impact and subsequent change, support the strategic framework for the business to align operational changes with strategic goals, measure maturity from current state, gaps, and future state goals and mitigate risk associated to knowledge loss in the transition stages of implementation.

5. Conclusion

The key contribution of the research is that it offers an insight into the reality of human dimensions in ECM-institutionalisation, occurring in an intricate environment characterised by complex human behaviour, as part of multiple complex systems. Change management best practices should be adapted to fit the specific context and environment of the organisation, tailoring these practices in a practical and relevant way to address each situation's unique challenges and dynamics. ECM initiatives often suffer from isolated efforts by various organisational functions. Information technology, records management, various business units and change management initiates are often siloed and disjointed due to the project-by-project approach. Instead, an interdisciplinary approach that conveys a unified change message and orchestrates cultural transformation is suggested that considers emotions, motivations, and social dynamics. This approach fosters change strategies towards greater employee engagement, already the mandate that KM brings to the organisation.

Interdisciplinary cooperation is particularly beneficial in complex digital transformation environments, as it helps achieve coherence and flow, which are challenging when disciplines work independently. The disciplinary backgrounds of role players in ECM-institutionalisation offers a multiplicity of perceptions that can be applied to handle new technologies, information behaviours, and the psychological effects of workplace changes (Syed 2020). Each discipline involved in ECM-institutionalisation should contribute to the training strategy, ensuring a comprehensive and effective programme. The KM team should facilitate change management with collaboration among the various disciplines to develop a shared understanding of goals and methods. Clear articulation of expectations and a unified approach to addressing behavioural issues are essential. Engaging experts from diverse fields, such as information science, business management, organisational behaviour, and technology, will help address ECM challenges collaboratively. Interdisciplinarity combines knowledge and techniques for effective problem-solving and, combined with orchestrated cultural transformation, offers a comprehensive approach to complex issues, a capability that KM already fulfils in practice.

Ethics Declaration: Ethical clearance was received in 2017 (EBIT/104/2017), which included the use of existing secondary sources (2014-2017) and primary data collected (2017-2024).

AI Declaration: None used.

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Variation, Selection, and Retention in Knowledge Management: An Evolutionary Integrative Review

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Abstract: The aim of this paper is to develop an interpretation of the temporal development of Knowledge Management (KM) through the lens of variation-selection-retention (VSR) logic. More specifically, it examines how KM arrangements emerge, gain support, become stabilised, and subsequently follow different post-retention trajectories over time. Although KM research has generated rich insights into knowledge creation, transfer, innovation, and technological enablement, it has been less explicit in theorising what happens after KM arrangements are introduced and retained within organisations. This paper addresses that gap by proposing an evolutionary reading of KM that extends beyond implementation and performance. The study adopts a PRISMA-informed, theory-driven integrative review of Scopus-indexed journal articles in the Business, Management and Accounting subject area published between 2000 and 2026, complemented by a focused VOSviewer term co-occurrence analysis. The final corpus of 25 studies was analysed through interpretive synthesis, with VSR used as a sensitising framework and bibliometric mapping employed to support the identification of recurring thematic configurations. The analysis identifies four connected configurations of KM scholarship: KM as routinised capability, ecologically embedded knowledge creation, sharing-driven innovation, and technology-mediated infrastructure. These configurations show that KM literature already contains important temporal and evolutionary insights, but that these remain dispersed across adjacent streams. Building on them, the paper develops an evolutionary conceptual model in which retention is not treated as an endpoint. Instead, retained KM arrangements may follow four post-retention trajectories: renewal, dormancy, replacement, or obsolescence. These trajectories are shaped by the interaction of functional relevance, organisational support, social legitimacy, and adaptive renewability. The paper contributes in three ways. First, it offers a temporally oriented reinterpretation of KM as an evolving organisational phenomenon. Second, it extends existing debate beyond implementation and performance by foregrounding differentiated post-retention trajectories. Third, it proposes a conditions-based framework that can guide future empirical research on the long-run viability, adaptation, and decline of KM practices and systems across different organisational settings.

Keywords: Knowledge management, Variation-selection-retention, Post-retention trajectories, Conceptual model, Temporal dynamics, Bibliometric mapping, Organisational learning, Knowledge management systems

1. Introduction

Knowledge Management (KM) has long been central to management and organisation studies because it addresses a persistent organisational problem: how knowledge can be mobilised to support learning, coordination, innovation, and competitive advantage (Argyris 1977, 1999; Kogut and Zander 1992; Spender 1996; Barney 2001). Foundational contributions established KM as a field concerned with knowledge creation, codification and transfer, and the organisational role of knowledge management systems (Polanyi 1958; Nonaka 1994; Davenport and Prusakv2000; Wiig 1997; Alavi and Leidner 2001).

As the field expanded, however, its internal logic became harder to capture within a single interpretive frame. Over time, KM scholarship moved beyond storage and transfer towards routines, inter-organisational knowledge flows, digitally mediated coordination, and capability development (Grant and Baden-Fuller 1995), making the temporal development of KM arrangements harder to theorise in an integrated way. Much of the literature still approaches KM primarily through adoption, implementation, and performance, while giving less attention to what happens after knowledge arrangements are introduced: how they become stabilised, reworked, weakened, or displaced over time. KM scholarship itself suggests that such arrangements are embedded, reshaped by use, and sometimes neglected as priorities, technologies, and work practices change. Even when prior studies refer to routines, institutionalisation, adaptation, or path dependence, these temporal insights are usually developed in a partial way rather than integrated into a broader developmental account of KM (Korac-Kakabadse et al. 2002; Huang 2009; Asif 2021).

An evolutionary lens provides a useful way of addressing this fragmentation. Campbell's (1960) variation-selection-retention (VSR) model offers a parsimonious account of how organisational forms emerge, gain support, and become stabilised. Related perspectives similarly foreground environmental fit, routines, path dependence, and internal competition for legitimacy and resources (Hannan and Freeman 1977; Nelson and Winter 1982; Burgelman 1991). Taken together, these perspectives suggest that KM can be understood as an evolving set of organisational arrangements whose viability depends on multiple interacting conditions.

This perspective is not entirely external to the KM field. Several studies point in an evolutionary direction, even if they do not consolidate their insights within a common framework. Huang (2009) explicitly approaches knowledge creation from an evolutionary perspective; Filippini et al. (2012) show how KM projects may develop into broader learning contexts; Kane (2017) highlights how social media alters the conditions under which knowledge is created, shared, and retained; and Li et al. (2024) show how discontinuous technological change compels firms to reconfigure KM in order to preserve dynamic capabilities. Related work on knowledge loss and organisational forgetting further suggests that the persistence of KM cannot be assumed (Daghfous et al. 2013; Agrawal and Muthulingam 2015).

The gap addressed in this paper is therefore not the absence of process-oriented KM research, but the lack of an integrative evolutionary framework capable of connecting emergence, stabilisation, adaptation, weakening, and possible obsolescence within a single interpretive account. Existing scholarship is more developed in explaining adoption, transfer, and innovation outcomes than in theorising persistence, dormancy, replacement, or obsolescence as part of KM's longer-run development. This imbalance is especially visible in contexts marked by digital disruption and discontinuous technological change, where organisations must not only introduce new knowledge arrangements but also renew, reconfigure, or abandon existing ones (Kane 2017; Li et al. 2024). Against this background, the paper addresses two research questions:

RQ1. How can VSR logic help interpret the thematic structure and temporal assumptions of a selected body of KM literature?

RQ2. What theoretical propositions does a VSR perspective support regarding the conditions under which KM arrangements may be retained, renewed, displaced, or rendered obsolete within different organisational settings and contexts?

The paper pursues two closely related aims. The first is interpretive: to reread a selected body of KM literature through an evolutionary vocabulary that clarifies how KM arrangements emerge, gain traction, and become stabilised over time. The second is conceptual: to develop a conditions-based framework capable of explaining not only retention, but also adaptive renewal, dormancy, replacement, and obsolescence as possible post-retention trajectories.

To address these aims, the study adopts a PRISMA-informed, theory-driven integrative review, complemented by focused bibliometric mapping. The selected corpus is analysed to identify recurring thematic configurations and, on that basis, to develop an evolutionary reinterpretation of KM. The paper contributes by offering a temporally oriented reinterpretation of KM, extending debate toward post-retention trajectories, and proposing a conditions-based framework for future empirical research. The paper is structured as follows. Section 2 revisits dominant KM framings and positions VSR as an organising lens. Section 3 presents the review design and corpus construction. Section 4 examines the thematic configurations emerging from the literature, and Section 5 develops the evolutionary conceptual model. Section 6 discusses the findings, Section 7 outlines their implications, and Section 8 concludes with limitations and future research directions.

2. Theoretical Background and Analytical gap

The development of KM scholarship has been shaped by several influential framings, each of which has captured a distinct aspect of how organisations create, mobilise, and sustain knowledge. These include KM as capability and routine, KM as contextually embedded knowledge creation, KM as sharing-driven innovation, and KM as technology-mediated infrastructure (Clarke and Rollo 2001; Michailova and Nielsen 2006; Moustaghfir 2008; Kane 2017). These streams show that KM is not reducible to storage or codification alone, but they foreground different explanatory moments: creation, circulation, innovation, and technology. What remains less consistently developed across these streams is a common temporal vocabulary for understanding the longer-term development of KM arrangements. Even where the literature refers to routines, institutionalisation, adaptation, forgetting, or discontinuity, such insights often remain attached to specific themes rather than integrated into a broader developmental account of KM over time (Korac-Kakabadse et al. 2002; Filippini et al. 2012; Daghfous et al. 2013; Li et al. 2024). As a result, the field remains less explicit about the longer-term trajectories of KM arrangements.

2.1 VSR as an Organising Lens

Variation-selection-retention (VSR) provides a useful organising lens because it offers a minimal temporal grammar without presupposing a single substantive form of KM. Variation concerns emergence, selection concerns fit and support, and retention concerns stabilisation through repetition and embedding (Campbell

1960). Related traditions reinforce this logic from different angles. Population ecology foregrounds selection pressures and environmental fit (Hannan and Freeman 1977), evolutionary economics stresses routines and path dependence (Nelson and Winter 1982), and internal selection perspectives show that organisations are arenas in which initiatives compete for endorsement and survival (Burgelman 1991).

Thus, VSR does not replace established KM explanations; rather, it relates them within a more explicit temporal frame. It enables KM arrangements to be viewed not only as managerial tools or socio-technical systems, but also as evolving organisational forms whose trajectories depend on interacting organisational and contextual conditions.

2.2 Analytical gap

Taken together, the dominant KM framings and the VSR lens clarify the paper's analytical gap. The issue is not a lack of relevant KM insight, but the need for a more integrated temporal vocabulary through which these insights can be related within a coherent developmental account. This paper addresses this gap by using variation-selection-retention logic as an organising lens for a selected corpus of KM studies and by theorising trajectories that extend beyond implementation and retention alone.

3. Methodology

This study adopts a PRISMA-informed, theory-driven integrative review complemented by focused bibliometric mapping. This combined design supports the identification of conceptually relevant patterns within the KM literature and provides the basis for conceptual development through an evolutionary reinterpretation of the field.

3.1 Database Selection and Search Strategy

Scopus was selected as the source database because it offers broad coverage of peer-reviewed journal literature in management and organisation studies and supports direct export of bibliographic data for analysis in VOSviewer. The search was conducted in January 2026 using the title, abstract, and keywords fields. The search strategy combined core KM terms with concepts associated with evolutionary and organisational dynamics in order to identify studies relevant to an evolutionary interpretation of KM.

The search string was as follows:

> *TITLE-ABS-KEY(("knowledge management" OR "knowledge management system") AND ("variation selection retention" OR "selective retention" OR "organizational ecology" OR "organisational ecology" OR "population ecology" OR "evolutionary theory" OR "evolutionary perspective" OR "path dependence" OR "organizational routine" OR "organisational routine*" OR routinization OR routinisation)) AND PUBYEAR > 2000 AND PUBYEAR < 2027 AND (LIMIT-TO(SUBJAREA, "BUSI")) AND (LIMIT-TO(SRCTYPE, "j")) AND (LIMIT-TO(DOCTYPE, "ar")) AND (LIMIT-TO(LANGUAGE, "English"))*

The search was limited to the period 2000–2026, to journal articles published in English, and to the bBusiness, Management and Accounting subject area. After applying these filters, the search returned 61 records. This strategy provided a focused basis for the subsequent analysis.

3.2 Inclusion Criteria and Screening Process

The screening process followed a PRISMA-informed logic and is summarised in Figure 1. Titles, abstracts, and keywords were screened manually. Studies were retained when KM or KMS was central and relevant to an evolutionary interpretation of KM, including themes such as adaptation, routines, path dependence, organisational ecology, selective retention, persistence, transformation, or knowledge loss. Articles were excluded when KM was marginal, when evolutionary terminology lacked substantive relevance, or when the study focused primarily on technical or computational issues. Following screening, 36 records were excluded and 25 retained for the final sample.

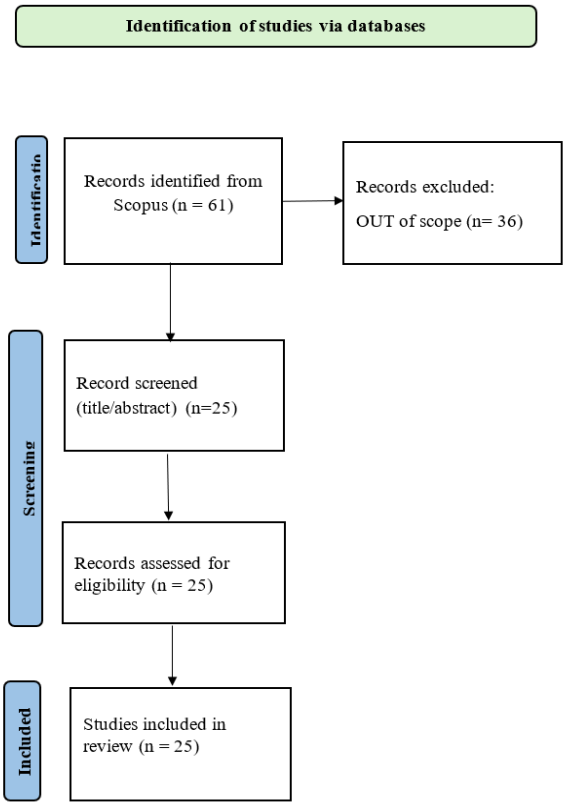


Figure 1: PRISMA-informed flow chart of the search and screening process. Source: Author's elaboration.

3.3 Analytical Strategy

The analysis proceeded in two stages. First, the 25 retained studies were examined through interpretive synthesis to identify recurring themes, conceptual tensions, and temporal assumptions concerning KM development over time. This reading was guided by VSR as a sensitising framework, with attention to variation, selection, retention, and post-retention dynamics. Second, a focused term co-occurrence analysis was conducted in VOSviewer using title and abstract terms from the final corpus. Terms with a minimum occurrence threshold of 2 were retained, while lexical variants, duplicates, and generic non-analytical terms were manually removed. The resulting clusters were interpreted alongside the close reading of the retained studies.

4. Results

The final corpus reveals a compact but conceptually differentiated body of literature. Rather than converging around a single understanding of KM, the selected studies point to four interconnected configurations through which knowledge-related arrangements are formed, stabilised, and transformed over time. Across the review period, the literature also suggests a shift in emphasis from codification, routines, and knowledge flows towards organisational ecology, capability development, knowledge loss, digital infrastructures, and adaptation under discontinuous technological change. The VOSviewer term co-occurrence analysis identified 21 items grouped into four clusters, with 83 links and a total link strength of 993. Figure 2 summarises these configurations, which were interpreted alongside the qualitative reading of the final corpus.

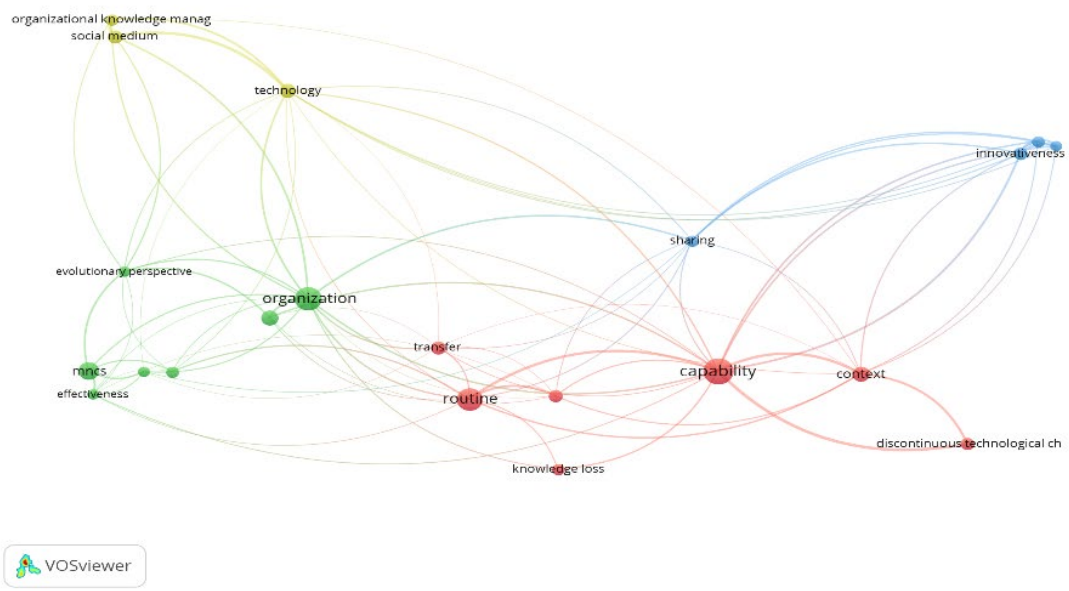


Figure 2: Term co-occurrence map. Source: Author's elaboration.

4.1 KM as Routinised Capability

The first configuration presents KM as a routinised organisational capability. Terms such as capability, routine, context, and transfer reflect a view of KM as becoming effective when embedded in recurring practices and everyday coordination. This reading aligns with research treating KM as enacted through use rather than simply stored or codified, and with studies showing that routines can support learning and capability development (Clarke and Rollo 2001; Sandhawalia and Dalcher 2011; Filippini et al. 2012). Yet routinisation does not ensure permanence: embedded KM arrangements may erode or lose fit under conditions of knowledge loss, forgetting, or discontinuous technological change (Daghfous et al. 2013; Agrawal and Muthulingam 2015; Li et al. 2024).

4.2 KM as Ecologically Embedded Knowledge Creation

A second configuration situates KM within a broader organisational and environmental ecology. Terms such as organisation, knowledge creation, organisational ecology, and effectiveness point to a view in which knowledge processes are shaped by contextual interdependencies rather than operating independently of their setting. This interpretation aligns with studies emphasising distributed expertise, boundary conditions, and the organisational environments in which knowledge is enacted (Michailova and Nielsen 2006; Becker 2007; Hu et al. 2022). In this configuration, KM viability depends not only on design quality but also on contextual fit and the conditions that sustain enactment over time.

4.3 KM as Sharing-driven Innovation

A third configuration links KM to innovation through knowledge sharing. Terms such as sharing, innovation, and innovativeness reflect a view in which KM supports learning, responsiveness, and adaptive performance. This reading aligns with studies that treat knowledge circulation as a mechanism for enhancing innovation outcomes (Moustaghfir 2008; Lakshman et al. 2023; Acevedo and Diaz-Molina 2023). While this configuration helps explain why certain KM arrangements gain traction, it places greater emphasis on the value they generate than on their longer-term durability.

4.4 KM as Technology-mediated Infrastructure

A fourth configuration foregrounds the infrastructural role of technology in shaping KM. Terms such as technology and social media reflect a line of research showing that digital systems do not simply support KM, but reshape the conditions under which knowledge is generated, shared, and retained. This interpretation is consistent with studies on KMS diffusion, digital platforms, and social media, which show that technologies

alter not only the speed of knowledge circulation, but also the forms through which it is coordinated and sustained (Lee et al. 2009; Kane 2017). In this configuration, technology appears not as a neutral support, but as a driver of variation, reconfiguration, and, at times, displacement under conditions of discontinuous change (Li et al. 2024).

4.5 Interim Synthesis

Taken together, the four configurations show that the selected corpus already contains the main ingredients for an evolutionary interpretation of KM. What remains to be articulated more explicitly is a temporal framework capable of relating these elements within a common explanation of KM trajectories. The next section addresses this issue by integrating these configurations into an evolutionary conceptual model of KM trajectories.

5. Toward an Evolutionary Conceptual Model of KM Trajectories

Building on the four configurations identified above, KM can be read through a temporal logic centred on variation, selection, and retention. This shift makes it possible to consider how KM arrangements emerge, become stabilised, and subsequently follow different trajectories over time. *Variation* refers to the emergence of alternative KM forms, whether through new systems, revised routines, novel transfer mechanisms, or digitally mediated practices. Such variation may arise incrementally through experimentation or more discontinuously through technological and environmental change (Huang 2009; Filippini et al. 2012; Kane 2017). KM should therefore not be treated as a stable category, since what is enacted as knowledge management may change across organisational settings and over time.

Selection refers to the differential viability of KM variants. Not all arrangements gain traction equally. Selection depends on more than technical efficiency alone: KM forms are more likely to be selected when they fit organisational structures, support coordination and innovation, align with patterns of use, and respond to the wider organisational context (Claver-Cortés et al. 2007; Lindner and Wald 2011; Hu et al. 2022; Lakshman et al. 2023).

Retention refers to the stabilisation of selected KM forms through routines, infrastructures, process integration, and repeated use. Retention occurs when a KM practice becomes part of the organisation's ordinary way of operating rather than remaining an isolated initiative (Clarke and Rollo 2001; Korac-Kakabadse et al. 2002; Asif 2021). Retention is not treated here as an endpoint: retained arrangements may still weaken when they lose relevance, become decoupled from practice, or fail to adapt (Daghfous et al. 2013; Agrawal and Muthulingam 2015; Li et al. 2024).

Taken together, these three mechanisms provide the basic evolutionary grammar of the model. The conceptual extension proposed here is that retention is not a common endpoint: stabilised KM arrangements may follow different trajectories depending on the conditions under which they continue to operate.

Four post-retention trajectories are proposed: *renewal, dormancy, replacement, and obsolescence*.

Renewal emerges when an established KM arrangement preserves sufficient continuity of purpose or identity but is actively reconfigured in response to changing demands. *Dormancy* refers to arrangements that remain formally available and recognisable, yet are only weakly enacted in practice and receive limited day-to-day support. *Replacement* develops when an older arrangement remains visible but is progressively displaced by an alternative that offers greater functional or organisational viability. *Obsolescence* arises when a KM arrangement loses not only use, but also recoverable relevance, legitimacy, and adaptive capacity to such an extent that it no longer operates as a meaningful organisational resource. Unlike dormancy, obsolescence implies not merely weak enactment, but a deeper loss of recoverable organisational usefulness. Movement from retention to one of these trajectories is shaped by four interacting conditions

These concern whether the arrangement continues to solve coordination, learning, transfer, or decision problems, receives managerial and structural support, remains trusted and enacted by organisational members, and can be updated in response to discontinuous change.

Taken together, these conditions help explain why retention does not produce uniform outcomes. The same retained KM form may be renewed in one context, remain dormant in another, be replaced in a third, and become obsolete in a fourth. KM evolution is therefore best understood as conditional, path-dependent, and contextually situated. These trajectories should not be understood as mechanically determined by single conditions, but as more likely under particular combinations of interacting factors.

This interpretation is summarised in four propositions:

P1. Renewal emerges when retained KM arrangements remain functionally relevant, socially legitimate, and adaptable, while continuing to receive organisational support for active reconfiguration in response to changing demands.

P2. Dormancy characterises KM arrangements that remain formally retained and recognisable, but whose everyday enactment weakens and whose organisational support becomes intermittent, without full abandonment or displacement by an alternative.

P3. Replacement occurs when retained KM arrangements lose comparative viability relative to alternatives that better fit prevailing coordination, innovation, or technological demands.

P4. Obsolescence develops when functional relevance, organisational support, social legitimacy, and adaptive renewability deteriorate in combination, thereby undermining both the current usefulness and the meaningful recoverability of the arrangement as an organisational resource.

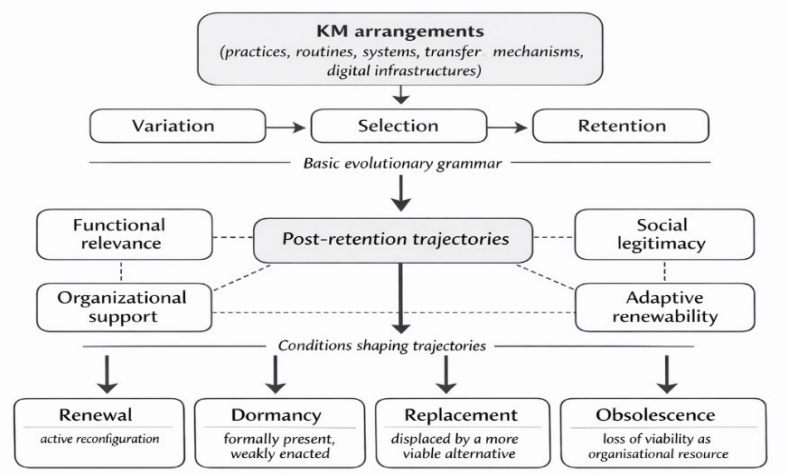


Figure 3: An evolutionary conceptual model of KM trajectories. Source: Author's elaboration

6. Discussion

The analysis suggests that an evolutionary reading helps connect themes that are often treated separately in KM research within a more explicit temporal framework. Across the selected literature, routines, contextual embeddedness, innovation, and technological change can be read not as isolated concerns, but as related dimensions of how KM arrangements emerge, gain support, stabilise, and respond to changing conditions over time. VSR does not replace existing KM explanations; rather, it clarifies a temporal dimension that is often implicit within them, especially by distinguishing between initial stabilisation and the divergent trajectories that may follow retention.

This reading extends attention beyond initial uptake and outcome-oriented accounts, showing that KM arrangements may be renewed, become only partially enacted, or be displaced once established.

The viability of KM arrangements cannot be understood independently of the settings in which they operate. Organisational structures, patterns of use, and technological environments shape whether a given arrangement remains meaningful, is adapted, or gradually loses relevance. The framework is therefore best read not as a universal sequence through which all KM arrangements necessarily pass, but as an interpretive model that highlights how different trajectories may emerge under different conditions.

Taken together, these points support a view of KM as an evolving organisational phenomenon rather than a stable managerial toolkit. Implementation, transfer, and innovation outcomes remain important, but they form only part of a longer temporal story in which knowledge arrangements may persist, change form, or fade from use. In this sense, the framework is offered not as a definitive general theory of KM evolution, but as a structured interpretive model that opens further analytical space around KM's longer-term dynamics.

7. Theoretical and Managerial Implications

Theoretically, the framework provides a basis for analysing KM not only in terms of creation, transfer, or performance, but also in terms of differentiated post-retention trajectories. This introduces greater temporal coherence by extending analysis beyond initial stabilisation. The framework also has implications for empirical research design. It points towards the value of longitudinal and comparative studies capable of examining how KM arrangements evolve across different organisational settings and contexts. In particular, it offers a basis for analysing why apparently similar KM practices follow different trajectories across settings, or why arrangements that seem well established at one moment later lose relevance or enactment.

Managerially, the analysis suggests that KM should be approached not only as a question of implementation, but also as one of ongoing viability. Knowledge systems and practices may therefore require periodic reassessment in relation to four conditions: continuing functional relevance, organisational support, social legitimacy, and adaptive renewability. This is especially important in digitally intensive environments, where newer tools often coexist with inherited knowledge practices.

8. Conclusion, Limitations and Future Research

This paper examined whether VSR logic provides a useful lens for interpreting a selected body of Knowledge Management literature and for thinking more explicitly about how KM arrangements evolve over time. The analysis indicated that the reviewed literature already points toward a more developmental understanding of KM, even though such insights are not usually brought together within a common temporal framework.

On this basis, the paper proposed an interpretive framework in which retained KM arrangements may follow four post-retention trajectories: renewal, dormancy, replacement, and obsolescence. Its contribution lies in providing a more explicit vocabulary for examining how knowledge arrangements persist, change, or lose relevance under changing organisational conditions. Several limitations should be acknowledged. First, the review is based on a single database and on a corpus restricted to Scopus-indexed journal articles in the Business, Management and Accounting subject area. Relevant contributions from adjacent subject areas or other databases may therefore fall outside the present analysis.

Second, the final sample is intentionally selective and theory-driven. The aim was not to provide an exhaustive review of the KM field, but to identify a body of literature capable of supporting an evolutionary reinterpretation. The findings should therefore be read as interpretive rather than representative of KM scholarship as a whole.

Third, the bibliometric component was used in a focused and supportive way. The term co-occurrence mapping helped clarify thematic configurations within the selected corpus, but it was not intended to provide a field-wide bibliometric account.

Finally, the study does not examine organisational cases directly. The framework developed here is literature-based and remains open to empirical refinement and testing.

Future research could develop this framework in several directions. One priority is empirical examination through longitudinal studies of KM arrangements in different organisational settings. Such work could help clarify how knowledge practices move across stages of emergence, stabilisation, renewal, weakening, or decline, and whether the post-retention trajectories identified here are observable in practice.

It could also examine whether similar KM arrangements follow different post-retention trajectories across multinational firms, temporary organisations, universities, public agencies, or digitally intensive platform environments. An other direction would be to investigate post-retention dynamics more directly, particularly in relation to dormancy, replacement, and obsolescence. These dynamics in fact may become increasingly important in contexts marked by rapid technological change and overlapping knowledge infrastructures.

More broadly, KM research may benefit from a stronger temporal perspective that asks not only how knowledge is created, transferred, or implemented, but also how it becomes enduring organisational judgement and remains viable, is reconfigured, or gradually loses relevance over time.

Ethics Declaration: Ethical clearance was not required for this research, as the study is based exclusively on published literature and does not involve human participants, personal data, or primary empirical data collection.

AI Declaration: No AI-based tools were used in the preparation of this manuscript. The authors take full responsibility for the conception of the study, the analysis and interpretation of the findings, and the writing and final revision of the text.

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Use of AI in Education to Support KM Processes in Organizations

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Abstract: AI-tools are being used in some organizations and there is little doubt that AI-tools may be powerful aids in a stressful worklife. However, it is important to choose tools that will enable a productive use, and with the plethora of tools at hand today, it may be difficult to evaluate and decide on tools that will suit the needs of an organization. As an academic organization providing education also within the lifelong learning segment, we should integrate use of AI-tools in our courses. As many in the lifelong learning segment are already working in organizations, we should offer learning about AI-tools, as well as learn from our students regarding the use of AI-tools. Our project on using AI-tools to evaluate student assignments has been undertaken in cooperation with our students. After the students being provided feedback on their mandatory assignments from our faculty staff, the same assignments have received an evaluation from an AI-tool. The investigations have been threefold; about how the students evaluated their AI-evaluation (compared to the evaluation from the lecturer), about how the students predict or present similar AI-tools can be used back in their organizations, and from the perspective of the faculty staff; how lecturers can best integrate teaching AI-tools to students that are in a worklife. The paper presents results from the qualitative investigations and provide valuable insights that will define the further use of AI-tools for evaluation for their next courses.

Keywords: AI-tools, Organizational learning, Knowledge management processes, Work relevance

1. Introduction

Artificial intelligence (AI) tools are increasingly being introduced into organizational settings to support knowledge-intensive work (Brynjolfsson and McAfee, 2014, Davenport and Ronanki, 2018). In contemporary work life, employees often face high cognitive and emotional demands, tight deadlines, and a constant flow of information. AI-based tools, ranging from recommendation systems and intelligent search to generative language models, promise to assist workers in dealing with these demands by automating routine tasks, enhancing decision-making, and providing on-demand access to relevant knowledge (Russell and Norvig, 2010, Shrestha et al., 2019). There is little doubt that such tools may become powerful aids in a stressful work life.

However, organizations face a major challenge: the sheer number and diversity of AI tools available on the market. This abundance makes it difficult to evaluate which tools are reliable, ethically acceptable, and well-suited to the organization's specific needs and practices (Davenport et al., 2020). The challenge is particularly acute in knowledge-intensive organizations such as universities, where both staff and students are expected to engage in continuous learning, critical thinking, and responsible use of digital technologies (Laurillard, 2012, Selwyn, 2017).

As an academic institution providing education not only to traditional full-time students but also to lifelong learners—many of whom are already employed in various organizations—we have a dual responsibility. On the one hand, we must integrate the use of AI tools into our teaching and assessment practices to ensure that our courses are relevant to current and future work life (Kong et al., 2025). On the other hand, we have a unique opportunity to learn from our students' experiences with AI tools in their own organizations. This bidirectional learning can contribute to both academic development and organizational innovation (Argyris and Schön, 1996, Wenger, 1998).

The present paper reports on a project in which AI tools were used to evaluate student assignments in cooperation with the students themselves. After students had received formative feedback on mandatory assignments from faculty staff, the same assignments were evaluated by an AI tool. The project had three overarching aims:

1. To explore how students evaluated the AI-generated assessment compared to the feedback from the lecturer.
2. To investigate how students predict or envision the use of similar AI tools in their own organizations.
3. To examine, from the perspective of faculty staff, how lecturers can best integrate AI tools into teaching for students who are already embedded in work life.

The paper is based on qualitative investigations involving both students and faculty. The findings provide valuable insights into how AI tools can be meaningfully integrated into educational practice, how such tools might transfer to organizational contexts, and how they may influence knowledge processes, both within the university and in workplaces where students are employed (Nonaka, 1994, Nonaka and Takeuchi, 1995). These insights will inform the further use of AI tools for evaluation in future courses.

2. Theoretical Foundation

Here we will present the theoretical framework that we have based our understanding on.

2.1 Knowledge Management and Organizational Learning

Knowledge Management (KM) focuses on how organizations create, capture, share, and apply knowledge in order to achieve their goals (Alavi and Leidner, 2001, Hislop et al., 2018). Effective KM involves enabling the conversion between tacit and explicit knowledge through processes such as socialization, externalization, combination, and internalization—often referred to as the SECI model (Nonaka, 1994, Nonaka and Takeuchi, 1995).

From a KM perspective, AI tools can be understood as socio-technical mechanisms that support or transform these knowledge processes (Pan and Scarbrough, 1999, Grant, 1996). For instance, AI-based recommendation systems and search engines can support the combination and retrieval of explicit knowledge. Generative AI tools (such as large language models) may assist in externalizing tacit knowledge by helping users articulate ideas, draft texts, and structure arguments. At the same time, the use of AI requires individuals to critically evaluate AI outputs and integrate them into their own understanding, thereby supporting internalization (Shrestha et al., 2019).

Another important aspect of KM is the role of communities of practice and social learning (Wenger, 1998, Brown and Duguid, 1991). Knowledge is not only stored in documents or systems but is embedded in the practices and interactions of people. When AI tools are introduced into such communities, they may change the patterns of communication, the distribution of expertise, and the norms of knowledge sharing (Leonardi and Treem, 2012). In educational settings, this implies that AI tools are not merely technical add-ons but become part of the learning environment and influence how students and lecturers co-create knowledge.

In addition, KM emphasizes knowledge flows across organizational boundaries (Easterby-Smith and Lyles, 2011). Lifelong learners who attend university courses while working act as knowledge brokers between the university and their organizations (Hargadon and Sutton, 1997). They bring practical experiences and organizational know-how into the classroom and, in turn, transfer theories, methods, and tools from the university back into their work contexts. The introduction of AI tools into teaching can therefore have ripple effects beyond the educational institution, potentially affecting knowledge processes in the students' organizations.

2.2 AI Tools in Organizations and Education

AI tools can be defined broadly as computational systems that perform tasks which typically require human cognitive capabilities, such as perceiving, reasoning, learning, or generating content (Russell and Norvig, 2010). In organizational contexts, AI is increasingly used to support decision-making, automate routine tasks, and personalize services (Davenport and Ronanki, 2018, Dwivedi et al., 2021). Examples include predictive analytics, intelligent document processing, conversational agents, and generative text or image tools.

Recent developments in generative AI, especially large language models, have particular relevance for knowledge work and education (Bommasani et al., 2021). These models can summarize texts, generate explanations, draft documents, and provide feedback on written content. As such, they blur the boundaries between human and machine contributions to knowledge production. This raises both opportunities and concerns. On the opportunity side, generative AI can reduce mundane workload, provide rapid formative feedback, and support creativity and reflection. On the concern side, issues of accuracy, bias, transparency, academic integrity, and over-reliance on AI must be addressed (Selwyn, 2019, O'Neil, 2016).

In education, AI tools have been explored in several roles: as tutors that provide feedback and guidance, as tools that support teachers in assessment and course design, and as objects of study that students learn about and learn to critically evaluate (Holmes et al., 2019). The use of AI for assessment is particularly sensitive, as it touches upon fairness, validity, and the trust relationship between students and instructors (Williamson and Eynon, 2020). AI-generated feedback can be timely and scalable, but may lack contextual understanding, nuance, or alignment with course learning outcomes if not carefully calibrated.

The idea of "human-in-the-loop" AI has been proposed as a way to balance automation with human judgment (Shneiderman, 2020). In this view, AI tools do not replace teachers or professionals but augment their capabilities. The human retains responsibility for critical decisions, while AI supports by providing analyses, suggestions, or alternative perspectives. In the context of our project, AI is used to provide an additional layer of evaluation on student assignments, which students and lecturers can compare with human feedback.

2.3 AI Tools as Knowledge Management Instruments

By integrating knowledge management perspectives with AI research, we can conceptualize AI tools as instruments that not only process data but also mediate knowledge processes (Dwivedi et al., 2021, Shrestha et al., 2019). For example, in the evaluation of student assignments, an AI tool might:

- Help externalize tacit criteria by making explicit the aspects of an assignment it deems strong or weak (Nonaka & Takeuchi, 1995).
- Serve as a repository of codified evaluative knowledge in the form of prompts, rubrics, and examples (Alavi and Leidner, 2001).
- Support knowledge sharing by generating feedback that can be discussed and refined in interaction between student and lecturer (Wenger, 1998).
- Stimulate organizational learning by revealing differences between AI and human evaluations and thereby prompting reflection on assessment practices (Argyris and Schön, 1996).

In our project, the university can be seen as a knowledge-intensive organization experimenting with AI-based KM instruments in collaboration with students who themselves are embedded in other organizations (Hislop et al., 2018). Through this experiment, the university not only supports student learning but also gathers knowledge about how AI tools may function in diverse work contexts. Students' reflections on AI evaluation in their own organizations thus become a source of organizational learning for the university and contribute to a broader understanding of AI as a KM technology (Easterby-Smith and Lyles, 2011).

3. Method of Inquiry

The study employed a qualitative research design to explore how AI tools can be used to evaluate student assignments and how such use is experienced by both students and faculty. Qualitative methods were chosen to capture the nuances of participants' perceptions, interpretations, and reflections, which are central when investigating emerging technologies and complex knowledge processes (Creswell, 2022, Braun et al., 2021).

The project was conducted in the context of a university course aimed at lifelong learners, many of whom are employed in various organizations while studying part time. The course included mandatory written assignments that are normally evaluated by faculty staff. For the purposes of this project, an AI tool capable of generating evaluative feedback on written texts was introduced as a supplementary evaluator.

Participants consisted of 9 students enrolled in the course and the lecturers responsible for teaching and assessment. The students represented a variety of professional backgrounds, including public administration, private sector companies, and non-profit organizations. Most participants were experienced professionals seeking to update their competences and to engage in lifelong learning (Jarvis et al., 2003).

The AI tool was introduced after students had submitted a mandatory written assignment and received formative feedback from their lecturer. Students were informed about the project's purpose, the role of the AI tool, and the voluntary nature of participation in the qualitative investigation.

3.1 Data Collection

Data were collected from three main sources aligned with the threefold focus of the project:

Student evaluations of AI-generated feedback

After receiving both the lecturer's feedback and the AI-generated evaluation, students were invited to reflect on and compare the two. This was done through written reflective notes and semi-structured interviews or focus groups (Kvale & Brinkmann, 2015). The reflections addressed questions of accuracy and usefulness, the difference between AI feedback and teacher feedback, and how they perceived the *combination* of AI and lecturer feedback regarding learning outcome.

Students' envisioned use of AI tools in their organizations

Students were also asked to consider how similar AI tools might be used in their current or future workplaces. Data were collected through focused questions in the interviews and through an assignment prompt asking students to describe potential applications, benefits, and challenges of AI-based evaluation tools in their own organizational context (Easterby-Smith and Lyles, 2011).

Faculty perspectives on integrating AI in teaching

Lecturers involved in the course participated in interviews and reflective discussions about their experiences of using AI tools for evaluation. They were asked to reflect on 1) how AI-generated feedback compares to their own assessments, 2) how the use of AI affected their teaching and assessment practices, and 3) what considerations might be important when teaching students who are already in work life about AI tools. These reflections relate to broader debates about digitalization and AI in higher education (Selwyn, 2017).

All qualitative data (student reflections, interview transcripts (from notes), and faculty reflections) were analysed using thematic analysis (Braun & Clarke, 2006). The data was coded, aligning it with the three research aims ensuring coherence and to relate findings back to the theoretical framework of knowledge management and AI in organizations.

Throughout the analysis, we adopted a reflexive stance, acknowledging our dual role as lecturers and researchers and being sensitive to the power dynamics in educational settings (Finlay, 2002). The aim was not to produce generalizable findings in a statistical sense, but to provide rich, contextualized insights that can inform further experimentation and theory development.

4. Results and Discussion

4.1 Students' Evaluation of AI-generated Feedback

Overall, students reported that the AI feedback was surprisingly coherent and relevant, especially regarding surface-level aspects such as structure, language, and clarity. Many appreciated the immediacy of the AI feedback, which could be obtained quickly after the assignment was processed (Holmes et al., 2019).

However, when comparing AI feedback to the lecturer's evaluation, students consistently highlighted the lecturer's feedback as deeper and more closely aligned with the course learning outcomes. The lecturer's comments were perceived as better at capturing the nuances of argumentation, theoretical understanding, and the specific expectations of the assignment. AI feedback, in contrast, was often described as more generic, sometimes repetitive, and occasionally misaligned with the specific context of the course. This resonates with concerns about the context-insensitivity of automated feedback systems in education (Selwyn, 2019).

From a knowledge management perspective, this finding reflects the difference between codified, explicit criteria and the tacit judgment of an experienced lecturer (Nonaka and Takeuchi, 1995). The AI tool appears to operate primarily on explicit, surface-level features of the text, while the lecturer draws on tacit pedagogical knowledge, familiarity with the curriculum, and knowledge of the student's progression. This confirms the importance of keeping a human in the loop and suggests that AI tools are best used as complementary, not substitutive, evaluators (Shneiderman, 2020).

At the same time, some students reported that the AI feedback prompted them to reconsider aspects of their work that the lecturer had not emphasized, such as overall coherence or specific phrasing. In this sense, the AI tool contributed to knowledge combination by offering an additional perspective (Alavi and Leidner, 2001). When students engaged critically with both sources of feedback, the result could be a richer learning experience, exemplifying the internalization of knowledge from multiple inputs (Nonaka and Takeuchi, 1995).

4.2 Envisioned Use of AI Tools in Organizations

A second major theme concerned how students imagined the use of similar AI tools in their own organizations. Many participants saw clear potential for AI-based evaluation in HR processes, training programs, and organizational learning initiatives (Dwivedi et al., 2021). For instance, some suggested that AI tools could provide rapid feedback on internal reports, project proposals, or policy drafts, helping employees improve their writing and argumentation before documents are formally submitted.

Students working in organizations with extensive documentation burdens highlighted the possibility of using AI to summarize documents, extract key points, or assess whether texts adhere to established templates or guidelines. In such scenarios, AI tools function as knowledge management instruments that support the

combination and retrieval of explicit knowledge (Grant, 1996, Shrestha et al., 2019). Several participants emphasized that AI could help reduce repetitive cognitive work, thereby freeing time for more complex problem-solving and interaction with colleagues.

However, students also identified significant challenges. Concerns were raised about data privacy, confidentiality, and the risk of uploading sensitive documents to external AI services (O'Neil, 2016, Dwivedi et al., 2021). In some sectors, such as public administration and health care, strict regulations limit how data can be processed and stored, making the use of external AI tools particularly problematic. Participants stressed the need for clear organizational policies and technical safeguards, such as on-premise solutions or anonymization routines, to mitigate these risks.

In addition, several students emphasized the need for training and guidelines to ensure responsible use and avoid over-reliance on AI. Some worried that AI-based evaluation could reinforce existing biases or lead to standardized, less creative forms of expression if employees adapt too strongly to what they perceive as "AI-approved" writing (O'Neil, 2016, Selwyn, 2019). A few participants expressed concern that middle managers might be tempted to use AI feedback as a proxy for human evaluation, potentially delegating important judgments to systems that are not fully understood.

These reflections align with KM theories' emphasis on socio-technical systems and the importance of organizational context (Pan and Scarbrough, 1999, Leonardi and Treem, 2012). Introducing AI evaluation tools is not merely a technical implementation but a change in knowledge processes and power relations. For example, when AI tools evaluate employees' texts, questions arise about who controls the evaluation criteria, how transparency is ensured, and how feedback is integrated into performance management. Students' awareness of these issues underlines the importance of involving end-users in the design and governance of AI-based knowledge systems (Easterby-Smith and Lyles, 2011).

Overall, students' envisioned uses of AI tools in their organizations suggest a strong potential for AI to support knowledge work, especially in relation to document handling, internal communication, and training. At the same time, they point to a need for organizational learning about AI—developing collective understanding of what AI can and cannot do and establishing norms for responsible and effective use (Argyris and Schön, 1996, Wenger, 1998).

4.3 Faculty Perspectives on Teaching AI Tools to Working Students

The third theme focused on faculty reflections on the integration of AI tools into teaching, particularly when students are already embedded in work life. Lecturers reported that the project challenged them to articulate their own assessment criteria more explicitly in order to compare their feedback with that of the AI tool. This process of externalization contributes to organizational learning within the university, as tacit pedagogical knowledge is made more explicit and potentially shareable among staff (Nonaka and Takeuchi, 1995, Alavi and Leidner, 2001).

The lecturers noted that comparing their feedback to the AI-generated evaluation made them more aware of their own assumptions and preferences in assessment. In cases where AI feedback diverged significantly from human feedback, this prompted discussions among staff about what constitutes quality in student writing and how criteria are communicated to students. In this way, the AI tool functioned as a "mirror" on existing assessment practices, encouraging reflection and potential refinement.

Lecturers also observed that students' experiences from their organizations enriched the classroom discussions about AI. Students brought concrete examples of AI adoption, resistance, and experimentation from diverse sectors, which allowed the course to function as a space of cross-organizational knowledge exchange (Hargadon and Sutton, 1997, Wenger, 1998). In KM terms, students acted as knowledge brokers, facilitating knowledge flows between their workplaces and the university.

At the same time, faculty expressed concerns about how best to teach AI literacy and critical AI use. They emphasized the need to go beyond technical demonstrations and to engage students in discussions about ethics, bias, and the limitations of AI (O'Neil, 2016, Selwyn, 2019). Lecturers also highlighted the importance of setting clear expectations for the use of AI in assignments to safeguard academic integrity while encouraging responsible experimentation. This involved clarifying when AI assistance is allowed, how it should be documented, and how students are expected to critically assess AI-generated content.

From a pedagogical perspective, the project illustrated the value of positioning AI tools both as "resources" for students (e.g., for drafting and receiving feedback) and as "objects of reflection and critique" (Holmes et al.,

2019). By experiencing AI-generated evaluation themselves, students were better prepared to reflect on the implications of introducing similar tools in their organizations. This dual orientation supports deeper learning and strengthens the link between academic theory and professional practice (Laurillard, 2012).

5. Conclusion

This paper has presented a qualitative study of using AI tools to evaluate student assignments in an academic course targeted at lifelong learners who are already engaged in work life. The project combined perspectives from knowledge management and AI research to explore three main questions: how students evaluate AI-generated feedback compared to lecturer feedback, how students envision the use of similar AI tools in their organizations, and how faculty can integrate AI tools into teaching for working students.

The findings indicate that students generally appreciate the immediacy and coherence of AI-generated feedback, particularly for structural and linguistic aspects of their assignments. However, they regard lecturers' feedback as deeper, more contextualized, and more closely aligned with course objectives. AI tools are therefore best understood as complementary evaluators that can enrich, but not replace, human assessment.

Students identified multiple potential applications of AI tools in their organizations, particularly in supporting documentation, training, and internal communication. At the same time, they expressed concerns about privacy, governance, and the risk of over-standardization. These reflections underscore the importance of viewing AI implementation as a socio-technical change in knowledge processes, rather than a purely technical upgrade.

For faculty, the project acted as a catalyst for articulating assessment criteria more explicitly and for engaging with students' real-world experiences of AI in organizational contexts. Teaching AI tools to working students requires not only demonstrating their capabilities but also fostering critical reflection on their limitations and ethical implications. From a KM perspective, the project illustrates how AI tools can function as instruments for externalizing, combining, and internalizing knowledge, while also highlighting the irreplaceable role of human judgment and communities of practice.

For future courses, the insights gained from this project suggest 1) a transparent integration of AI evaluation using this as a part of a deliberate pedagogical strategy to stimulate critical reflection on assessment criteria and on the nature of expertise, 2) strengthening AI literacy and critical competence to include understanding how AI systems work, their biases and limitations, and how to critically evaluate their outputs, and 3) link university experiments to organizational practice through collaborations with students' organizations as this could be developed further to explore real-world pilots of AI-based evaluation tools, with the university contributing research-based guidance and evaluation. Such collaborations could support organizational learning about AI, while providing authentic contexts for academic inquiry.

In sum, AI tools hold significant promise as aids in both educational and organizational contexts, but their value depends on careful selection, critical use, and alignment with human and organizational knowledge processes. Universities, especially those serving lifelong learners, are well positioned to act as laboratories for developing such responsible and productive uses of AI tools.

Ethics Declaration: The data has been collected with consent from the informants and where they have been informed about their rights to withdraw from the study. No names have been disclosed, and we got a permission to disclose the sex of one of the main informants (who is referred to as "she"). As we in this part of the research did not use any recordings or video where the informants could be recognized by name or appearance, no application has been forwarded to the Norwegian Agency for Shared Services in Education and Research.

AI Declaration: AI has been used in this article for two purposes: to translate our writings and to improve the quality English. The tool used is the Norwegian developed tool from the Norwegian Agency for Shared Services in Education and Research (SIKT KI Chat – sikt.no).

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Leadership as a Cultural Enabler of Knowledge Management in High-reliability Organisations

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Abstract: In the context of high-reliability and high-consequence organisations, knowledge management initiatives are often impeded by cultural barriers that hinder the disclosure, sharing, and utilisation of sensitive knowledge. The present paper examines how leadership shapes organisational culture conditions that determine the effectiveness of knowledge management, drawing on empirical evidence from nuclear security culture (NSC) self-assessment processes conducted in medical organisations using radioactive sources. The study conceptualises NSC self-assessment not as a compliance exercise, but as a structured knowledge management intervention aimed at eliciting tacit knowledge, weak signals, and experiential insights related to organisational vulnerabilities and human performance. The present paper builds on qualitative and mixed-method evidence from the first Polish self-assessment of nuclear security culture in a medical facility, supported by the International Atomic Energy Agency. The paper analyses how leadership behaviours influence knowledge creation, psychological safety, and the translation of assessment findings into organisational learning and change. The findings of the study indicate that leadership plays a decisive role in reducing cultural barriers to knowledge management, including fear of blame, formalism, and low trust in governance structures. The presence of visible leadership engagement, non-punitive responses to reported weaknesses, and active sense-making of assessment results have been found to significantly enhance knowledge sharing and learning outcomes. Conversely, leadership approaches that prioritise regulatory compliance have been shown to impede the practical application of knowledge derived from assessments and to diminish the efficacy of change processes. The present paper contributes to the knowledge management literature by positioning leadership as a cultural enabler of KM effectiveness in contexts where knowledge is sensitive, risk-laden, and ethically constrained. The present study extends the existing research in the fields of knowledge management (KM) and organisational culture by demonstrating how assessment-based KM initiatives can support sustainable change when embedded within leadership-driven cultural frameworks. Practical implications are offered for leaders and KM practitioners designing and governing knowledge initiatives in high-risk organisational settings.

Keywords: Knowledge management, Leadership, Organisational culture, Knowledge sharing, Organisational learning

1. Introduction

High-reliability organisations (HROs) function in environments where failures are infrequent but potentially disastrous. In such contexts, performance is contingent on the timely availability, interpretation, and utilisation of knowledge, encompassing experiential know-how, weak signals, near-miss narratives, and cross-functional expertise. While KM is often discussed in terms of repositories and systems, in HRO contexts it is equally (and sometimes primarily) a cultural and behavioural problem: whether people notice, report, and share what they know when it is uncomfortable or reputationally risky.

Healthcare organisations that utilise high-activity radioactive sources (e.g., radiotherapy, PET, nuclear medicine) represent a distinctive high-consequence, high-reliability-like setting. The technical and regulatory controls are strict, yet work is carried out through interdependent professional groups and in environments that must remain accessible to patients, visitors, and contractors. This predicament gives rise to a dual challenge: The necessity for reliable knowledge is evident across various roles and shifts. Concurrently, there exists a pronounced inclination to impede disclosure, primarily attributable to concerns regarding attribution of blame, apprehension of legal and regulatory ramifications, and the presence of hierarchical impediments.

This paper employs the concept of nuclear security culture (NSC) self-assessment as a methodological framework for the examination of knowledge management (KM) in high-stakes conditions. NSC self-assessment is conventionally conceptualised within the domain of security, serving as a mechanism for the evaluation of beliefs, behaviours, and management systems. In this paradigm, KM intervention is conceptualised as a structured approach to the capture of tacit knowledge and weak signals, with the objective of their conversion into shared interpretations, thereby facilitating organisational learning and change.

Empirically, the paper draws on the first Polish NSC self-assessment in a medical facility using radioactive sources, conducted within an IAEA-coordinated research project. The self-assessment was not regarded as an audit, but rather as a participatory diagnostic process, incorporating pilot testing, staff engagement, and follow-up sensemaking with leaders.

The central research question guiding this study is as follows: This study seeks to explore the way leadership behaviours enable or constrain the knowledge processes generated by NSC self-assessment in a high-reliability medical setting. The paper makes three key contributions. Firstly, it integrates knowledge management (KM) and security culture literatures through an assessment-based intervention model. Secondly, it provides rare empirical evidence from a security-sensitive healthcare context. Thirdly, it proposes leadership mechanisms – legitimisation, protection and translation – that explain when assessment knowledge becomes organisational learning.

Positioning of the study: This is a theory-building case study with analytic generalisation. It does not aim to statistically validate established KM constructs; instead, it refines and integrates them by specifying leadership-enabled mechanisms (legitimisation, protection and translation) that explain how assessment-based KM interventions convert sensitive knowledge into organisational learning in high-reliability settings.

2. Literature Review

2.1 Leadership as an Antecedent of Knowledge Sharing and Organisational Learning

The influence of leadership on KM outcomes is multifaceted, encompassing both direct choices, such as investments and governance, and indirect cultural shaping. This cultural shaping encompasses norms regarding openness, trust, and the acceptable expression of ideas. The KM literature has seen an increasing focus on leadership styles that emphasise knowledge behaviours, such as knowledge-oriented leadership. The extant literature suggests an association between knowledge-oriented leadership and psychological safety, as well as employee voice. These phenomena are two mechanisms through which knowledge is surfaced and used (Ononye, 2024).

In high-risk settings, the influence of leadership is amplified because knowledge is often socially costly: the disclosure of vulnerabilities can imply error, negligence, or noncompliance. Research on just culture in healthcare has demonstrated that an environment focused on blame can result in reduced reporting and learning, while leadership commitment and open communication have been shown to encourage disclosure and facilitate improvement (Kumah, 2025; Badran, 2026). Even though these studies are not framed as KM research, they map directly to KM constructs such as knowledge sharing, feedback loops and learning from incidents.

Beyond formal structures, intangible human factors have the capacity to either activate or suppress knowledge processes. Recent ECKM research connects emotional intelligence and other intangible capabilities to knowledge activation in human–AI collaboration, reinforcing the wider KM point that 'soft' factors shape whether knowledge is shared and used (Tsakalerou et al., 2025b).

The impact of leadership on sensemaking within organisations is a significant area of interest. Leaders play a pivotal role in shaping how organisational members interpret events and signals. This influence determines whether signals are regarded as meaningful evidence or disregarded as irrelevant noise. In practice, leaders can institutionalise sensemaking through structured debriefs, cross-functional reviews, and transparent decision rationales.

2.2 Cultural Barriers to Knowledge Management in Regulated and High-Consequence Settings

Cultural barriers to KM include fear of negative evaluation, low trust, rigid hierarchy, formalism, and weak reciprocity (i.e., people do not share because they do not receive feedback). A review of knowledge sharing barriers posits that perceived risk, absence of incentives, and negative organisational climates function as inhibitors to knowledge exchange even in circumstances where information systems are in place (Chua et al., 2023).

Formalism is a particularly salient concept in regulated environments. In circumstances where compliance assumes a predominant role within an organisation, learning-oriented dialogue may be superseded by defensive documentation and behaviours that are oriented towards producing the 'right answer'. This phenomenon has deleterious effects on tacit knowledge, which encompasses experiential nuances, weak signals, and near-miss narratives. These knowledge types are precisely those least likely to be captured by formal reporting when fear is high.

Recent studies have also established a correlation between organisational culture and capability development, as well as knowledge processes. These findings lend support to the paper's core assertion that culture serves as a mediator in the effectiveness of KM. A recent review in the Journal of Innovation & Knowledge synthesises

evidence on how cultural determinants shape organisational capability and knowledge flows, providing a bridge between culture and KM outcomes (Tsakalerou et al., 2025).

2.3 Knowledge Management in High-reliability Organisations: Weak Signals, Vigilance, and Cross-boundary Learning

The prevailing focus in HRO research is on preoccupation with failure, reluctance to simplify interpretations, sensitivity to operations, commitment to resilience and deference to expertise. These principles are compatible with KM approaches that prioritise the detection of weak signals and the rapid diffusion of learning across organisational boundaries.

Recent open-access research in a high-reliability context has reported that knowledge sharing mediates the relationship between vigilant leadership and safety performance. This implies that leadership improves outcomes through knowledge processes rather than through control alone (Li et al., 2025). This finding reinforces the central idea of this paper: that leadership enables reliability by facilitating knowledge flows.

Similarly, healthcare-oriented HRO work emphasises system-wide learning and staff engagement. For example, NEJM Catalyst (2021) suggests that the development of HRO capabilities requires a cultural environment, leadership and established routines that encourage transparency and ongoing improvement. While the primary objective of learning in nuclear security culture (NSC) is security rather than the prevention of clinical errors, the knowledge dynamics are analogous: in both cases, early disclosure and learning reduce the likelihood of severe outcomes.

The paper's emphasis on the elicitation of tacit knowledge and weak signals is aligned with research in knowledge management (KM) on knowledge acquisition and elicitation. A study in Procedia Computer Science explicitly distinguishes knowledge acquisition and elicitation as complementary KM processes and emphasises that elicitation requires structured mechanisms beyond repositories (Akhmadi and Tsakalerou, 2022).

3. Conceptual Framework and Propositions

The paper conceptualises NSC self-assessment as an assessment-based KM intervention comprising five stages:

- Elicitation: the capture of tacit knowledge and weak signals through survey items, comments, and discussions.
- Aggregation: the transformation of individual signals into patterns.
- Sensemaking: the interpretation of patterns, including divergences and convergences.
- Mobilisation: the decision of actions and the allocation of responsibility.
- Institutionalisation: the embedding of changes into routines and the repetition of the cycle. (IAEA, 2008).

The leadership mechanisms proposed in this study are refinements of established KM enablers (psychological safety, employee voice, sensemaking and feedback loops) which are aligned to the stages of an assessment-based KM intervention in a high-reliability setting. The leadership of the institution exerts a profound influence on the cultural dynamics that are in place at each stage of the institution's development. The impact of this phenomenon is facilitated by three distinct mechanisms, which are outlined below:

- The process of legitimisation is characterised by the leaders' indication that the disclosure of information is both valued and secure. This, in turn, engenders a perception of credibility in the elicitation of knowledge.
- The establishment of psychological safety within a professional context is of paramount importance, and leaders must take responsibility for creating an environment in which individuals feel able to speak up and take responsibility for their actions.
- Translation: leaders convert assessment knowledge into action via the mechanisms of prioritisation, the allocation of resources, and the establishment of feedback loops.

Table 1 maps the three mechanisms onto KM processes and typical cultural barriers addressed.

Table 1: Mapping leadership mechanisms to KM processes and cultural barriers addressed

Leadership mechanism	KM process enabled	Barrier reduced	Typical leadership practices
Legitimisation	Elicitation; initial sharing	Silence; apathy; fear of speaking up	Visible sponsorship; clear purpose; time allocation; credible anonymity
Protection	Voice; learning discussions; deeper sharing	Fear of blame; retaliation; defensive compliance	Non-punitive framing; consistent response; fair accountability; psychological safety
Translation	Mobilisation; institutionalisation	Futility; no change after feedback'; formalism	Sensemaking meetings; prioritisation; action ownership; feedback loops; repeat cycles

It is posited that three propositions may be derived from this framework. The following hypothesis is proposed: leadership legitimization (P1) will increase the volume and quality of tacit knowledge and weak signals disclosed during self-assessment. The second point pertains to the notion of leadership protection (P2), which has been demonstrated to serve as a mitigating factor in the context of cultural barriers to knowledge sharing. These barriers, which have been observed to include concerns such as fear of blame and formalism, are believed to be diminished by the presence of leadership protection. The process of leadership translation (P3) has been demonstrated to enhance the probability of assessment outputs being utilised for the purpose of organisational learning and the establishment of sustained change.

4. Methodology

This study employs an embedded case study design, incorporating qualitative and quantitative elements. The case study focuses on a private medical oncology and radiotherapy organisation in Poland that utilises Category 1 radioactive sources. The self-assessment was conducted as part of a research project coordinated by the International Atomic Energy Agency (IAEA). The objective of the project was to develop a self-assessment tool and to promote security culture among personnel with access to radioactive sources.

4.1 Data Sources and Collection

The data collection process encompassed three primary components: (1) document review; (2) survey-based self-assessment; and (3) interactive elements, including pilot group discussions and subsequent leadership sensemaking. The document review concentrated on the presence of safety and radiation protection procedures, and the absence of explicit nuclear security documentation at the baseline. This highlighted an initial knowledge gap, which motivated the intervention.

The self-assessment instrument was based on IAEA guidance and comprised a title page, instructions, contact details, and statements rated on a 7-point Likert scale from 'strongly disagree' (1) to 'strongly agree' (7), with a comment space under each statement to elicit qualitative insights. The design placed explicit emphasis on anonymity with a view to reducing disclosure risk and encouraging candour. (IAEA, 2017; IAEA, 2021).

4.2 Pilot Study and Instrument Refinement

The project commenced with a pilot testing phase in the radiotherapy department. Approximately 30% of staff (13 participants) completed the preliminary survey. Conduct of the pilot was necessitated by two factors: firstly, the absence of staff, and secondly, operational constraints. The pilot was thus conducted in two waves. The first method employed was a group-based completion with interaction, which comprised seven participants and yielded rich comments. The second method was an individual completion, which comprised six participants and was completed quickly, yielding fewer comments. The team employed a dual-pronged approach of pilot feedback and consultancy meetings to refine items for clarity and contextual relevance.

The pilot produced a key methodological insight relevant to KM: interactive contexts generate more tacit knowledge and narrative explanation than isolated individual completion. This lends further support to the argument that assessment-based KM interventions should deliberately design social mechanisms for knowledge elicitation.

Following the optimisation process, the questionnaire was reduced from 50 to 30 statements, thus enhancing its usability while ensuring the retention of coverage of the key NSC dimensions.

4.3 Final Survey and Participants

The final self-assessment targeted the full radiotherapy department workforce (35 staff) and achieved 97% voluntary participation (34 respondents). The participants were drawn from seven occupational groups. One member of staff refused to participate without providing a reason. In consideration of the inherent characteristics of clinical practice, the completion of the task was structured in a variety of formats. The survey was completed by some groups in pairs or small teams, while others responded individually. The mean duration of the task was 50–60 minutes.

4.4 Analysis Strategy

The qualitative analysis employed a mixed deductive–inductive approach. The deductive analysis entailed the coding of comments and discussion notes against the three leadership mechanisms (legitimisation, protection and translation) and the five-stage KM intervention model. The creation of additional codes was driven by the emergence of recurring themes, such as perceived futility, 'right answer' behaviour, and role-based differences. The subsequent step involved the consolidation of the codes into the themes that are reported in Section 5.

The operationalisation of convergence/divergence is outlined as follows. For each statement, convergence was recorded when a minimum of 70% of responses fell within a two-point band on the 7-point scale, and the standard deviation was ≤ 1.0, indicating aligned perceptions. The occurrence of divergence was documented when responses exhibited dispersion (standard deviation ≥ 1.4) or when two clusters were discernible (e.g., concurrent peaks in low and high agreement), signifying inconsistent experiences across roles or shifts. Divergent items were treated as triggers for targeted inquiry.

Quantitative analysis entailed the calculation of statement-level means and the identification of strength and weakness patterns. Thematic analysis was conducted on the comments and discussion notes collected, with a focus on leadership-related themes. A convergence/divergence analysis was applied: convergence indicated a clear cultural message (positive or negative); divergence indicated disagreement or inconsistent experiences requiring further inquiry.

5. Findings

5.1 Leadership Legitimisation: Making Disclosure Possible

The legitimisation of leadership was evidenced by senior endorsement of the initiative, explicit framing of self-assessment as improvement-oriented, and allocation of staff time and expert oversight. Furthermore, leadership established and communicated anonymity safeguards, thereby reducing the fear of retaliation and increasing participation. In the leadership-focused analysis, these actions were regarded as critical decisions that engendered legitimacy and credibility for the process.

Participation provides indirect evidence of legitimacy; a 97% response rate suggests that staff considered the process sufficiently safe and worthwhile engaged with. As demonstrated in the pilot study, group-based completion yielded a substantially higher number of comments than individual completion. This finding suggests that social interaction and permission structures can significantly enhance the disclosure of tacit knowledge.

5.2 Leadership Protection: Psychological Safety and the Reduction of Cultural Barriers

The case demonstrates how cultural barriers manifest in assessment settings. Staff members may approach survey statements as a means of demonstrating compliance rather than as opportunities for reflection, potentially forgoing the inclusion of comments if they anticipate being held accountable or perceive the exercise as futile. The concept of leadership protection has been demonstrated to reduce these barriers by engendering psychological safety, defined as a credible belief that speaking up will not result in punishment or humiliation.

These findings are consistent with the evidence from healthcare just culture that leadership commitment and psychological safety increase reporting and reduce silence (Kumah, 2025; Badran, 2026).

5.3 Leadership Translation: From Assessment Outputs to Learning and Change

The knowledge outputs resulting from the NSC self-assessment process manifested in three distinct forms: The first consists of numerical patterns, which are defined as the means and distributions. The second is qualitative narratives in comment fields. The third is convergence/divergence signals. Translation can be defined as the process of converting these outputs into organisational actions and routines.

The project yielded a comprehensive analysis, encompassing a detailed inventory of the project's strengths and weaknesses, along with a curated list of recommendations directed towards department managers. The results of the convergence process provided unequivocal signals for the establishment of priorities. Divergence refers to a split in staff opinions about a statement. This was treated as a diagnostic indicator of inconsistent communication, unclear procedures, or differing experiences across roles and shifts. The recommended response to divergence was targeted inquiry (in the form of interviews or small-group discussions) to clarify the underlying causes.

5.4 Quantitative Signals as Knowledge Objects

While the survey's primary analytic focus pertains to cultural mechanisms, the quantitative signals it produced functioned as 'knowledge objects' for leadership sensemaking. Even though leaders do not regard mean scores as being statistically definitive, they provide an actionable map of where perceptions are strong, weak, or inconsistent. In the study, leaders employed statement-level averages to identify areas of confidence, such as awareness of policies, and areas requiring attention, including participation in procedure development and the clarity of reporting pathways.

The instrument linked numeric signals to contextual explanations via comment fields, thereby reducing the interpretive gap that often undermines survey-based KM initiatives.

5.5 Convergence and Divergence as Indicators of Knowledge Alignment

A distinctive analytic feature of the project was the convergence/divergence approach. Convergence was defined as the consistency of answers (positive or negative) from most respondents and was treated as a clear cultural signal. The presence of divergence indicated a division in opinions about a statement and was interpreted as evidence of knowledge misalignment. This was due to different subgroups holding different understandings of the same security expectation or experiencing management practices differently.

The way leadership behaviour is exhibited has the capacity to influence the trajectory of conflict, determining whether it will serve as a catalyst for learning or if it will devolve into defensive conflict. When leaders treat divergence as a legitimate diagnostic issue, inviting discussion without searching for 'who is wrong', employees are more likely to supply the contextual knowledge needed to resolve misalignment. When leaders perceive divergence as a reputational risk, they may become inclined to suppress discussion, thereby reinforcing formalism and reducing future disclosure.

5.6 How Assessment Knowledge was Mobilised: Examples of Translation

The recommended responses were categorised into three tiers: firstly, reinforce strengths through routine communication; secondly, address convergent weaknesses through implementation-focused problem solving; and thirdly, investigate divergent items through targeted qualitative inquiry.

The tiered translation logic under discussion here has notable parallels with 'knowledge-to-action' pipelines in KM: first, validation of the signal; second, interpretation with stakeholders; and third, embedding into routines. Examples of translation actions discussed in leadership debriefs included clarifying reporting expectations, increasing leadership presence during drills, strengthening feedback loops after irregularity reports, and involving staff in refining procedures to improve usability. Such actions directly target the common KM failure mode in assessment programmes, namely the collection of data without the demonstration of change, which results in employees perceiving disclosure as futile.

A further translation insight was the importance of repeating the cycle. The project team recommended periodic reassessment, on the grounds that culture and threats are in a constant state of evolution, and that self-assessment should become an integral part of the organisational rhythm (for example, every 18–24 months). From a Knowledge Management perspective, repetition has been found to support institutionalisation, thereby transforming a one-time knowledge capture event into an ongoing learning capability.

6. Discussion

The findings support the central argument that NSC self-assessment can be treated as an assessment-based KM intervention in a high-reliability context, creating a structured forum for eliciting tacit knowledge and weak signals and converting perceptions into shared understanding.

The legitimisation–protection–translation mechanisms provide an explanatory bridge between leadership and KM outcomes. In high-consequence settings, knowledge is not withheld due to its absence, but rather due to

the perceived risk of its dissemination. The process of legitimisation has been found to reduce perceived risk and increase participation. In contrast, the use of protection has been demonstrated to reduce the fear of blame and encourage deeper disclosure. Finally, translation ensures that knowledge does not die at the point of disclosure but becomes learning and change.

The case also clarifies a key tension for KM in regulated environments: compliance is necessary, but compliance mindsets can crowd out learning. When assessment is approached from an audit perspective, the predominant behavioural strategy that emerges is one risk avoidance. When assessment is regarded as a tool for learning, the predominant strategy becomes knowledge creation and improvement. It is therefore incumbent upon leadership to manage the compliance-learning balance explicitly.

The pilot also suggests that facilitated, interactive formats can elicit richer tacit knowledge than isolated completion.

6.1 Theoretical Contributions to KM and Organisational Culture

The present study contributes to the field of KM theory by specifying an assessment-based intervention pathway that is suitable for ethically constrained, high-consequence contexts. NSC self-assessment functions as a boundary object, facilitating cross-role discussion of vulnerabilities without framing contributions as personal failure (Schein, 2004).

The legitimisation–protection–translation mechanism extends leadership–KM models by unpacking leadership into stages that correspond to knowledge processes. The concept of legitimisation affects the dissemination of knowledge within organisational frameworks, with protection influencing the depth of knowledge, which may be tacit or contextualised, as opposed to superficial. Translation, in turn, affects the conversion of knowledge into established routines, training programmes, and governance mechanisms. This stage-based approach has the capacity to complement capability-oriented KM models by demonstrating where interventions are unsuccessful (e.g. strong elicitation but weak translation).

The empirical setting also serves to reinforce the argument that psychological safety is a KM variable, rather than being exclusively a 'people' variable. In environments characterised by a high degree of security sensitivity, the concept of psychological safety assumes particular significance. It is here that the distinction between weak signals and organisational knowledge is determined, with the former remaining private concerns. The case therefore supports the integration of just culture and HRO scholarship into KM's treatment of organisational culture, particularly in domains where the primary learning object is risk and resilience rather than innovation.

7. Practical Implications for Leaders and KM Practitioners

Five actionable implications for high-reliability organisations are proposed:

- Design self-assessment as a KM intervention: capture tacit knowledge (comments, facilitated discussion), not only scores.
- Build psychological safety: credible anonymity, fair accountability, and consistent managerial responses.
- Use convergence/divergence diagnostically: prioritise convergent negatives; investigate divergence via targeted inquiry.
- Create feedback loops: show what changed due to reporting to prevent perceptions of futility.
- Institutionalise cycles: repeat assessments, track trends, and integrate outputs into governance and training.

These findings are consistent with broader evidence on just culture and reporting systems yet extend this to the context of nuclear security culture, where knowledge sensitivity is particularly high.

8. Limitations and Future Research

The study is based on a single case, which limits the statistical generalisability of the findings. Nevertheless, the objective is analytic generalisation: to develop mechanisms transferable to other high-reliability contexts. It is recommended that future research be conducted to test the framework across a range of sites and sectors, including but not limited to aviation security, critical infrastructure and laboratory biosafety.

Evidence indicates that further research is required to explore the interaction between digital tools (e.g. incident reporting platforms, analytics) and cultural barriers. Digitalisation has been found to increase reporting volume, but it can also increase perceived surveillance, thereby reducing psychological safety. A mixed-methods

approach could facilitate the examination of the conditions under which digital KM tools amplify learning as opposed to intensifying formalism.

9. Conclusion

This study examined the role of leadership in facilitating knowledge management in a high-reliability medical setting involving the use of radioactive sources. The study reframed the NSC self-assessment as an assessment-based KM intervention, thereby demonstrating how leadership behaviours shape the conditions for disclosure of tacit knowledge and weak signals, reduce cultural barriers such as fear of blame and formalism, and translate assessment outputs into organisational learning and change.

The proposed legitimisation–protection–translation mechanism offers a portable explanation for why KM initiatives that rely on employee voice and sensitive knowledge succeed or stall. In high-consequence settings, leadership is not merely an enabler of KM; it is the creator of the cultural and governance architecture that engenders knowledge sharing that is safe, meaningful, and actionable.

Ethics Declaration: Ethical clearance was not required because the paper reports anonymised organisational self-assessment data and document analysis without collecting sensitive personal data. Participation was voluntary and anonymous, and results are reported only in aggregate.

AI Declaration: The utilisation of AI tools has been instrumental in facilitating language editing, structural drafting, and consistency checking processes. The author was tasked with the review, validation and revision of all content, including the interpretation of findings and the selection of references. The author bears full responsibility for the paper.

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Diversity Wisdom: From Diversity Management to Value Creation

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Abstract: This study aims to position diversity wisdom as a subsequent, qualitatively distinct stage in the evolution of organisational approaches to diversity, and to identify its key constitutive dimensions. The article responds to the need to overcome the limitations inherent in existing approaches and to more fully leverage diversity as a sustainable source of organisational value, extending beyond the logic of regulatory compliance and instrumental efficiency. Organisational approaches to diversity have evolved from reactive efforts focused on legal compliance to strategic diversity management, and now to DEI initiatives and ESG frameworks. This evolution reflects growing awareness of diversity's value-creating potential. However, each stage has revealed significant limitations, underscoring the need to shift from managing diversity to a reflective, normative approach grounded in organisational wisdom. The study is based on a systematic literature review that covers the evolution of diversity management, various approaches, and existing conceptualisations of wisdom in management and organisation studies. The synthetic analysis focuses on identifying the barriers that earlier approaches to diversity management sought to address and on delineating areas in which a wisdom-based perspective offers a qualitative advantage. The study is embedded within the theoretical frameworks of the Resource-Based View, the Deep Rational Theory of Wisdom, and the Pragmatic Theory of Wisdom. Diversity wisdom constitutes a distinct organisational meta-capability that integrates knowledge, values, experience, and the capacity for deep reflection on diversity in the context of long-term goals and social responsibility. Three constitutive dimensions are identified: flexibility, reflexivity, and empathy. Flexibility enables adaptive responses that transcend rigid compliance frameworks; reflexivity facilitates deep organisational learning and continuous refinement of diversity approaches; empathy allows authentic understanding and the valuing of diverse perspectives. Each dimension addresses specific barriers of previous approaches. From a wisdom-based perspective, diversity is not a problem to be managed but a fundamental source of value that requires conscious, responsible, and reflective cultivation.

Keywords: Diversity wisdom, Diversity management, DEI, ESG

1. Introduction

In 2025, Google announced the dissolution of its diversity, equity, and inclusion (DEI) programmes, citing changes in the legal and political environment. Within a short time, other major corporations followed suit, among them Meta, Ford, and Walmart, withdrawing from commitments previously presented as integral components of responsible business strategy. The pace and scale of this phenomenon raise a fundamental question: how could approaches declared to be strategic, values-based, and deeply embedded in organisational life be dismantled so readily?

This research advances the thesis that an explanation lies in a structural property of dominant approaches to diversity management that has hitherto remained theoretically underdeveloped. The common denominator across successive stages in the evolution of this field is a concentration on organisational systems as the principal vehicle for sustaining diversity commitments. These approaches are necessary, yet structurally insufficient: they do not fully account for the role of individual attitudes and decision-making dispositions, upon which the durability of any systemic solution ultimately depends. The regulatory compliance approach reduces diversity to a legal obligation; strategic management treats it as an instrument for competitive advantage; DEI programmes operationalise it through scalable yet revocable initiatives; ESG reporting captures it as measurable indicators. When these systems come under political, economic, or legal pressure, their mere presence proves an inadequate anchor for diversity commitments. Systemic mechanisms function durably only when grounded in the reflexive attitudes and values of organisational participants. More significantly from a theoretical standpoint, none of these approaches fully addresses which individual dispositions are necessary for diversity management tools to produce lasting effects. The complementary element that remains theoretically underdeveloped is wisdom.

This paper introduces the concept of diversity wisdom (DW) as a construct that overcomes the limitations of earlier approaches by grounding itself in individuals rather than procedures and reorienting organisational diversity efforts from managing diversity towards value creation. The central research question is: in what ways does a wisdom-based perspective complement existing approaches and address their structural limitations, enabling a more complete realisation of diversity's value-generative potential? The article pursues two related research objectives. The first, diagnostic in character, involves systematically identifying classes of structural limitations in diversity management as documented in the empirical literature. The second, conceptual in

character, demonstrates that the construct of DW, built on Deep Rationality Theory and the pragmatic conception of wisdom, systematically addresses each identified class of barriers. Strategic justification is provided by the resource-based view (Barney, 1991), which situates DW within the logic of sustainable competitive advantage grounded in value creation. Methodologically, the paper adopts a conceptual approach, the systematic literature review serves as a diagnostic instrument, providing the empirical basis from which the theoretical construct is derived, rather than constituting a research contribution in its own right.

2. Literature Review

2.1 The Evolution of Approaches to Diversity Management

Diversity management has evolved from reactive approaches focused on regulatory compliance to strategic orientations, and now to integrated DEI and ESG frameworks. Each stage brought a new understanding of the value of diversity while simultaneously revealing the limitations of preceding paradigms. This evolution reflects a growing awareness of diversity's potential as a source of value, a potential that no existing approach has yet fully captured.

Initially, the dominant logic was one of compliance, in which organisations treated diversity as a regulatory requirement, concentrating on representation and formal conformity without any deeper cultural change (Syed, Kramar, 2009; Tatli, 2011). A turning point came with the business case paradigm (Cox, Blake, 1991), grounded in the Resource-Based View (Barney, 1991), which recognised diversity as a strategic resource. This instrumental approach, grounded in economic logic, provides an important strategic justification for diversity efforts; however, it proves insufficient as a standalone basis for sustained commitment. Without embeddedness in organisational values, it remains vulnerable to withdrawal in the face of shifting external conditions (Ng, Wyrick, 2011; Georgeac, Rattan, 2023).

The next stage saw the emergence of DEI frameworks that expanded to encompass equity and inclusion and emphasised the need to dismantle systemic barriers (Bell, Leopold, 2021; Kendi, 2019). With the development of ESG, diversity was incorporated into broader corporate accountability frameworks (Hummel, Jobst, 2024). Their growing institutionalisation, as evidenced, *inter alia*, in S&P 500 companies' reporting, nevertheless failed to resolve the central problem: how diversity translates into lasting organisational value.

Despite increased organisational engagement, the outcomes of DEI implementation remain inconsistent and, at times, negative (Sieweke et al., 2024; Hudson, 2025). A visible manifestation of this is diversity washing, the declaratory communication of activity without genuine structural change (Bader et al., 2025). Research indicates that such activities frequently arise from institutional pressure rather than deep commitment (Hofer-Bonfim, Weder, 2025). The growing backlash against DEI initiatives confirms their susceptibility to reversal under volatile conditions (Ng et al., 2025). This indicates that existing approaches, by focusing on diversity management as a process, do not fully activate its value-generative potential, which requires the systemic tools to be complemented by the reflexive dispositions of those who deploy them.

2.2 Wisdom in Management and Organisation Studies

The concept of organisational wisdom, rooted in the tradition of phronesis, emphasises the capacity for sound action in complex situations. Wisdom is situated at a higher level than knowledge, encompassing ethical reflection, an orientation towards stakeholder well-being, and attentiveness to the long-term consequences of decisions (Bierly et al., 2000).

Two conceptualisations are of relevance to the present study. Ryan (2012) defines wisdom as a multidimensional cognitive disposition encompassing sound reasoning under conditions of uncertainty, epistemic reflexivity, and an orientation towards the good of others. Grossmann (2017) conceives of it as the capacity for reasoning in complex social situations, incorporating intellectual humility, multiperspectivism, and awareness of the limits of one's own knowledge. In both accounts, wisdom is not a resource but a decision-making capacity.

Placing the evolution of diversity management alongside theories of wisdom reveals a significant gap. Despite the proliferation of tools and policies, diversity initiatives are not grounded in the reflexive decision-making capacity of their participants. Compliance, the business case, and DEI frameworks provide structures for action but do not address how to act in conditions of ambiguity. The wisdom perspective fills this gap, offering a normative and reflexive foundation.

From an RBV perspective (Barney, 1991), procedural approaches to diversity management are readily imitable and fail to meet the VRIN criteria. DW, grounded in individual dispositions and organisational experience,

satisfies these conditions and constitutes a direct mechanism of value creation — enabling the integration of diverse perspectives and more reflexive decision-making under conditions of complexity.

3. Research Methodology

This paper adopts a conceptual research design, in which empirical analysis serves the purpose of theory development rather than constituting a research contribution in its own right. The study is conducted in two complementary stages. The first is inductive: a systematic literature review and reflexive thematic analysis empirically ground the diagnosis of diversity management failures. The second is deductive-analytical, demonstrating that the construct of DW, grounded theoretically in wisdom theory rather than emerging from thematic analysis, constitutes a systematic response to the identified barriers.

The systematic literature review followed a procedure designed to ensure transparency, replicability, and minimisation of selection bias (Tranfield et al., 2003; Denyer, Tranfield, 2009). The search was carried out in Scopus using a query covering titles, abstracts, and keywords:

(diversity management) AND (failure OR challenges OR issues OR barriers) AND (workplace OR organisation) AND (strategy OR policy OR practice OR initiative)

The use of Scopus as a single database and the application of an Open Access filter were deliberate methodological choices reflecting coverage adequacy and source verifiability respectively, with the resulting selection constraint acknowledged as a study limitation.

The search returned 3,706 documents. After applying five formal filters, the corpus was narrowed to 149 publications. A two-stage substantive assessment of titles and abstracts retained articles addressing barriers and conditions affecting the effectiveness of diversity management in organisations, excluding 96 irrelevant items and yielding a final corpus of 53 articles (see Table 1).

Table 1: Search Strategy for the Systematic Literature Review

Stage	Step	Procedure	Result
Identification	Database search in Scopus		n=3,706
Screening	Publication date	Filter:2016–2025	n=2,146
	Field	Business, Management; Accounting, Economics.	n=709
	Publication type	Peer-reviewed articles	n=388
	Language	English-language publications	n=367
	Access	Open Access	n=149
Eligibility	Thematic assessment of titles and abstracts	Excluded:96	
Inclusion	Final analytical corpus		n=53

Source: Own Study

The 53 articles were analysed using reflexive thematic analysis following the six-phase model of Braun and Clarke (2006), one of the most established qualitative approaches to content coding in organisational and management research (Maguire, Delahunt, 2017). The inductive, exploratory nature of the research question required codes to emerge from the empirical material rather than from pre-existing theoretical frameworks (Thomas, 2006).

In Phase 1, sources were read systematically with analytical notes on identified barriers, tensions, and contradictions. In Phase 2, relevant passages were extracted through keyword searching and analysis of the gap between declared and actual practice; first-order coding was inductive and semantic. In Phase 3, codes were grouped into thematic clusters based on semantic similarity, co-occurrence, and causal relationships. Phase 4 verified themes for internal coherence and external distinctiveness. Phase 5: assigned names, operational definitions, and detailed codes, illustrated by quotations from at least 3 sources. The resulting codebook (Phase 6) comprises 8 macro-themes with associated detailed codes.

A single coder conducted the analysis, a limitation partially offset by constant comparison and an audit trail of analytical notes and successive coding versions. Coding operated at both semantic and latent levels, capturing manifest content as well as underlying assumptions and tensions between declared and actual practice.

The second stage proceeds through analytical synthesis, systematically confronting the dimensions of the DW construct with each identified class of barriers and demonstrating their adequacy through causal mechanism analysis.

4. Findings

4.1 Results of the Thematic Analysis: Structural Sources of Diversity Management Failures

The analysis identified eight macro-themes documenting the structural limitations on the effectiveness of diversity management (see Table 2).

Table 2: Themes Identified in the Thematic Analysis

Code	Macro-Theme
T1	The gap between rhetoric and practice
T2	Structural and systemic barriers to equality
T3	Resistance and lack of managerial commitment
T4	Compliance-driven rather than value-driven approach
T5	Prejudice, stereotypes, and discrimination
T6	Insufficient resources, tools, and evaluation
T7	Contextual and institutional factors
T8	Selective inclusion and the neglect of intersectionality

Source: Own Study

The most pervasive theme is the gap between organisations' declared and actual commitment to diversity (T1). Organisations communicate commitment through mission statements and reports, while practices remain superficial or legitimatory (Ravazzani, 2016; Rosa, 2024). Diversity washing and SDG washing indicate the substitution of symbolic performance for substantive action (Hofer-Bonfim, Weder, 2025; Bader et al., 2025).

The second theme concerns the persistence of structural inequality operating independently of formal policies (T2). Routinised practices reproduce hierarchies despite declared equality (Omanović and Langley, 2023; Sang et al., 2022), and informal networks, communication practices, and performance criteria sustain exclusion even in organisations with well-developed DEI policies (Wolfgruber et al., 2022; Makuyana, du Plessis, 2025).

The third theme identifies leadership as a key factor in failure (T3). The literature documents both active resistance and passive non-compliance among managers (Skordoulis et al., 2024), as well as competence and volitional deficits (Ladwig, 2023; Gip et al., 2024), underscoring the decisive role of leadership in the fragility of procedural approaches (Mason, 2020).

The fourth theme concerns the dominance of compliance-driven approaches (T4). Organisations implement diversity practices under regulatory or institutional pressure (Ravazzani, 2016; Mason, 2020), resulting in bureaucratic, superficial actions that are documented as ineffective across diverse contexts (Uslu et al., 2025; Hudson, 2025).

The fifth theme addresses the persistence of prejudice and stereotypes (T5). Recruitment bias (Tran et al., 2024), leadership stereotypes (Gulati et al., 2024), and intersectional discrimination (Ladwig, 2023) are widely documented. These biases are dispositional and do not readily yield to training-based correction (Lämsä et al., 2019).

The sixth theme identifies an implementation deficit (T6): declarations are not accompanied by resource allocation (Ravazzani, 2016; Rosa, 2024), while the ineffectiveness of training programmes and the absence of systemic evaluation constrain organisational learning and accountability (Morin, Burrell, 2025; Hosoi et al., 2020).

The seventh theme points to the strong contextual conditioning of diversity management (T7). Competing institutional logics, regulatory weaknesses, and the cultural misfit of imported models all limit the effectiveness of universal approaches (Lindheim, 2024; Mushaathoni, 2025).

The final theme concerns the selectivity of diversity approaches (T8). Concentration on certain dimensions marginalises groups such as refugees, migrants, and persons with disabilities (Maj et al., 2025; Allin et al., 2024), while tokenism reproduces existing hierarchies (Morin, Burrell, 2025; Fonseca, Kogut, 2023; Mason, 2020).

Collectively, these themes indicate that diversity management tools, though necessary, reach the limit of their effectiveness where complementary grounding in the reasoning and conduct of organisational participants is absent. Systems create conditions but cannot substitute for the dispositions upon which their durable functioning depends. Effectiveness requires not better procedures, but a qualitatively different form of engagement rooted in individual dispositions.

4.2 Diversity Wisdom as a Theoretical Response to the Identified Barriers

DW is defined as the capacity to act within conditions of organisational diversity through reflexive, context-sensitive reasoning, oriented towards the epistemic, practical, and moral dimensions of rationality.

Three elements of this definition merit emphasis. First, DW is a capacity, not a collection of practices: in accordance with Ryan's (2012) Deep Rationality Theory, it signifies a deep commitment to rationality in its epistemic, practical, and moral dimensions, not a checklist of prescribed behaviours. This is precisely what distinguishes DW from DEI. DEI can be implemented as a programme, DW can only be cultivated as a disposition. Second, DW resides primarily in individuals. It is grounded in the person, tacit in character, and developed through experience. Because it is constitutively person-embedded, it cannot be switched off by an organisational decision. Third, organisational conditions do not substitute for individual wisdom; they create the environment within which wisdom can be expressed, practised, and developed.

At the individual level, the theoretical framework adopted in this study identifies three fundamental dimensions of DW: reflexivity, flexibility, and empathy. The eight macro-themes of diversity management failure identified through thematic analysis cluster along these three domains, demonstrating that each dimension of DW addresses a distinct class of structural barriers documented in the empirical literature (see Table 3).

Table 3: Dimensions of DW, and the Barriers They Address

Dimension	DRT	Pragmatic Conception of Wisdom	Themes Addressed
Reflexivity	Epistemic rationality	Intellectual humility	T1,T3,T5,T6
Flexibility	Practical rationality	Situationally wise reasoning	T3,T4,T7
Empathy	Moral rationality	Perspectivism	T2,T5,T8

Source: Own Study

The assignment of dimensions to themes follows from the type of barrier each addresses. Reflexivity pertains to themes where the source of limitation is an inability to examine one's own assumptions and behaviours critically. It directly addresses the gap between rhetoric and practice (T1): where systems may produce an appearance of commitment, reflexivity exposes its absence and confers moral significance upon it. It also mitigates managerial resistance (T3) by undermining the unreflective assumptions of dominant groups, and combats bias and stereotypes (T5) by generating sustained self-awareness inaccessible to standard training interventions. Finally, it counteracts the evaluation deficit (T6) by introducing internal accountability, as a reflexive individual perceives the discrepancy between declarations and practice independently of external indicators.

Flexibility pertains to themes in which the barrier lies in rigidly applying universal solutions without contextual sensitivity. In Ryan's (2012) framework, it corresponds to practical rationality, and in Grossmann's (2020) account to the capacity to read and accommodate situational specificity. Flexibility mitigates resistance and backlash (T3) because engagement grounded in practical rationality does not depend on institutional legitimation. It overcomes the compliance-driven approach (T4) by replacing standardisation with contextual judgement and enables effective navigation of institutional and cultural complexity (T7) where universal solutions fail.

Empathy pertains to situations in which the limitation is the inability to understand others' perspectives and experiences genuinely. It renders structural mechanisms of exclusion visible (T2), making legible the informal practices and hierarchies that formal policies cannot reach. It mitigates bias and stereotypes (T5) by enabling perception of subtle, intersectional forms of discrimination, and counteracts selective inclusion (T8) by extending attentiveness to the full spectrum of diverse experiences.

DW is not an alternative to diversity management tools, nor a denial of their value. It is the condition that enables those tools to function as intended. Programmes can create structures conducive to inclusion, but only the wisdom of their participants determines whether those structures become enduring practice or merely temporary infrastructure.

5. Discussion and Conclusions

The research procedure leads to a structural diagnosis: diversity management tools reach the limit of their effectiveness where they are not reinforced by the complementary engagement of organisational participants at the level of individual dispositions. The eight identified themes do not constitute discrete implementation failures but manifestations of a single structural problem. The construct of DW, grounded in Deep Rationality Theory and the pragmatic conception of wisdom, addresses this problem through three dimensions: reflexivity, flexibility, and empathy. Reflexivity reduces the gap between rhetoric and practice (T1) and the evaluation deficit (T6) by exposing discrepancies from within. Flexibility counteracts resistance and backlash (T3) and compliance logic (T4) by anchoring action in a practical rationality resilient to shifting external conditions. Empathy mitigates structural barriers (T2), bias and intersectional exclusion (T5), and selective inclusion (T8). These dimensions are complementary and only in combination constitute the capacity for durable transformation.

The Google case and the wave of corporate DEI rollbacks in 2025 do not attest to the failure of DEI as such; they reveal its vulnerability to external change and expose the structural fragility of approaches grounded exclusively in systemic mechanisms. The solutions in use remain important tools, but their effectiveness depends on the configuration of knowledge, processes, and relationships within which they are embedded. DW defines the developmental framework necessary for these mechanisms to produce lasting effects. Programmes can create conditions for representation, but only wisdom enables authentic belonging.

The article makes three theoretical contributions. First, it identifies classes of structural limitations in existing approaches to diversity management through a systematic literature review, providing empirical grounding for the proposed construct. Second, it introduces DW as an integrated theoretical response, demonstrating the utility of Deep Rationality Theory and the pragmatic approach in this domain. Third, it establishes that the effectiveness of diversity management tools depends on the wisdom of those who deploy them and cannot be achieved solely through procedural refinement.

The study has several limitations. The systematic literature review relied on a single database (Scopus) with an Open Access filter, potentially introducing selection bias. The analysis was conducted by a single coder, limiting inter-rater verification. The construct of DW requires further empirical validation. The present article is conceptual in character and provides a theoretical grounding for future empirical research, encompassing measurement instrument development, longitudinal studies, comparative analyses across organisations at different levels of diversity practice maturity, and investigations into the antecedents of DW and its impact on organisational effectiveness.

Ethics Declaration: This research didn't involve human participants; therefore, ethical clearance was not required.

AI Declaration: AI tools wern't used during the preparation of this paper.

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Knowledge Management and Digitalization Potential in Employee Sickness Absence Management Processes

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Abstract: Employee sickness absence generates significant costs for organizations, and its reduction requires a structured management approach. Sickness absence management (SAM) constitutes a function of human resource management (HRM) that remains underdeveloped in organizational practice and insufficiently emphasized in the academic literature. By collecting, disseminating, and effectively utilizing knowledge on sickness absence to enhance managerial efficiency and effectiveness, SAM should also be considered an important component of organizational knowledge management. Accordingly, the first objective of this paper is to identify and systematize the key functions of SAM. The second objective is to assess the potential of digitalization to supplement SAM functions, which are currently reserved mainly for HRM, with additional functions in the area of knowledge management related to sickness absence (KM-SA). This, in turn, may facilitate its broader adoption among organizations that lack sufficient financial and human resources to sustain such management practices. The identification of SAM functions in HRM was conducted using a narrative literature review. The starting point for identifying KM-SA functions was a systematic literature review, the result of which was the identification of a research gap that provided the rationale for conducting empirical research based on a commercial IT platform, widely used in Poland by organizations facing high levels of sickness absence. In addition to systematizing SAM functions in HRM, the study provides examples of benefits resulting from their digitalization and extension to include KM-SA functions. The use of digital tools for absence monitoring enables partial cost reduction through improved workforce planning, earlier identification of adverse trends, and making both more informed staffing decisions and strategic decisions based on knowledge of the phenomenon of sickness absence not only within the organization but also in the labour market. Data derived from commercial platforms, such as sickness absence barometers, make it possible to identify absence patterns, segment problems by departments or employee groups, and link absence to working conditions and organizational policies. In practice, knowledge management of sickness absence (KM-SA) should contribute to increasing the accessibility of such solutions, particularly for organizations with limited resources.

Keywords: Knowledge management, Digitalization, Sickness absence, Personnel management, HR management

1. Introduction

Employee sickness absence represents a specific category of work absence, directly caused by illness or injury, formally certified and resulting in temporary incapacity for work. As such, it constitutes a phenomenon with medical, economic, and organizational dimensions (Ćikeš et al., 2018). While absence is broadly defined as any non-attendance during scheduled working time (Cascio, 2001), this study focuses specifically on sickness absence, as recognized within legal and insurance systems and in cost-of-illness analyses (Striker, 2013a).

High levels of sickness absence have both economic and organizational consequences. A review of one hundred key studies indicates that absence is typically associated with reduced operational productivity, declining process quality, and diminished overall organizational performance (Ćikeš et al., 2018). Furthermore, panel data from Norwegian firms demonstrate that increases in long-term absence lead to a nonlinear decline in operating revenues and total productivity (Aarstad, Kvitastein, 2023).

Research on sickness absence is inherently interdisciplinary. It is discussed in the literature on medicine and public health (Piha et al., 2010), economics and public finance (Kocakulah et al., 2011), as well as management. In this latter dimension, sickness absence management (SAM) emerges as a distinct function of human resource management (Striker, 2013a). Despite growing awareness of the costs associated with sickness absence, many organizations still lack coherent SAM policies and tools, while its strategic importance remains insufficiently recognized (Striker, 2013b).

Against this background, a clear research gap emerges. Although the literature extensively discusses the definitions, determinants, and consequences of sickness absence, the potential for digitalizing individual SAM functions and the possibilities of standardizing them within IT tools remain insufficiently explored (Striker, 2013a), especially in the context of extending the issue of SAM beyond the area of HRM alone to the area of

knowledge management (KM). The starting point for this study is the authors' proposition that knowledge management of sickness absence fits into the classical understanding of knowledge management as the identification and use of collective organizational knowledge to enhance competitiveness (Alavi, Leidner, 2001).

The identified gap justifies the following objectives of the study: (1) to identify and systematize the detailed functions of SAM from the perspective of HRM and organizational effectiveness; and (2) to examine the digitalization potential of these functions, culminating in a proposal to extend SAM with a knowledge management function focused on sickness absence.

The approach presented in this study also addresses contemporary challenges in knowledge management by incorporating: the critical role of human factors in management processes (Khadir, Durst, 2025), the importance of functional organizational cultures (Kucharska, Bedford, 2023), and issues related to intra- and inter-organizational knowledge transfer (Pedersen et al., 2023).

2. Literature Review

2.1 SEM Functions Within HRM and Barriers to Their Implementation

Typical SEM functions included within HRM are: reducing sick leave through return-to-work interviews, training for managers, and the preparation of reports on absenteeism (MacLean, 2008), analysis of organizational factors such as workplace conflicts (Lakiša et al., 2021), improving working conditions to reduce absenteeism, promoting a culture of attendance and accountability (MacLean et al, 2008), a flexible approach to employees' return to work after illness, and others.

Their implementation faces numerous barriers within organizations, including, among others: a lack of commitment from management or employees (Akerstrom et al., 2024), insufficient managerial competencies, inflexible procedures (Rasmussen et al., 2025), data challenges (Rasmussen et al., 2024), lack of confidentiality, and GDPR and legal restrictions (Klasen et al., 2021), as well as individual psychological barriers and a culture of silence.

2.2 Towards Digitally Supported Knowledge Management of Employee Sickness Absence

There are many similarities between HRM and knowledge management (KM), for example: employees are regarded as a central organizational resource (Nonaka, 1994), an organizational culture based on trust, openness, and learning determines the effectiveness of both KM and HRM (Alavi, Leidner, 2001), learning and development constitute a shared research area (Ferreira et al., 2022), but the development of digitalization processes in the organization makes it possible to incorporate into SEM many KM functions that are typical of it and distinguish it from HRM. Examples of inherent features of KM that distinguish it from HRM include: an emphasis on organizational knowledge as a resource (Nonaka, Takeuchi, 1995) as opposed to people as a resource (Ulrich, 1997), the key role of IT and information systems (Alavi, Leidner, 2001) as opposed to the key role of relationships and human behavior (Huselid, 1995), an emphasis on the team and organizational level of analysis and knowledge bases (Alavi, Leidner, 2001) in contrast to individual, firm-level HR practices (Wright, McMahan, 1992), an emphasis on the continuous spiral of knowledge creation (Nonaka, 1994) rather than on strategies or programs closed within defined time periods (Ulrich, 1997), and responsibility distributed across multiple centers within and outside the organization (Davenport, Prusak, 1998) rather than located mainly within the HR department (Ulrich, 1997).

Due to the nature of KM, it generally demonstrates a significantly greater potential for the use of IT systems and digitalization than HRM. This also applies to SEM. On the one hand, digital HRM streamlines administrative processes, enables the analysis of sickness absence, thereby increasing the objectivity and effectiveness of managerial decision-making (Strohmeier, 2020; Meijerink et al., 2021). The implementation of digital tools in SEM makes it possible to overcome numerous organizational barriers, including difficulties in identifying absence patterns, limited analytical competencies of managers (Graczyk-Kucharska et al., 2023; Dasari, Devi, 2025), and personal biases of supervisors leading to reduced effectiveness of managerial interventions (Colquitt et al., 2022).

On the other hand, digitalization facilitates the extension of SEM to knowledge management of employee sickness absence (KM-SA), providing managers not only with standard information on individual employees or basic analytical cross-sections, but also with the possibility of building behavioral models and analyzing the impact of absence on the achievement of the organization's strategic objectives.

Unfortunately, scientific literature contains almost no studies on the digitalization of sickness absence management processes in the context of KM-SA. The use of the SCOPUS query: (TITLE-ABS-KEY("knowledge management") AND TITLE-ABS-KEY("sickness absence")), returned one result. In the publication (Connolly et al, 2010), the authors presented the outcome of cooperation between a university and a healthcare service provider, namely a Management Information System (MIS) for Occupational Health. Although the context of its development was social rather than business-oriented, the essence of the cooperation was knowledge transfer, among other things, in order to reduce the costs of sickness absence in the workplace. The use of the query: (TITLE-ABS-KEY("knowledge management") AND TITLE-ABS-KEY("sick leave")), produced two results, but they were not related to the topic under study. The systematic literature review was conducted on 17 May 2026.

Digitalization for KM-SA creates the potential for continuous improvement of management in the organization, including through:

- identifying absence patterns that are difficult to detect using traditional methods, especially short-term, recurring absences of 1 to 3 days, which generate significant operating costs and disrupt the functioning of the organization (Grimani et al., 2019),
- automation of decision-making processes (Dasari, Devi, 2025),
- deepening knowledge of natural fluctuations in absence and distinguishing them from absence-related behaviors that produce effects contrary to those intended (Sakib et al., 2025).

The literature emphasizes the need to maintain a balance between analytical approaches and the humanistic dimension of human resource management (Carnevale, Hatak, 2020). Digital tools should support dialogue with employees and contribute to building organizational cultures based on trust and fairness.

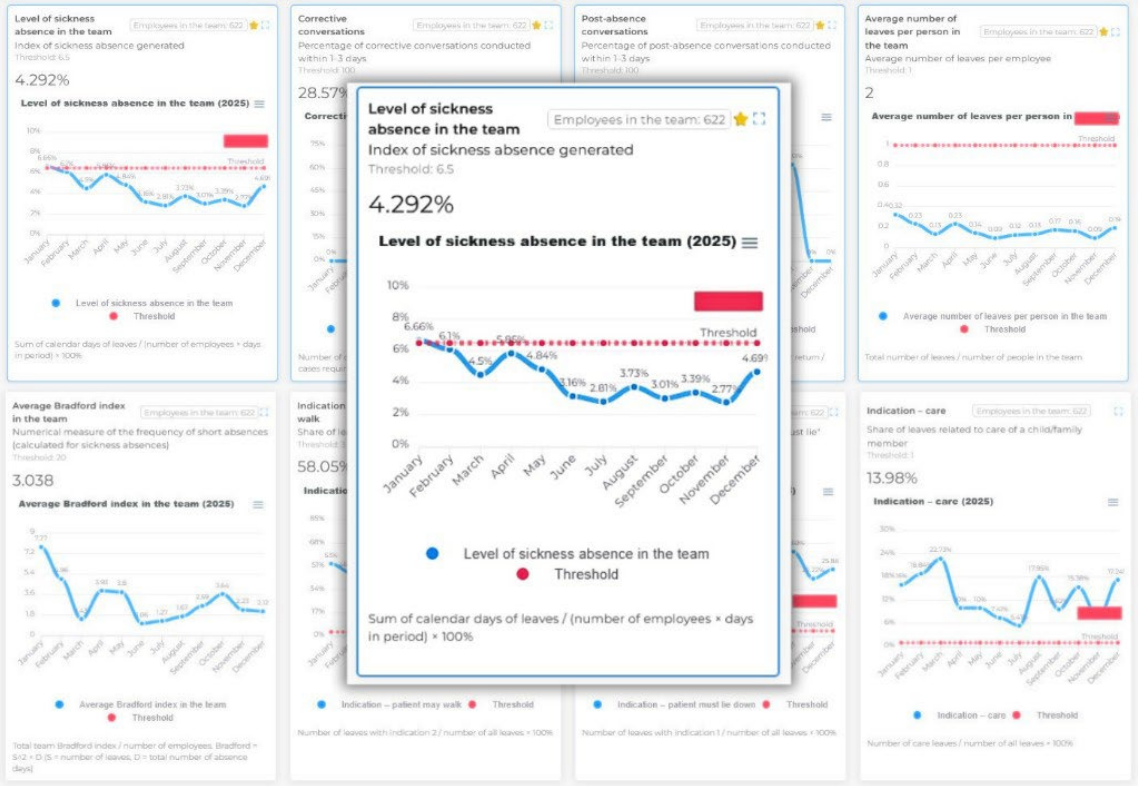
3. Methodology

The subject of the study is the digitalization potential of SAM for the implementation of knowledge management of sickness absence (KM-SA) functions simultaneously across multiple organizations served by a single service provider.

The object of the study is the IT system “Absence Dashboard,” designed to support KM-SA, developed and implemented by the Polish consulting company Conperio, which specializes in providing services supporting clients in the field of SAM. As of March 31, 2026, the system was used by over 300 organizations, primarily manufacturing companies. Collectively, these organizations employ approximately 250,000 employees (ranging from 300 to 40,000 employees per organization). These entities adopt the tool in response to rising sickness absence costs, the lack of effective analytical tools, and difficulties in managing the issue at the operational level. The choice of a single system is justified by the limited number of analogous systems available on the market and the scarcity of scientific studies in which such systems would constitute either the object or the subject of research, and to which the present study could therefore refer.

The “Absence Dashboard” constitutes the central component of the SAM platform. The tool was designed as a response to the limitations of traditional absence management methods within individual organizations. It enables the transformation of raw data into actionable knowledge regarding employee sickness absence (Figure 1).

The research method applied is a case study, justified by the specific nature of the phenomenon under investigation and its strong embedding in an institutional and legal context. As a result, the market for such services in Poland remains limited, and Conperio—as the only specialized provider (as of March 2026)—has a unique capacity to collect and process sickness absence data into organizational knowledge. The case study approach allows for an in-depth analysis of the phenomenon in its real-life context and facilitates the identification of mechanisms that are not accessible through quantitative research methods.



Source: Authors' own elaboration based on the "Absence Dashboard" system (Conperio)

Figure 1: Illustrative Screenshot of the "Absence Dashboard" application – level of sickness absence in the team

The initial premises for undertaking the study, derived from Conperio's empirical experience gained through SAM implementations for business clients, include the following:

- a low level of managerial preparedness for analyzing absence data and limited ability to interpret its significance,
- entrenched interpersonal relationships leading to a lack of objectivity in employee evaluation,
- the influence of supervisors' personal sympathies or antipathies on decisions regarding employee-related actions, resulting in perceived organizational injustice and reduced effectiveness of managerial interventions,
- a tendency among organizations to overestimate the scope and quality of available information on employee absence behavior, while in reality such data are incomplete, fragmented, or insufficiently processed for decision-making purposes,
- the fact that sickness absence behavior in Poland is not solely determined by health conditions; sick leave is often treated as an opportunity to obtain paid time off work,
- according to Conperio statistics, approximately one-third of a sample of 33,000 controlled sick leaves were used improperly (Zając et al., 2025).

These premises are consistent with factors identified in the existing literature. In light of these findings, a key value proposition for business clients is the possibility of accessing codified knowledge on employee sickness absence without the need to invest in proprietary IT solutions, collect and analyze data independently, identify relationships and dependencies, manage analytical tools, define decision points and action triggers, or search for appropriate benchmarking entities.

The analysis of the digitalization potential of SAM was conducted in three interrelated research stages. In the first stage, key managerial problems related to sickness absence were identified and mapped to corresponding SAM functions. In the second stage, the digitalization potential of these functions was assessed by referencing them to the functionalities of the "Absence Dashboard" system, with particular emphasis on process automation, data integration, and aggregation capabilities. In the third stage, the scope of knowledge

management of sickness absence (KM-SA) functions was defined, emerging as a result of the digitalization of SAM functions and the use of aggregated data derived from multiple organizations.

4. Research Findings

This section presents the findings concerning the digitalization potential of sickness absence management (SAM) functions, along with the identification of knowledge management of sickness absence (KM-SA) functions emerging as a result of this digitalization.

Stage 1: Identification of Key Managerial Problems and Corresponding SAM Functions

Due to the diversity and complexity of managerial challenges, the analysis focused exclusively on key problems, as presented in Table 1. Each identified problem was linked to a corresponding management function, the implementation of which enables its resolution.

Table 1: Relationship between managerial problems and sickness absence management functions in HRM

Problem ID	Managerial problem in a single organization	Function ID	SAM Function in HRM
P1	What is the appropriate level of sickness absence?	F1	Defining the appropriate level of sickness absence
P2	Identification of atypical behaviors	F2	Identifying employees requiring intervention
P3	Measuring process effectiveness	F3	Evaluating implemented actions at all management levels
P4	Calculation of the Bradford factor	F4	Monitoring and identifying frequent short-term absences
P5	Non-actionable absence	F5	Objective reporting of actual sickness absence levels
P6	Return-to-work interviews	F6	Supporting managers in conducting return-to-work interviews
P7	Enterprise-level KPIs	F7	Benchmarking absence-related indicators against other organizations

Stage 2: Digitalization Potential of SAM Functions and Stage 3: KM-SA Functions

Digitalization of SAM Function F1: Defining the Appropriate Level of Sickness Absence

A key challenge in managing sickness absence is determining an appropriate reference level that allows organizations to assess whether observed absence rates fall within the range typical for comparable entities.

The digitalization of this function involves:

- automating the collection of employee sickness absence data across supported organizations,
- storing and aggregating absence data within the system,
- developing benchmarks based on comparable organizations and establishing a representative point of reference (RPR).

KM-SA Function F1: Benchmark-Based Determination of Absence Levels

The collection and codification of sickness absence knowledge from multiple organizations enable benchmarking processes, supporting the identification and monitoring of the representative point of reference (RPR). This, in turn, allows organizations to compare their absence rates with typical values observed in similar entities.

Digitalization of SAM Function F2: Identifying Employees Requiring Intervention

Organizations seeking to actively manage sickness absence typically rely on overall absence rates expressed as a percentage of the workforce. However, such aggregated indicators are insufficient for planning targeted actions, as they require deeper analysis, often at the level of individual case studies. Moreover, effective management requires adopting a behavioral model indicating which employee patterns should trigger managerial responses.

KM-SA Function F2: Identification of Absence Behavior Patterns

The processing and analysis of employee absence data enable the systematic identification of absence behavior patterns. Based on these patterns, deviations can be detected, allowing for the objective selection of employees who require intervention.

Digitalization of SAM Function F3: Evaluation of Actions Across Management Levels

Effective sickness absence management should involve managers at all organizational levels, supported by HR departments acting in an advisory and control capacity. A common challenge is the lack of clearly defined roles and decision-making criteria across management levels.

KM-SA Function F3: KPI Definition and Performance Management

Digitalization enables the establishment of KPIs for managers at all levels, as well as ongoing monitoring and evaluation of their achievement. These KPIs may range from operational targets, such as conducting return-to-work interviews, to strategic objectives, including maintaining acceptable absence levels at team or organizational levels.

Digitalization of SAM Function F4: Monitoring and Identifying Frequent Short-Term Absences

Employee absence constitutes a significant organizational challenge affecting overall performance. Employers incur not only direct costs related to sick pay but also substantially higher indirect costs resulting from unperformed work. Short-term absences (typically 1–2 days) are particularly disruptive in this regard.

KM-SA Function F4: Identification of Patterns in Short-Term Absence Behavior

The automated monitoring and analysis of the frequency of short-term absences, through continuous calculation of the Bradford factor, enable the rapid identification of potentially problematic absence patterns and support managerial decision-making.

Digitalization of SAM Function F5: Objective Reporting of Actual Sickness Absence Levels

Despite legal permissibility, certain types of sickness absence should not be subject to managerial intervention for ethical reasons (as reflected in Conperio's policy). Two such categories arise directly from the nature of sick leave: absences related to hospitalization and maternity-related leave ("type B"). Another category includes employees with chronic illnesses, who are also excluded from monitoring. Due to personal data protection regulations, employers do not have access to information regarding the nature of an employee's medical condition; therefore, active absence management is not pursued in such cases.

KM-SA Function F5: Incorporation of Equality and Privacy Considerations

These categories have a significant impact on overall absence rates. The "Absence Dashboard" enables their identification and quantification within total absence levels. Factors such as gender and age naturally increase the proportion of non-actionable absence. Their identification allows for more precise estimation of absence indicators and ensures objective reporting of results.

Digitalization of SAM Function F6: Supporting Managers in Conducting Return-to-Work Interviews

A key tool for direct supervisors in managing sickness absence is the conduct of return-to-work and corrective interviews. Digitalization facilitates the selection of employees requiring such interviews and enables the digitization of interview records, reporting based on their content, and the generation of advanced statistics derived from these data.

KM-SA Function F6: Knowledge Management of Return-to-Work Interviews

The collection of digitized interview records enables the codification of knowledge derived from these interactions, the parameterization of conclusions, and the development of statistical analyses supporting the improvement of interview processes and their outcomes.

Digitalization of SAM Function F7: Benchmarking Absence Indicators Across Organizations

Ensuring the comparability of absence-related KPIs both within organizational units and across different companies facilitates a reliable assessment of managerial effectiveness. Digitalization enhances the ability to identify areas requiring intervention and to recognize best practices.

KM-SA Function F7: Monitoring Typical Absence Characteristics in the Labor Market

The "Absence Dashboard," combined with aggregated data from multiple organizations, enables the calculation of typical (e.g., average) parameters of sickness absence, such as average absence duration, the proportion of short-term absences, hospitalization rates, and the number of employees on sick leave on a daily basis.

5. Discussion and Conclusions

Sickness absence represents a significant cost-related challenge for organizations. At the same time, it is a highly complex phenomenon, exhibiting different characteristics across countries.

The case study of the "Absence Dashboard" illustrates a tool that supports organizations in managing knowledge related to employee sickness absence, enabling early identification of excessive and unjustified absence patterns that generate organizational losses.

The study applied a structured research process to identify the digitalization potential of SAM functions and to support the implementation of KM-SA functions. The research was conducted in three stages: (1) identification of key managerial problems and corresponding SAM functions, (2) assessment of the digitalization potential of these functions, and (3) identification of KM-SA functions emerging from this digitalization.

In the first stage, SAM functions with high digitalization potential were identified. The literature review indicates that functions related to absence monitoring (F1, F3, F5, F7), supporting return-to-work processes (F6), and early detection of long-term absence risk (F2, F4) are particularly significant (Alonso, 2022).

In the second stage, the identified functions were mapped onto IT solutions. In sickness absence management, reporting and data analytics systems play a critical role by enabling data collection, integration, and visualization. The analyzed tool demonstrates the feasibility of digitalizing multiple SAM functions, which is consistent with existing literature emphasizing the importance of accessible and easily interpretable data for line managers engaged in decision-making processes (Rasmussen et al., 2024).

The digitalization of sickness absence management is enabled by several factors. First, absence-related processes are repetitive and data-driven, which facilitates their standardization and automation. Second, advances in digital technologies enable real-time monitoring and analysis of absence (Lawpoolsri et al., 2014). Third, the use of digital health tools, such as applications and e-health systems, enhances the effectiveness of absence management and supports return-to-work processes (Alonso, 2022).

The third stage focused on defining the scope of KM-SA functions, whose implementation is made possible through the codification of knowledge provided by digital systems operated by service providers. The development of these functions, resulting from the digitalization of selected management processes, enables real-time absence monitoring, rapid response, and the implementation of preventive measures (Lawpoolsri et al., 2014).

The conducted research achieved the stated objectives and contributed to reducing the identified research gap. The study was subject to certain limitations, including reliance on a single IT system, restriction to the Polish context, and the focus on selected SAM functions within the case study. Future research should address these limitations. An important direction for further research is the development of procedures for evaluating the effectiveness of KM-SA implementation, in order to accurately assess the relationship between cost savings achieved and the costs associated with accessing such knowledge-based services.

Ethics Declaration: Ethical clearance was not required for the research, as the study did not involve human participants but focused solely on the functions of a system containing anonymized data. These anonymized data were also not the object of the study.

AI Declaration: No AI tools were used for this paper.

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Knowledge-intensive Activities and Regional Inequalities in Poland: A Spatial Centre–periphery Analysis

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Abstract: This paper examines the spatial differentiation of knowledge-intensive activities in Poland within the centre–periphery framework. Contemporary regional development increasingly depends on knowledge-related processes; however, these are unevenly distributed across space. Despite extensive research on the knowledge-based economy, limited attention has been given to the joint spatial patterns of high- and medium-high-technology industries and knowledge-intensive services at lower territorial levels. The aim of the study is to identify the spatial distribution of these sectors and assess their role in shaping regional inequalities. The analysis is conducted at the county (powiat) level using data from the REGON register of the Central Statistical Office. An indirect approach is adopted, treating the sectoral structure of the economy as a proxy for regional knowledge systems. Spatial patterns are examined using descriptive measures and **global Moran's I**. The results reveal a strong concentration of knowledge-intensive activities in metropolitan regions and their functional areas, confirming the persistence of the centre–periphery structure. High- and medium-high-technology industries exhibit stronger spatial clustering, while knowledge-intensive services show greater dispersion but remain concentrated in more developed regions. The findings also indicate increasing spatial autocorrelation over time, pointing cumulative development processes. The study contributes to the literature by integrating sectoral and spatial approaches and demonstrating the usefulness of structural indicators as proxies for knowledge processes at the regional level.

Keywords: Knowledge-based economy, Knowledge processes, Knowledge-intensive services, Spatial differentiation, Centre–periphery, Regional development, Poland

1. Introduction

Contemporary approaches to regional development emphasize the role of knowledge as a key driver of economic growth, innovativeness, and territorial competitiveness. In the knowledge-based economy, regional advantages stem not only from access to traditional production factors but primarily from the ability to create, transfer, and apply knowledge (Lundvall, 1992; Cooke, 2001; Nonaka and Takeuchi, 1995). These processes are systemic and embedded in spatial structures, resulting in their **uneven intensity and effects across regions**.

Numerous studies indicate that knowledge-intensive activities, including high- and medium-high-technology industries and knowledge-intensive services, tend to concentrate in metropolitan regions and more developed areas. This concentration reflects agglomeration advantages such as access to human capital, research and development infrastructure, advanced labour markets, and dense institutional networks (Audretsch and Feldman, 2004; Boschma, 2005; Polèse and Shearmur, 2004). Consequently, the knowledge-based economy contributes to the persistence of the centre–periphery structure.

This issue is particularly relevant for peripheral regions, which are typically characterized by weaker knowledge resources, lower density of economic interactions, and limited access to such activities. These conditions constrain innovativeness, entrepreneurship development, and the formation of more advanced economic structures. **Therefore**, the spatial distribution of knowledge-intensive enterprises reflects differences in regional development potential (Rodríguez-Pose, 2018).

Despite the growing literature on the knowledge-based economy, limited attention has been paid to the spatial differentiation of various segments of these activities at lower territorial levels. Existing research often focuses on R&D, firm-level innovativeness, or general economic structures, while less frequently addressing the joint spatial distribution of high- and medium-high-technology industries and **knowledge-intensive services** within the centre–periphery framework. In particular, there is a lack of studies examining how these two segments reflect the spatial organization of knowledge processes at the local level (Květoň et al., 2022).

The aim of this paper is to identify the spatial differentiation of high- and medium-high-technology enterprises and **knowledge-intensive services** in Poland and to assess their role in **shaping** knowledge processes within the centre–periphery framework. The study adopts an indirect approach, using the sectoral structure of the

economy as a proxy for regional knowledge systems. Specifically, the share of these sectors, defined according to the OECD/Eurostat classification, is used as an indicator of knowledge-intensive activity at the local level.

The analysis is conducted at the county (powiat) level in Poland, enabling the identification of differences between metropolitan and peripheral areas. It is based on statistical data from the REGON register (GUS) and applies spatial analysis methods, including Moran's I, to identify patterns of concentration.

The contribution of this paper lies in integrating sectoral structure analysis with a spatial perspective on knowledge-intensive activities and providing an empirical assessment of their local differentiation. The findings contribute to a better understanding of the concentration mechanisms of knowledge-intensive enterprises and their role in shaping regional inequalities within the centre–periphery framework.

2. Literature Review

2.1 Knowledge-based Economy and the Spatial Dimension of Development

Contemporary concepts of regional development emphasize that knowledge constitutes a key driver of economic growth and territorial competitiveness. In the context of the knowledge-based economy, the importance of traditional resources is **reduced in favour of regions' capacity** to generate, absorb, and utilize knowledge (Noni et al., 2017; Willett, 2020). Within this perspective, a region is understood as a socio-economic system in which development processes result from interactions between firms, public institutions, and the scientific sector (Harmaakorpi and Rinkinen, 2020). This approach is consistent with the concept of regional innovation systems, which highlights the importance of institutional embeddedness of knowledge processes and the quality of linkages among regional actors (Cooke, 2001; Doloreux and Parto, 2005).

An essential element of this perspective is the spatial character of knowledge processes. Knowledge, particularly tacit knowledge, remains strongly embedded in specific territorial contexts, and its diffusion depends on geographical, institutional, and organizational proximity (Wenting, 2008). In this sense, local innovation systems and knowledge spillovers are selective and spatially embedded, with their intensity depending on the density of relationships between actors **as well as** on cognitive and organizational proximity (Breschi and Lissoni, 2001; Boschma, 2005). As a result, the development of the knowledge-based economy is uneven across space, leading to the concentration of innovative activities in selected regions and the emergence of spatial development inequalities (Květoň et al., 2022).

2.2 Knowledge-intensive Enterprises as a component of Regional Economic Structure

Within the analysis of the knowledge-based economy, particular attention is given to enterprises operating in high- and medium-high-technology industries and **knowledge-intensive services**. Both groups constitute important components of the modern economic structure of regions, although they perform different functions in development processes.

High- and medium-high-technology enterprises are associated with advanced production activities and the adaptation and implementation of new technologies. Their operation requires access to specialized labour resources, appropriate infrastructure, and a well-developed institutional environment, which **favours their concentration in more developed regions** (Wachowska, 2014; Murzyn, 2013).

In contrast, knowledge-intensive services encompass activities based on expert competences, information processing, and high levels of qualifications. They play an important role in regional economies by supporting knowledge transfer, enhancing the professionalization of economic activity, and fostering entrepreneurship. Their presence increases the capacity of regions to adapt to technological change and facilitates knowledge diffusion among economic actors, particularly in environments characterized by developed cooperation networks (Alberti and Pizzurno, 2015).

From a regional development perspective, the complementarity of these two segments is of key importance. Industrial enterprises strengthen the technological and production base of a region, while knowledge-intensive services enhance the system's capacity for knowledge diffusion. Their coexistence enables more integrated and knowledge-based development.

2.3 Spatial Concentration of Knowledge-intensive Activities and the Centre–periphery Pattern

The literature indicates that knowledge-intensive activities tend to concentrate in metropolitan regions and growth centres. This results from agglomeration effects such as access to human capital, the presence of

research and development institutions, and well-developed networks of economic linkages (Noni et al., 2017; Willett, 2020).

A consequence of these processes is the spatial polarization of development, manifested in the centre–periphery structure. Core regions attract **such activities** and accumulate development resources, whereas peripheral areas remain less integrated into knowledge-based processes (McCann, 2015). This implies that knowledge flows are selective and depend on the absorptive capacity of regions as well as on the quality of their institutional environment (Cohen and Levinthal, 1990).

It is also important to note that different segments of these activities may exhibit distinct spatial patterns. High- and medium-high-technology industries tend to be more strongly concentrated within specific production and technological systems, whereas knowledge-intensive services may display greater locational flexibility, although they also tend to concentrate in regions with high availability of human capital.

The analysis of these phenomena increasingly relies on spatial statistics tools, such as Moran's I, which enable the identification of clusters of high and low values and the assessment of the degree of spatial concentration of economic activities (Polèse and Shearmur, 2004). This approach allows for a better understanding of the mechanisms underlying the location of knowledge-intensive enterprises and their role in shaping regional inequalities.

3. Methodology

The aim of the empirical part of the study is to identify the spatial differentiation of knowledge-intensive activities in Poland and to determine their distribution within the centre–periphery framework. An indirect approach was adopted, assuming that the sectoral structure of the economy may serve as an empirical proxy for knowledge processes at the regional level.

This study is based on secondary data analysis using aggregated statistical data obtained from the REGON register of the Central Statistical Office (GUS). The use of secondary data allows for a consistent and comparable assessment of the sectoral structure of the economy across all counties in Poland. However, it also implies certain limitations, as the analysis is based on structural indicators rather than direct measures of innovation or knowledge creation processes.

The analysis was conducted at the level of counties (powiats) in Poland, allowing for the identification of spatial differences between metropolitan areas and peripheral regions. This unit of analysis ensures a relatively high level of detail while maintaining the availability of comparable statistical data.

The study applies a sectoral classification based on the OECD and Eurostat methodology (OECD, 2011; Eurostat, 2020), which takes into account the intensity of technology and knowledge. On this basis, two main groups of activities were identified:

- high- and medium-high-technology manufacturing enterprises (HMHT),
- knowledge-intensive services (KIS).

Both groups were treated as indicators of knowledge-intensive activity at the regional level. HMHT enterprises primarily reflect the presence of advanced technological and production activities, while KIS indicate the development of functions related to knowledge transfer, information processing, and support for economic processes.

To operationalize the analysed phenomena, structural indicators were used, defined as the share of enterprises belonging to the identified sectors in the total number of economic entities registered in the REGON system. This approach ensures spatial comparability and allows for the identification of differences in the economic structure at the local level. The empirical analysis was conducted in two stages. In the first stage, changes in the sectoral structure of the economy in Poland between 2010 and 2023 were analysed, allowing for the identification of transformation trends in knowledge-intensive activities. In the second stage, the spatial distribution of HMHT and KIS enterprises was examined using cartographic methods and sectoral share indicators at the county level.

To deepen the analysis, the global spatial autocorrelation statistic Moran's I (Moran, 1950) was applied.

Moran's I was selected because it allows for the identification of global spatial patterns and clustering tendencies in regional economic structures. This measure makes it possible to assess whether similar values of

the analysed variable tend to occur in neighbouring territorial units. It enables the identification of the degree of spatial ordering of the analysed phenomena and the assessment of their concentration.

Formally, Moran's I statistic is expressed as:

$$I = \frac{n}{W} \cdot \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

where:

n – number of spatial units,

x_i, x_j – values of the variable in units i and j,

$\bar{x}$ – mean value of the variable,

w_{ij} – elements of the spatial weights matrix,

$W = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}$ – sum of all spatial weights.

A key element of the analysis is the spatial weights matrix, which defines the neighbourhood structure between spatial units. In this study, a contiguity-based weights matrix was applied, in which $w_{ij} = 1$ indicates that units i and j are neighbours, while $w_{ij} = 0$ otherwise. Positive values of Moran's I indicate positive spatial autocorrelation, meaning a tendency for similar values to cluster in space. Negative values indicate negative autocorrelation (spatial contrasts), while values close to zero suggest no significant spatial dependence.

4. Results

4.1 Sectoral Structure as a Manifestation of Knowledge-intensive Activities

The analysis of changes in the sectoral structure of the Polish economy indicates a gradual increase in the importance of knowledge-intensive activities in the period 2010–2023. In particular, a significant rise in the share of knowledge-intensive services was observed, accompanied by a decline in the share of less knowledge-intensive services. These changes are presented in Table 1.

Table 1: Changes in the structure of enterprises by knowledge and technology intensity in Poland (2010–2023)

Year/Change	Low-technology industry (LT)	Medium- and high-technology industry (HMHT)	Less knowledge-intensive services (LKIS)	Knowledge-intensive services (KIS)	Agriculture (AGR)
2010	20.8%	0.8%	45.4%	30.6%	2.4%
2023	22.0%	0.7%	38.0%	37.9%	1.4%
Change	+1.2 pp	–0.1 pp	–7.4 pp	+7.3 pp	–1.0 pp

Source: Own elaboration based on GUS data.

The data presented in Table 1 indicate that the share of knowledge-intensive services increased from 30.6% to 37.9%, representing a rise of 7.3 percentage points. At the same time, the share of less knowledge-intensive services declined by 7.4 percentage points. These changes reflect broader economic transformation processes typical of developed economies, where knowledge-intensive sectors are becoming increasingly important.

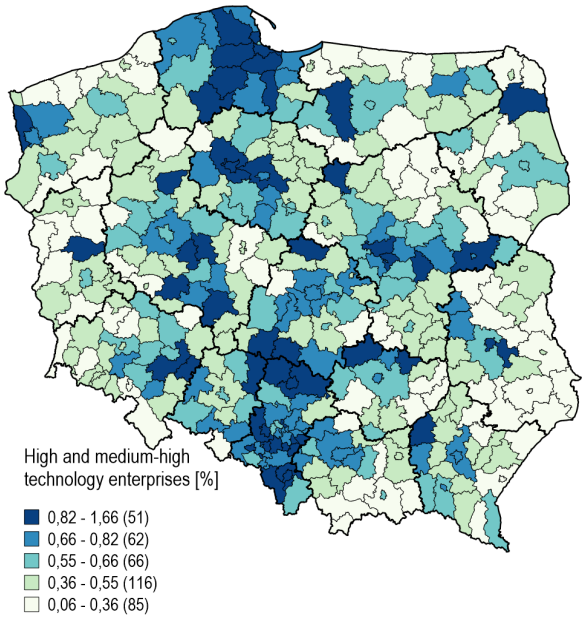
At the same time, the share of medium- and high-technology industry remains relatively low and shows no significant change, suggesting persistent structural limitations in the development of advanced technological and manufacturing activities.

From the perspective of the overall economic structure, this pattern indicates an asymmetric development of knowledge-intensive activities, service sectors are expanding more dynamically than industrial ones. This may point to the growing importance of knowledge diffusion and service-oriented functions in the economy, accompanied by a limited development of an advanced production base.

Consequently, the transition towards a knowledge-based economy appears to be incomplete and uneven, with its development being selective and concentrated primarily in activities requiring the absorption and processing of knowledge.

4.2 Spatial Differentiation and the Centre–periphery Pattern

The spatial analysis reveals clear regional disparities in the concentration of knowledge-intensive activities. Medium- and high-technology sectors are primarily concentrated in large urban centres and their functional areas. The spatial distribution of these enterprises is presented in Figure 1.

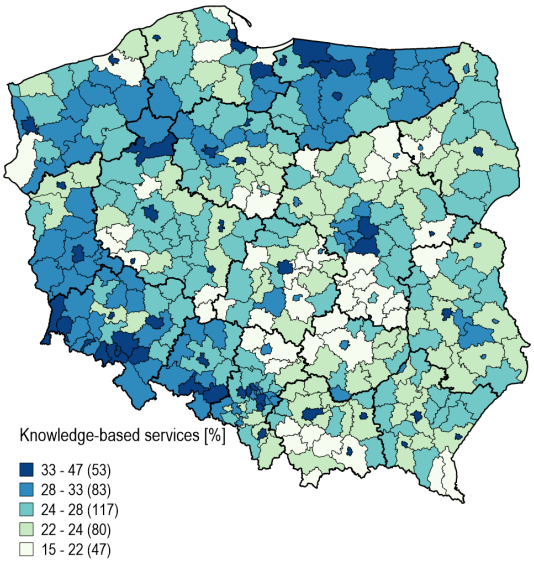


Source: Own elaboration based on GUS data.

Figure 1: Share of high- and medium-high-technology enterprises in total enterprises across Polish counties (2023)

The spatial pattern shown in Figure 1 indicates a clear concentration of technologically advanced activities in metropolitan regions such as Warsaw, Kraków, Wrocław, and Poznań. These areas are characterized by a high level of human capital, well-developed infrastructure, and a favourable institutional environment, all of which support the location of advanced technological activities.

A similar pattern can be observed for knowledge-intensive services (Figure 2), although their spatial distribution is more dispersed. This suggests greater locational flexibility and the ability of these activities to operate beyond major metropolitan centres.



Source: Own elaboration based on GUS data.

Figure 2: Share of knowledge-intensive services in total enterprises across Polish counties (2023)

A comparison of Figures 1 and 2 shows that industrial activities with higher technological intensity exhibit stronger spatial concentration than knowledge-intensive services. These differences result from distinct locational determinants of the two segments of the economy.

The observed pattern corresponds to the classical centre–periphery structure, in which central regions act as the main poles of concentration of knowledge-intensive activities, while peripheral areas are characterized by a lower share of these sectors and a less diversified economic structure.

From a regional development perspective, this indicates that such activities are strongly linked to the availability of resources , infrastructure, and the quality of the institutional environment, leading to the persistence of spatial development disparities.

4.3 Spatial Autocorrelation of Knowledge-intensive Activities

To further explore the spatial patterns, the global Moran's I statistic was applied to assess the degree of spatial concentration of the analysed phenomena. The results indicate the presence of clear spatial patterns in the distribution of knowledge-intensive activities. The values of the statistic are presented in Table 2.

Table 2: Global Moran's I statistics for sectors by knowledge and technology intensity in Poland (2010 and 2023)

Year	LT	HMHT	LKIS	KIS	AGR
2010	0.301	0.351	0.361	0.244	0.363
2023	0.298	0.381	0.288	0.310	0.386

Source: Own elaboration using GeoDa.

Note: positive values of Moran's I indicate positive spatial autocorrelation.

Positive values of Moran's I indicate a tendency for similar levels of development knowledge-intensive activities to cluster in neighbouring territorial units. This implies the existence of clusters of high values in developed regions and clusters of low values in peripheral areas.

The obtained values indicate a moderate level of spatial autocorrelation, suggesting a significant but not complete level of spatial concentration.

This suggests that the spatial concentration of knowledge-intensive activities is strengthening over time, implying that regions with initially higher levels of such activities tend to reinforce their advantage. This pattern is consistent with cumulative causation mechanisms observed in regional development.

In particular, the increase in Moran's I for knowledge-intensive services from 0.244 to 0.310 suggests a strengthening of spatial concentration processes in this sector. Similarly, the increase in the index for medium- and high-technology industry (from 0.351 to 0.381) confirms the intensification of agglomeration tendencies in technologically advanced activities.

These results are consistent with the visual patterns presented in Figures 1 and 2, reinforcing the interpretation **their spatial concentration**..

Overall, the findings indicate that the development of these sectors is uneven and selective, with knowledge-intensive activities concentrating in specific areas, thereby reinforcing their competitive advantages. At the same time, lower levels of knowledge-intensive activity persist in peripheral regions, confirming the durability of existing spatial disparities.

5. Discussion

The results indicate that knowledge-intensive activities in Poland exhibit a clearly differentiated spatial pattern and are primarily concentrated in metropolitan regions and their functional areas. This confirms the existence of a centre–periphery structure, in which central regions act as the main poles of concentration of high- and medium-high-technology enterprises and knowledge-intensive services, while peripheral areas remain relatively weakly integrated into knowledge-based processes. These findings are consistent with the literature on regional innovation systems and the knowledge-based economy, which emphasizes the role of institutional conditions, human capital availability, and the density of relational networks in shaping the location of

knowledge-intensive activities (Harmaakorpi & Rinkinen, 2020; Noni et al., 2017). Metropolitan regions offer favourable environments for technologically advanced firms and knowledge-intensive services, leading to the accumulation of these activities and the reinforcement of their competitive advantages.

At the same time, the analysis reveals significant differences between the examined segments of the economy. High- and medium-high-technology enterprises show stronger spatial concentration due to their dependence on specialized infrastructure, technological facilities, and linkages with research and development activities, whereas knowledge-intensive services demonstrate greater locational flexibility, although they also tend to concentrate in more developed regions. These differences highlight the distinct nature and spatial determinants of both segments. An important conclusion is the asymmetric character of structural transformation: the growing importance of knowledge-intensive services, combined with the stagnation of medium- and high-technology industry, indicates the dominance of service-oriented and diffusion functions over technologically advanced production. This suggests that the development of the knowledge-based economy in Poland is driven more by the capacity to absorb and utilize knowledge than by its generation within advanced industrial activities.

The spatial autocorrelation analysis further confirms that knowledge-intensive activities are not randomly distributed but exhibit a clear tendency toward spatial clustering. The presence of high-value clusters in developed regions and low-value clusters in peripheral areas points to cumulative development processes, reinforcing existing regional disparities. This observation is consistent with cumulative causation mechanisms described in regional development theory. The findings also indicate that the spatial distribution of knowledge-intensive activities is strongly influenced by the availability of human capital and institutional resources, as regions with better access to these assets are more capable of attracting and sustaining such activities, while peripheral regions face structural barriers limiting their development potential.

From a regional development perspective, the results suggest that the location of knowledge-intensive enterprises depends on institutional quality, resource availability, and the ability to participate in economic and technological networks. Therefore, policy interventions should not focus solely on strengthening existing growth centres but also on enhancing the development potential of peripheral regions. Key priorities include human capital development, improved infrastructure accessibility, and the strengthening of linkages between firms, research institutions, and public organizations. In conclusion, knowledge-intensive activities represent a key factor differentiating regional development, and their spatial concentration contributes to the persistence of the centre–periphery structure, making an understanding of these mechanisms essential for designing more balanced and inclusive development policies.

6. Conclusions

The analysis confirms that knowledge-intensive activities in Poland exhibit a clearly differentiated spatial pattern and are strongly concentrated in metropolitan areas and their functional hinterlands. The distribution of high- and medium-high-technology enterprises and knowledge-intensive services reflects a persistent centre–periphery structure, with central regions playing a dominant role in the knowledge-based economy. Peripheral regions are characterized by a limited presence of knowledge-intensive activities and a less diversified economic structure, which reduces their capacity to participate in knowledge-based development processes and constrains the emergence of more advanced economic functions.

The findings also demonstrate that different segments of knowledge-intensive activities are shaped by distinct spatial determinants. High- and medium-high-technology enterprises exhibit stronger spatial concentration, while knowledge-intensive services show greater locational flexibility, although they also tend to concentrate in more developed regions. Moreover, the results confirm the existence of significant spatial dependencies, as indicated by positive values of Moran's I, suggesting that these activities follow a cumulative and clustering pattern in which more developed regions attract and reinforce such activities, while peripheral areas remain outside the main zones of concentration.

The study also indicates that the availability of human capital and institutional resources plays a crucial role in shaping the spatial distribution of knowledge-intensive activities. The contribution of this paper lies in demonstrating that the sectoral structure of the economy can serve as a useful proxy for analysing the spatial differentiation of such activities. The integration of structural and spatial approaches provides deeper insight into the mechanisms of concentration of knowledge-intensive enterprises and their role in shaping regional inequalities.

From a policy perspective, the findings highlight the need for targeted interventions aimed at strengthening the development potential of peripheral regions. Key priorities include human capital development, improving infrastructure accessibility, and fostering linkages between enterprises, research institutions, and public organizations. Such measures may enhance the ability of regions to attract knowledge-intensive activities and reduce spatial disparities.

However, the study has several limitations. The applied indicators are indirect and based on the sectoral structure of the economy, which does not allow for a direct assessment of innovativeness. In addition, the use of global Moran's I does not capture local spatial patterns. Future research should therefore incorporate local measures of spatial autocorrelation, spatial regression models, and qualitative approaches to better understand the mechanisms underlying knowledge-intensive activities in regions.

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Perceptions of the use of the Internet of Things in Banking: The Perspective of Students in Poland

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Abstract: The main objective of the article was to identify the perception of the use of Internet of Things technology in banking from the perspective of young people. The survey was conducted in 2025 using the CAWI method at the Faculty of Management of the University of Warsaw and covered 205 students. The survey form was divided into two parts. The first part examined the general perception of IoT technology. The second part focused on examining the perception of this technology in banking applications. The key conclusions include: respondents are concerned about the security of their data and, in the case of banking applications, financial losses as a result of data leaks and loss of privacy to government agencies. Data analysis aimed at improving the personalization of products and services are the main areas of IoT use in banking. They perceive the usefulness of speeding up the payment process as important. In addition, it can be concluded that there is a high level of knowledge about IoT technology. Theoretical implications include recognizing the use of Internet of Things technology in banking among young people in Poland and outlining how to study this phenomenon. Practical implications will be important for banks and financial institutions that use or plan to use IoT in their products and services. The limitation of the study was that the survey was conducted only among the academic community. Further research should focus on expanding the scope of the study to include a larger number of academic centres and deepening the understanding of the determinants of the use of Internet of Things technologies in banking in the context of knowledge management.

Keywords: Internet of Things (IoT), CAWI, Electronic banking, Technology acceptance, Perceived risk, Knowledge management

1. Introduction

Modern financial institutions, including banks, are increasingly using innovative technological solutions to enhance the efficiency of their services. The implementation of innovations is also becoming a key factor in building a competitive advantage. The development of information technologies used by both banks and their customers enables the collection of large amounts of data. It is important to note that data collection is increasingly taking place in real time. This data can be used to better understand changing needs and identify the behaviour of bank customers. By utilizing data obtained through solutions based on Internet of Things (IoT) technology, it is possible, for example, to create more personalized financial offers. IoT-based solutions can also support the automation of many operational processes in banking. Automation contributes to increasing the efficiency of financial institutions and reducing operating costs. Another important aspect of IoT technology is the ability to improve customer service quality through the use of modern analytical tools. This technology can also support the development of new communication channels between the bank and the customer. Another aspect of IoT technology in banking is the security of financial services. Systems that utilize IoT can help detect irregularities and potential financial fraud. The collection of large amounts of data is an integral part of using IoT technology. Banks are aware of the need to implement solutions related to the protection of this data. A concern related to the collection of customer data is customers' apprehension about the purpose for which this data is used. This issue is addressed in a number of academic articles on the application of IoT technology. Research on the application of IoT allows for a better understanding of both the benefits and the risks associated with its implementation. An analysis of this issue can support strategic decision-making in financial institutions. Research findings can be helpful in planning investments in modern technologies. It is also important to examine the impact of IoT technology on the evolution of existing business models or the development of new ones in banking. This technology can contribute to the creation of innovative financial services. Research on the use of IoT also allows for the identification of potential directions for the future development of banking. Consequently, analysis of this area is important both from a scientific perspective and for the practical functioning of the financial sector.

Although banking and finance are traditionally associated with digital data, risk analysis, and capital management, the integration of IoT introduces a whole new dimension—physical data sources are becoming an integral part of the processes of generating, processing, and applying knowledge. As a result, financial institutions are transforming into knowledge-based organizations in an even more dynamic, contextual, and predictive manner(Atzori et al., 2010) (Porter & Heppelmann, n.d.). The basis of this phenomenon is data generation by IoT devices. In a financial context, this may include data on customer behaviour, their location, how they use products, or even their lifestyle (Vermesan et al., n.d.). The next stage of data utilization involves

processing, which consists of filtering, integration, and analysis. Financial institutions use advanced analytical tools, including artificial intelligence and machine learning, to transform raw data into useful knowledge (Chen et al., 2014). The organizational knowledge generated in this way should be applied in business practice. In the broader picture, it is evident that financial institutions use knowledge derived from the IoT to make operational and strategic decisions and to personalize services (Dong & Mcintyre, 2014). It is also worth noting the organizational aspect. The use of IoT in knowledge management processes requires a cultural shift within the organization

These considerations led to the formulation of the following research question: How does the younger generation in Poland perceive the widespread use of Internet of Things (IoT) technology in banking? The primary research objective of this article is to examine awareness of the use of IoT technology in banking among young people in Poland.

The article is divided into five main sections: introduction, literature review, research methodology, discussion of results, and conclusion. The introduction describes the research problem, presents key aspects of the Internet of Things, formulates the research question and the purpose of the study, and outlines its structure. The literature review section includes a discussion of previous research on the perception of Internet of Things technologies, with particular emphasis on the banking sector. The methodology section presents the research procedure, describes the survey questionnaire used, and characterizes the research sample. The fourth section presents and discusses the research findings, comparing them with results obtained by other authors. The summary covers the most important conclusions drawn from the analysis, describes the limitations of the study, and indicates possibilities for the practical and theoretical application of the results. Finally, suggestions for further research directions are presented.

This article contributes to the existing literature on the implementation of IoT in banking. Furthermore, it is part of the author's long-term research on the perception of information technologies, which examines changes in the preferences of current or future users. These include, among others: the general perception of the quality of banking services available through electronic channels(Zborowski & Chmielarz, 2023) and security(Zborowski, 2025c), electronic payments(Chmielarz et al., 2021) and the recognition of cryptocurrencies(Zborowski, 2025b).

2. Literature Review

The primary objective of this article is to examine how young people perceive the use of Internet of Things (IoT) technologies in banking; therefore, it is important to review the current state of research on this topic.

In their article, Yilmaz et al.(Hazar & Yilmaz, 2019) present a study conducted among students majoring in accounting and finance. The study showed that perceptions of ease of use and usefulness have a positive impact on the intention to use a given technology. In their research conducted on customers of Indian banks, Almugari et al.(Almugari et al., 2020) analysed the factors influencing the adoption of IoT. The authors considered factors such as: awareness; privacy and security; cost; convenience; social influence; and habits. They demonstrated that: convenience, social influence, privacy and security, and awareness had a significant positive impact on IoT adoption in banks, while cost and habits were not significant. Singh et al.(Singh & Msibi, 2021) in their survey research conducted with students, sought to identify factors influencing the adoption of IoT devices and/or applications for individual use. Their study considered factors such as: education, work, security, and health. The study's results indicate that attitudes toward usability, ease of use, and user satisfaction positively influence the intention to use IoT and the actual adoption of these solutions, while affordability, basic knowledge of the technology, security concerns, and Internet access also influence the behaviour of users and non-users of these solutions. In their study involving students from a Malaysian university, Amy et al.(Amy et al., 2020) used a self-developed questionnaire to investigate intentions to adopt IoT technology. Their research focused on factors such as perceived benefits, digital mindset, technological motivation, barriers to technology adoption, attitude, and trust. The study found that attitude, technological motivation, and digital mindset have a significant impact on the intention to adopt IoT. Lonescu-Feleaga et al.(Lonescu-Feleaga et al., 2021), in their study involving economics students from four Romanian universities, examined the factors influencing the acceptance of IoT technology. The results of the study showed that students are willing to accept IoT technology and implement it in their future professional work. Additionally, the study found that individuals trained in the use of IoT technology tend to perceive products utilizing it as useful and easy to use. Tin(Tin et al., 2025), in his study involving students in Malaysia on IoT technology acceptance, utilized a set of core factors from the TAM model. He also included factors such as perceived usefulness, perceived ease of use, perceived security awareness, and perceived satisfaction. The results demonstrate the key role of perceived usefulness, ease of use, satisfaction, and security awareness in influencing user behaviour and their intentions toward IoT devices. Sim et al.(Liew et

al., 2017) used a similar research group in their study. They demonstrated that the dimension of perceived usefulness is the factor with the greatest influence on the acceptance of IoT technology. In their study conducted in Pakistan, Muhammad et al.(Muhammad et al., 2025) examined the level of acceptance of IoT technology among students. The results highlight the need to improve IoT infrastructure, incorporate IoT courses into the academic curriculum, and create an environment conducive to the successful implementation of the technology. Negm's(Negm, 2022) research on students' perceptions of IoT technology showed that an individual's level of technological optimism, discomfort, and uncertainty influences their intention to adopt IoT products and services for online learning. The psychological motivator, namely innovation, is irrelevant. Paśko et al. (Paśko et al., 2022) in their study, they focused on surveying students who assessed their own knowledge and skills in the areas of IoT, artificial intelligence, and e-commerce. The results obtained revealed the students' level of knowledge regarding these solutions, which can serve as a source of knowledge for industry. Khalifa et al. (Khalifa et al., 2024) emphasized the importance of knowledge management in modern organizations in their research. They highlighted the role of the Internet of Things (IoT) in streamlining knowledge management processes, such as creating, organizing, sharing, and utilizing knowledge, which leads to improved quality of services provided by these institutions. The study's results show that information institutions effectively use IoT applications to track physical and intangible assets on their premises. Chen("The Teaching Model of Integrating Professional, Entrepreneurial, and Smart Education in Accounting," 2025) analysed accounting programs at applied universities. He examined the internal implications and elements of digital intelligence associated with integrating education in innovation and entrepreneurship with vocational training. He proposed a teaching model characterized by "collaboration between the university and the business, triple helix integration, and synergy between competition and training": through collaboration with businesses to create a smart training platform in finance. Jasmani et al.,(Jasmani et al., 2024) in their survey involving 121 respondents, assessed these students' perceptions of various factors influencing the integration of IoT with accounting practices. The study provided insight into how the implementation of IoT among future accountants can help transform the accounting industry. Key findings indicated that perceived usefulness has a significant and positive impact on the behavioural intentions of future accountants, suggesting that they are more likely to adopt IoT if they perceive it as useful.

The cited literature shows that there are many studies on the acceptance of IoT technology among students. Most of them focus on identifying factors that may make students more likely to start using this technology. Unfortunately, there are few studies describing young people's perceptions of the use of IoT technology in banking. Furthermore, there are few studies in the literature conducted among business administration students. This group is of interest due to the nature of the work they will perform in the future. These are the individuals who will assume managerial positions. They will influence the implementation of various technologies, including IoT, both within organizations and externally as products incorporating this technology. This article fills that research gap.

The literature review indicates that understanding young people's perceptions of the use of Internet of Things (IoT) technology in banking is a broad phenomenon that requires a focus on various factors. Based on the literature review and the author's experience in researching perceptions of various information technologies(Sołtysik-Piorunkiewicz et al., 2025), the scope of the study was formulated. The study should examine: the sources from which respondents obtain knowledge about the technology in question, the financial risks to customers arising from the use of technology in banking, the areas where the technology is used in banking, the limitations, the benefits for the bank, and the drawbacks and risks associated with the use of IoT technology.

3. Research Procedure

Drawing on previous studies on the perception of information technology(Zborowski, 2025a),(Zborowski, 2025b) use, the research procedure adopted consisted of the following sequential stages:

- a literature review of the latest sources on the perception of new technologies, particularly the Internet of Things,
- development of a pilot version of the survey questionnaire to verify the accuracy and clarity of the questions,
- development and refinement of the survey questionnaire prototype based on the above assessment, followed by the creation of the final version of the questionnaire,
- conducting the survey using the CAWI (Computer-Assisted Web Interview) method,
- analysing and discussing the results of the calculations and their statistics,

- drawing conclusions, identifying limitations, and outlining future research directions.

An analysis of online and academic materials, supported by expert opinions, enabled us to define the requirements for a survey on the perception of Internet of Things (IoT) technology in the context of young users' expectations. It was assumed that the survey, in addition to assessing perceptions of the topic, should also serve as a source of substantive knowledge for respondents. The survey form included questions regarding: sources of knowledge about Internet of Things (IoT) technology, known examples of technology applications, definitions, and the elements that best characterize the technology. The survey also included questions about: the properties, limitations, challenges, benefits, and risks associated with the use of devices operating on IoT technology.

The survey was conducted from March 28 to April 11, 2025. For this purpose, the dedicated LimeSurvey platform, hosted on the Faculty of Management's own servers at the University of Warsaw, was used. After verifying the received survey results, 205 responses were included in the analysis. The collected results were averaged. MS Excel and MS Power BI software were used to analyse the results. Based on the results obtained, they were interpreted and conclusions were drawn.

4. Characteristics of the Research Sample

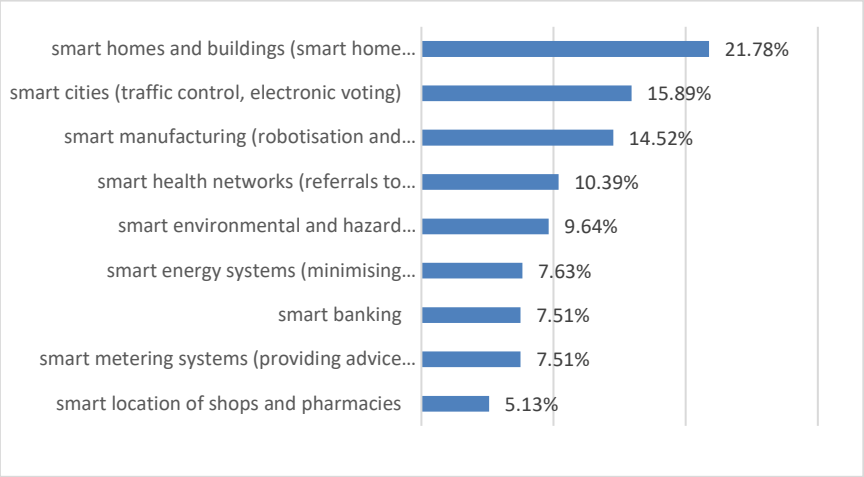
The research sample included 205 students from the Faculty of Management at the University of Warsaw. Women accounted for a significant proportion of the total respondents (63%), while men accounted for only 37%. Virtually all respondents (99%) were young people aged 19–24, 88% of whom had completed a bachelor's degree. Slightly more than half of the respondents, i.e., nearly 55%, came from large cities with over 200,000 residents. 25% came from rural areas, and the remaining 20% from cities with populations ranging from 21,000 to 200,000. Well over half (58%) of the survey participants described their financial situation as good, and 23% as very good. Those describing their situation as average or poor accounted for a combined 18%. The distribution of the respondents' employment status showed that over half (52%) were solely students, while nearly 36% had part-time or full-time jobs.

The study sample consisted of students. It should be noted that this group is not representative of the entire population of young people in Poland, but these individuals are highly active online and are the most open to innovation, particularly technological innovation.

5. Presentation of the Research Results

The first part of the survey examined general perceptions of Internet of Things (IoT) technology. Questions regarding the use of this technology in banking were included in the second part of the survey. The breakdown of responses to the questions in both groups is presented below.

Regarding awareness of IoT technology, respondents were asked about the areas where the Internet of Things concept is most commonly observed today. The distribution of responses to this question is shown in Figure 1. For this question, respondents could select multiple answers.

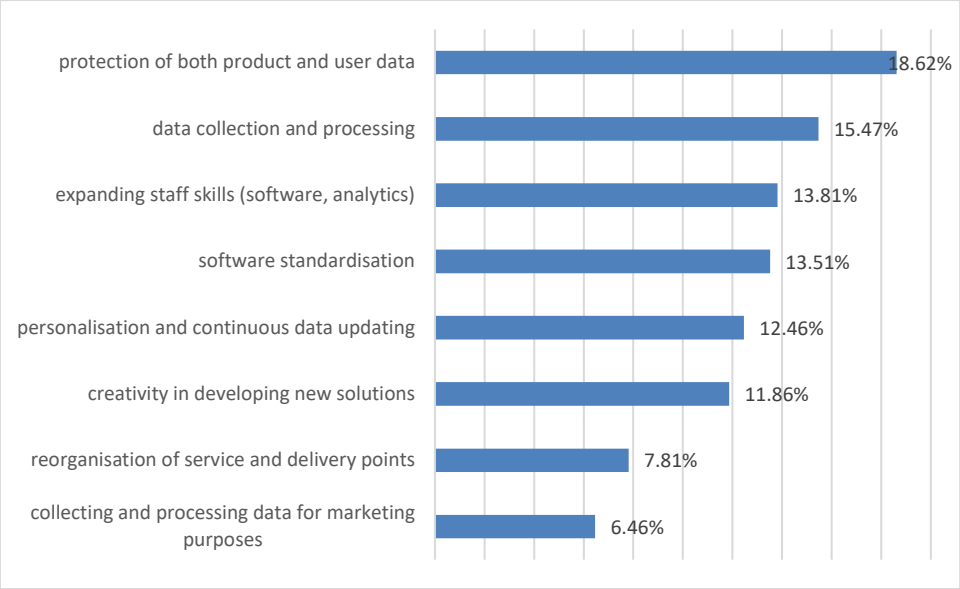


Source: Own work based on questionnaire

Figure 1: Areas of application for Internet of Things technology, according to respondents

Referring to Figure 1, it can be seen that the most frequently selected response (21,78%) is "*smart homes and buildings (smart home energy and security systems)*", followed by "*smart cities (traffic control, electronic voting)*" at 15,89%. The least frequently selected answer was "*smart location of stores and pharmacies*" (5,13%). It is worth noting that "*smart banking*" accounted for only 7,51%.

Among the challenges facing the widespread adoption of the Internet of Things concept, respondents primarily pointed to security. Respondents could select multiple answers, the distribution of which is presented in Figure 2.

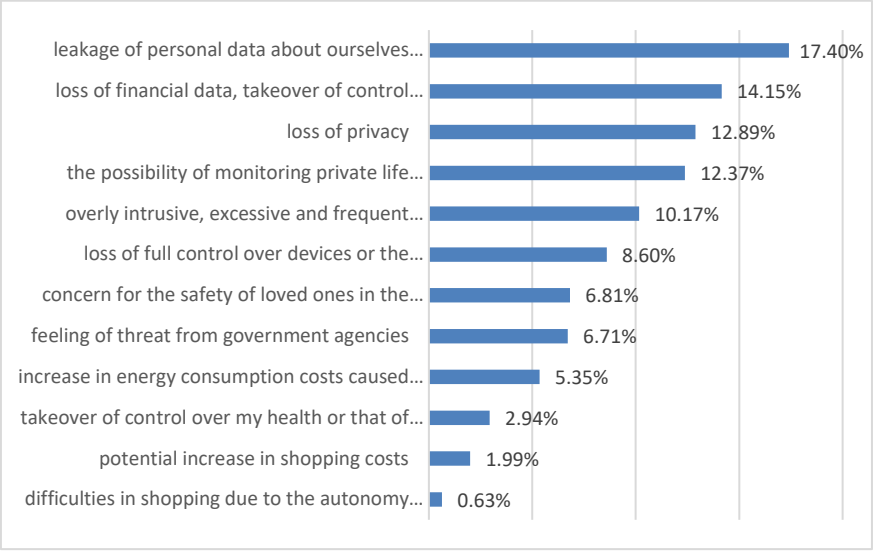


Source: Own work based on questionnaire

Figure 2: The significance of the challenges facing the widespread adoption of the Internet of Things

With reference to Figure 2, it should be noted that respondents identified "*protecting data related to both the product and the user*" (18,62%) as the greatest challenge to popularizing the concept of the Internet of Things. The least significant challenge was "*collecting and processing data for marketing*" (6,46%).

In the question regarding risks associated with the use of the Internet of Things, respondents highlighted security-related risks. Respondents could select multiple answers, the distribution of which is presented in Figure 3.

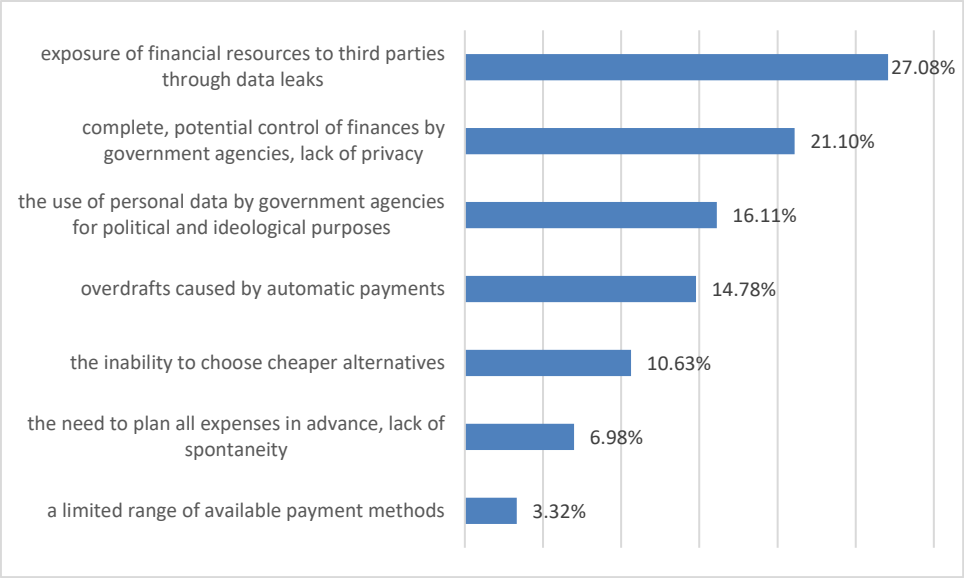


Source: Own work based on questionnaire

Figure 3: Risks associated with the widespread use of the Internet of Things, according to respondents

Referring to the data presented in Figure 3, it can be seen that the most frequently selected response was "*leakage of personal data about oneself and loved ones*" (17.40%). The next two most frequently selected responses were: "*loss of financial data, others taking control of our finances*" (14.15%) and "*loss of privacy*" (12.89%). The threat that respondents consider least significant is "*difficulties with online shopping due to the autonomy of software that places orders online*" (0.63%).

The next question examined the financial risks respondents fear regarding the use of IoT in banks. Respondents could select multiple answers, the distribution of which is presented in Figure 4.

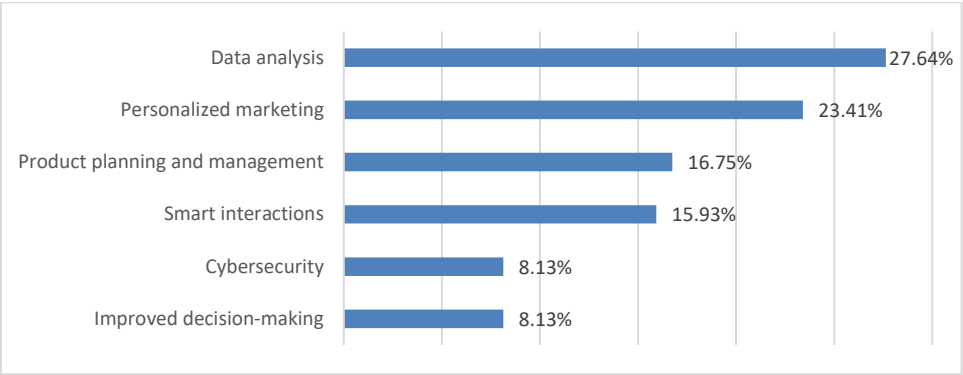


Source: Own work based on questionnaire

Figure 4: Financial risks associated with the use of IoT in banks, according to respondents

Referring to the data presented in Figure 4, it can be seen that the majority of respondents (27.08%) fear that their financial resources could be exposed to third parties through data breaches, as well as the potential for government agencies to gain complete control over their finances and a lack of privacy (21.10%). The third-largest concern is the use of personal data by government agencies for political and ideological purposes (16.11%).

Next, the study examined in which areas of the bank's operations the Internet of Things will be used most extensively. Respondents could select three answer options, the distribution of which is presented in Figure 5.



Source: Own work based on questionnaire

Figure 5: Areas of the bank's operations where the Internet of Things will be used most extensively

Based on the data presented in Figure 5, it can be seen that there are three groups of responses. The areas of the bank's operations where, according to respondents, IoT technology will see the strongest growth are: *Data Analysis* (27.64%) and *Personalized Marketing* (23.41%). Less significant were: *Product planning and management* and *Smart interactions*, at around 16.75% each. The least significant were: *Improved decision-making and Cybersecurity*, at exactly 8.13% each.

The next question concerned identifying areas where Internet of Things solutions could be applied in a bank. Respondents could select three answer options, the breakdown of which is presented in Table 1.

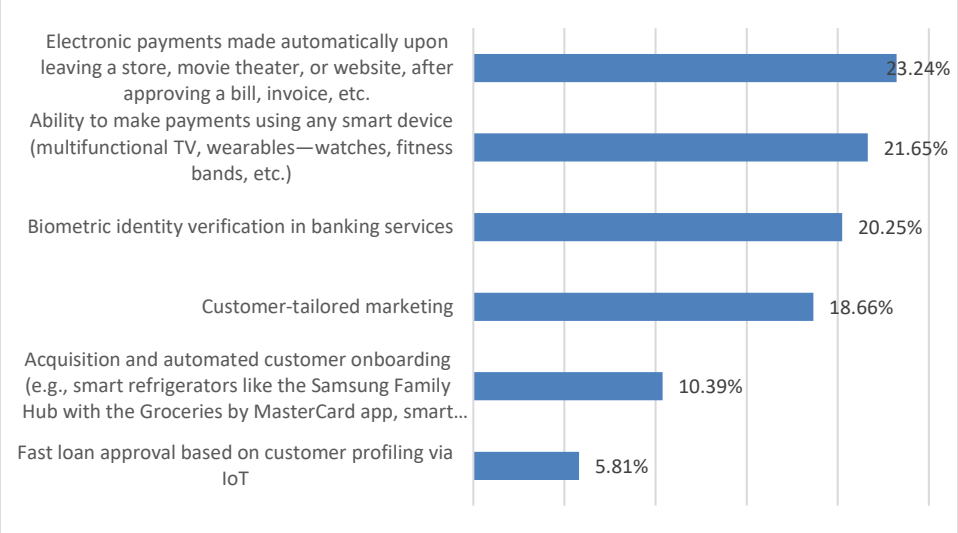
Table 1: Areas where the Internet of Things can be applied in a bank

Answers	Percentage
Data analysis helps understand customers and modify existing products	14,59%
The Internet of Things can help banks and financial institutions collect real-time customer data and analyze it	14,03%
Personalizing services and products helps attract and retain bank customers	12,06%
Collecting customer data helps banks and financial institutions identify customer needs and concerns	11,78%
Financial organizations can use smart interactive solutions, such as chatbots or apps—for example, in online banking—to assist customers anytime, anywhere	9,40%
Cybersecurity—by leveraging the Internet of Things, financial institutions can ensure safer and easier user identity verification	9,26%
Data analysis helps understand the value chain, from distributors and suppliers to retailers, which can enable banks to introduce new services	8,98%
With data from the Internet of Things, banks can develop robust strategies for managing their products	7,01%
By analysing customer data from the Internet of Things, banks can gain more of the information needed to shape organizational strategy	5,61%
With data from the Internet of Things, banks can increase product profitability	5,19%
With data from the Internet of Things, banks can protect organizational data	2,10%

Source: Own work based on questionnaire

The data presented in Table 1 suggest that, according to respondents, the IoT will enable data analysis that helps understand customers and modify existing products (14.59%) and will help banks and financial institutions collect real-time customer data and analyse it (14.03%). Slightly less important was the use of IoT to personalize services and products, which helps attract and retain bank customers (12.06%). The least important, according to respondents, would be the use of this technology to protect data held by the organization (2.10%).

Next, survey participants were asked about the benefits for individual customers of using IoT in online banking. Respondents could select multiple answers, the distribution of which is shown in Figure 6.



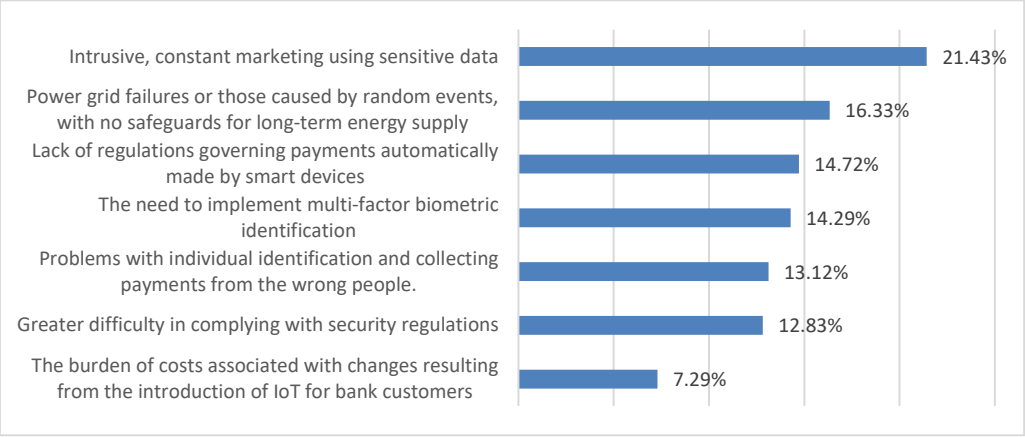
Source: Own work based on questionnaire

Figure 6: Benefits for individual customers of IoT applications in online banking

With regard to the data presented in Figure 6, respondents believe that the most important benefits of using IoT technology in online banking include: electronic payments made automatically upon leaving a store, movie theatre, or website, after approving a bill, invoice, etc. (23.24%), the ability to make payments using any smart device (smart TV, wearables—watches, wristbands, etc.) 21.65%, and biometric identity verification in banking

services 20.25%. The least significant benefit was the rapid granting of loans based on customer profiling via IoT 5.81%.

In the next question, respondents were asked to identify the disadvantages of using IoT in online banking. Respondents could select multiple answers, the distribution of which is presented in Figure 7.

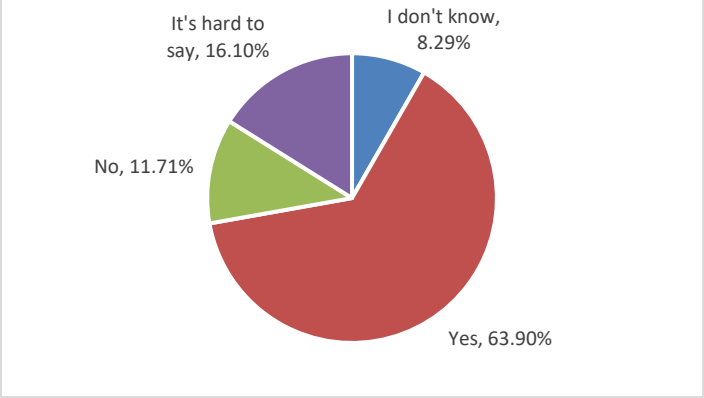


Source: Own work based on questionnaire

Figure 7: The drawbacks of IoT applications in online banking from the perspective of individual customers

Referring to the data presented in Figure 7, the response structure clearly shows that the dominant response was "Intrusive, constant marketing using sensitive data" (21.43%). The next two were: power grid failures or those caused by random events, with a lack of safeguards in the long-term energy supply (16.33%), and the lack of regulations governing payments automatically made by smart devices (14.72%). The least significant drawback was the cost burden associated with changes related to the introduction of IoT for bank customers (7.29%).

The next question concerned the projected increase in banks' spending on the implementation of Internet of Things technology. The distribution of responses is presented in Figure 8.

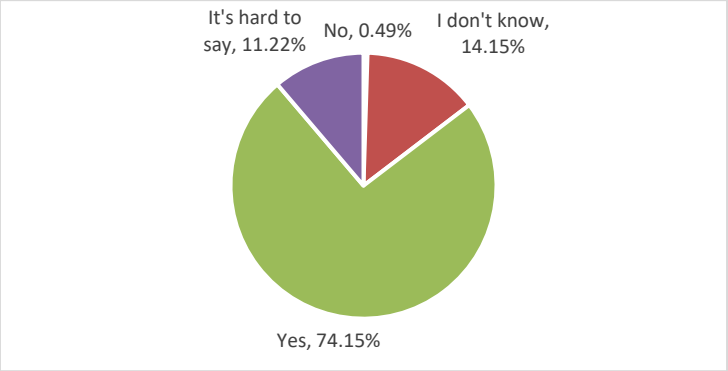


Source: Own work based on questionnaire

Figure 8: Projected increase in banks' spending on Internet of Things technology investments

Referring to the data presented in Figure 8, it is clear that more than half (63.90%) of the respondents indicated that these expenses will increase. Only 11.71% stated that this will not be the case.

Next, respondents were asked about the potential of the Internet of Things in banking as an incubator for new solutions. The distribution of responses is shown in Figure 9.



Source: Own work based on questionnaire

Figure 9: The use of Internet of Things solutions in banking can serve as an incubator for new solutions

Based on the data presented in Figure 9, it can be said that the positive attitude toward the use of IoT is even more pronounced than in response to the previous question. In this case, as many as 74.15% of respondents expressed a positive view, while only 0.49% expressed a negative one.

6. Discussion of Results

Respondents indicated that IoT technology is primarily used in smart home solutions, particularly for energy management and security support. This response aligned with another related to the challenges facing this technology, where the most frequently selected answer was the protection of data concerning both the product and the user. In the area of risks, the security aspect, including data security, was also dominant. Respondents indicated that they fear the leakage of personal data about themselves and their loved ones. The results obtained are consistent with a series of studies conducted in various countries on the acceptance of IoT technology, indicating that ensuring user data does not leak is crucial.

Research on perceptions of the use of Internet of Things (IoT) technology in banking has revealed the following picture. At the same time, it is difficult to relate these findings to the existing literature, as such literature is practically non-existent. Regarding financial risks associated with the use of IoT in banking, according to respondents: the disclosure of financial resources to third parties through data breaches, the potential for government agencies to gain complete control over finances, and the lack of privacy are the greatest threats. The responses indicate that when using IoT technology in banking solutions, respondents still fear financial losses resulting from data leaks and the loss of privacy to government agencies. It is worth noting that even the banking system's reputation as a guarantor of the highest levels of cybersecurity and protection of its customers' interests did not alleviate respondents' concerns. Nor did it shift their concerns toward, for example, the lack of cheaper alternatives.

When asked about the areas in which banks will utilize Internet of Things (IoT) solutions, respondents correctly identified data analytics-particularly those that help understand customers and modify existing products. These findings align with the limited research on IoT applications in banking, which points to improvements in both service quality and better alignment of products with customer needs.

Regarding the benefits that the application of IoT technology in banking can bring to individual customers, respondents cited the following: electronic payments made automatically upon leaving a store, movie theatre, or website after approving a bill or invoice, and the ability to make payments using any smart device (such as a smart TV, wearables-watches, wristbands, etc.). From the responses provided, it can be concluded that the benefits respondents can achieve through the use of IoT technology in banking solutions are important to them. These responses align with general research on the acceptance of this technology, where measurable benefits are crucial for technology adoption.

When asked about the drawbacks of using IoT in banking, respondents cited the following: intrusive, constant marketing that exploits sensitive data; and power grid failures or outages caused by random events, coupled with a lack of long-term security in the energy supply. The responses indicate that respondents have a good understanding of how data collected via their IoT-enabled devices might be used. The response regarding power grid failures confirms that respondents have a solid grasp of the technical aspects of this technology. The responses align with general research on technology acceptance, including IoT, which indicates that acceptance of technology increases as knowledge about it grows.

7. Conclusion

The primary objective of this article was to examine young people's perceptions of the use of Internet of Things (IoT) technology in banking. Key findings indicate that, as with general studies on the acceptance of IoT technology, respondents are concerned about the security of their data in the event of financial losses in banking resulting from data breaches and the loss of privacy to government agencies. When it comes to the application of IoT in banking, respondents see its use in data analysis aimed at improving the personalization of products and services. The research confirmed that respondents are well aware of examples of IoT technology applications in the form of accelerating the payment process, and this is an important factor for them. Regarding the drawbacks of using the technology in question in banking, respondents indicated that they are well-acquainted with both the potential ways banks could utilize IoT and the technical aspects of how the technology operates.

The theoretical implications include identifying the use of Internet of Things (IoT) technology in banking among young people in Poland and outlining a methodology for studying this phenomenon. The practical implications will be significant for banks and other financial institutions that use or are considering the use of IoT technology in their products.

The limitations of the research described in this article include the fact that it was conducted in the academic environment of a single research centre in Poland. Additionally, the study was limited to management students, which may make it difficult to generalize the results. Further research should aim to expand the scope of the study to include a larger number of academic centres and conduct a more in-depth examination of the determinants of the widespread adoption of Internet of Things (IoT) technology in banking solutions.

Ethics Declaration: Ethical clearance was not required for the research.

AI Declaration: AI tools were not used the creation of this paper.

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From Ad Hoc to Repeatable: A Knowledge-centric Framework for Introducing API Performance Testing

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Abstract: API performance testing is often introduced informally and remains dependent on individual expertise, which limits reuse and makes results difficult to repeat. This paper presents a lightweight framework and repository approach. It helps organizations establish a repeatable API performance testing process and capture knowledge for reuse. Using a Design Science Research (DSR) approach, a Knowledge-Centric API Performance Testing Framework with six components was developed: Scope & SLOs, Environment Setup, Data Preparation, Execution & Metrics, Analysis & Reporting, and Knowledge Capture & Sharing. A key distinguishing feature of the framework is its explicit inclusion of non-technical roles (e.g., Business Analysts and Product Owners), enabling them to contribute to performance testing through structured involvement in scope definition, governance, and knowledge capture. The framework was applied in a global IT organization during an initiative to validate API performance after a data source change. The case shows that a structured workflow and shared artefacts reduce repeated effort and support cross-functional collaboration. The paper contributes (1) a practical framework for organizations introducing API performance testing from scratch and (2) a knowledge management framing that treats performance testing outputs as reusable organizational assets.

Keywords: API performance testing, Knowledge management, Organizational learning, Framework, Design science research

1. Introduction

1.1 Problem and Motivation

In modern cloud-native and microservices-based architectures, APIs are critical components that connect systems, enable integrations, and directly affect user experience and business continuity. If APIs fail or degrade, business operations may be disrupted. API performance testing requires technical expertise, clear rules, and continuous organisational learning. Team members often develop personal know-how. Without structured documentation and shared repositories, this knowledge remains tacit. It is often lost when roles change or projects end. As a result, performance bottlenecks are often discovered only in production. This can lead to instability, missed service targets, and user dissatisfaction. In addition, the lack of reusable scripts, benchmarks, and reporting standards forces each initiative to start from zero. This leads to repeated mistakes and unnecessary effort.

Research literature mainly treats API performance testing as a technical activity. It gives limited attention to the knowledge management challenges behind fragmented practices. There is little guidance on how organizations with no established performance testing practice can introduce a repeatable approach and retain the resulting knowledge so it can be reused over time. Therefore, this study addresses the following research question: “How can an organization with no established API performance testing practice introduce a repeatable testing process and retain the resulting knowledge for reuse?”

1.2 Objectives and Contribution

The proposed framework addresses inconsistent and person-dependent testing practices. It introduces a structured and repeatable process that stabilises test conditions and produces predictable metrics. It reduces knowledge loss by treating performance testing as a knowledge-creation activity. Insights, scripts, and decisions are captured and reused across teams. The framework reduces role fragmentation by defining clear responsibilities across teams. This strengthens performance ownership and accountability. It also links performance testing with organisational governance. Results are integrated into SLO monitoring, risk assessment, and continuous improvement.

The framework was designed using the Design Science Research (DSR) paradigm, which focuses on solving real-world problems through the creation and iterative refinement of useful artefacts. Applying DSR ensures methodological rigor, problem relevance, and the integration of theoretical and empirical knowledge throughout the framework’s development.

The contributions of this paper are twofold:

- Practical contribution: a lightweight, structured methodology that guides teams in establishing performance testing from scratch, reducing ambiguity, and institutionalizing learning.
- Theoretical contribution: a knowledge management perspective that reconceptualizes API performance testing as an organizational learning process, transforming a technical task into a reusable knowledge asset.

The remainder of this paper is organized as follows. Section 2 reviews related work on API performance testing, knowledge management, and the Design Science Research paradigm. Section 3 presents the proposed framework and its six components. Section 4 describes the demonstration through a case study in a global IT organization. Section 5 provides evaluation results and lessons learned, followed by conclusions and future research directions in Section 6.

2. Related Work and Theoretical Background

2.1 Performance Testing in Complex API Landscapes

API performance testing in modern cloud-native systems is inherently complex and requires explicit scoping, planning, and coordination. Introducing this practice from scratch requires a shared and structured understanding. Without it, teams face blind spots and duplicated effort. API performance testing is complex. This complexity comes from technical, data, governance, and organisational factors. The review synthesised recurring themes related to performance testing practices. To synthesise prior research, studies published between 2015 and 2025 were reviewed across major databases (IEEE Xplore, Scopus, ACM DL), focusing on API and microservices performance testing. The most frequently cited challenges and corresponding solution patterns are summarised in Table 1.

Table 1: API performance testing: complexity, challenges, solutions and key references

Factors	Complexity of API Performance Testing	Challenges Still Identified in Literature	How to Transform Complexity into Clarity	Key References
Technical	Distributed architectures (microservices/SOA/cloud-native) with many interacting APIs.	End-to-end effects and service dependencies make endpoint-level tests insufficient.	Integrated methodologies that combine performance + reliability testing in DevOps pipelines (e.g., MIPaRT).	(Camilli et al., 2022); (Mingxuan Hui, 2025)
	Dynamic, elastic environments (containers/serverless/public cloud).	High result variability and limited reproducibility across runs.	Reproducible benchmarking/reporting practices and CI-based automation with clear provenance.	(Papadopoulos et al., 2021; Straesser et al., 2023)
Data-related	Data realism (synthetic vs. production-like).	Privacy/GDPR and lack of representative datasets undermine validity.	Metric standardization (e.g., p95/p99 latency, error %) and dashboards; causal analysis across services.	(Silva et al., 2022)
	Variable workloads (bursts/peaks/long sessions).	Capturing realistic user behavior is costly and effort-intensive.	Workload modeling and operational profiles to exercise peak and steady-state regimes.	(Feitelson, 2015) (Muhlbauer et al., 2023)
Governance	Lack of standardized processes, unclear ownership	Performance testing remains informal, inconsistent, and dependent on individual initiative rather than defined processes.	Define formal roles, responsibilities, and process steps; integrate performance testing into release and change management governance.	(Waseem et al., 2021); (Leite et al., 2021)
	Weak linkage to SLAs, risk, and decision-making	Performance insights rarely reach decision-makers; no structured escalation or acceptance criteria.	Introduce SLA-aligned performance thresholds, risk-based dashboards, governance gates for releases.	(Papadopoulos et al., 2021); (Eismann et al., 2020)

Factors	Complexity of API Performance Testing	Challenges Still Identified in Literature	How to Transform Complexity into Clarity	Key References
	Lack of metric governance and reporting standards	Fragmented reporting, incomparable metrics across environments and teams.	Implement standardized metrics (latency percentiles, throughput, error budgets), reporting templates, and governed telemetry.	(Thalheim et al., 2017); (Waseem et al., 2021)
	Cross-layer metrics (latency, throughput, errors) at scale	Fragmented metrics and weak governance impede analysis.	Metric standardization (e.g., p95/p99 latency, error %) and dashboards; causal analysis across services.	(Eismann et al., 2020; Thalheim et al., 2017; Waseem et al., 2021)
Organizational	"QA-only" ownership and silos	Limited collaboration/governance ; business not involved; low shared understanding of API performance testing	Cross-functional structures and shared telemetry/dashboards, as observed in industry studies of microservices delivery.	(Waseem et al., 2021) (Leite et al., 2021)
	Knowledge fragmentation (tacit results; lessons not institutionalized)	Repeated mistakes and low reuse.	Capturing tacit knowledge into repositories, reusable scripts	(Alves et al., 2024; De Souza et al., 2015; Nogeste & Walker, 2006; Wnuk & Garrepalli, 2018)

The literature highlights several recurring themes. Technically, distributed microservices architectures and dynamic cloud environments introduce variability and make endpoint-level testing insufficient. From a data perspective, realistic workloads and production-like datasets are difficult to prepare and reproduce. Governance challenges include unclear ownership and fragmented metric reporting. Organizationally, performance testing often remains siloed within QA teams, and knowledge generated during testing is rarely shared across the organization. The existing gaps justify the need for a framework that unifies technical, governance, and learning perspectives. Design Science Research (DSR) is therefore an appropriate paradigm for developing such a framework.

2.2 Knowledge Management and Organizational Learning in Testing

Studies show that applying KM to software testing improves effectiveness, efficiency, and reuse. Many testing activities depend heavily on tacit expertise that often remains undocumented (De Souza et al., 2015; Alves et al., 2024). When such knowledge is not captured, teams repeatedly face the same issues, resulting in duplicated effort, weak knowledge transfer, and "reinventing the wheel" across projects (Nogeste & Walker, 2006; Wnuk & Garrepalli, 2018). Prior studies indicate that KM mechanisms-such as reusable test assets, repositories, shared templates, and structured lessons-learned practices-significantly improve test efficiency and reduce waste in large-scale software development (Alves et al., 2024; Leite et al., 2021). In addition, reuse of historical insights, patterns, and root-cause analyses enhances test coverage and quality (Waseem et al., 2021).

Applied specifically to performance testing, KM practices enable the systematic documentation of test scripts, environment configurations, performance thresholds, and result interpretations. This shifts knowledge from individual memory to shared artefacts. Over time, this codification improves consistency, communication, and decision-making. From a KM perspective, this transition - from tacit, person-dependent practices to explicit, reusable knowledge assets - can be understood as organizational learning.

2.3 Design Science Research as the Chosen Paradigm

Design Science Research (DSR) focuses on developing and evaluating artefacts that address real-world problems (Hevner et al., 2004; Aparicio et al., 2023). It is particularly suitable when the goal is to design structured solutions-such as frameworks or methods-that can be applied in practice while contributing to theory. DSR emphasizes iterative cycles of problem identification, artefact design, demonstration, and evaluation.

In this study, DSR was selected because the research objective was not only to analyze API performance testing practices, but to design and evaluate a practical framework that organizations can use to introduce

testing from scratch. The Knowledge-Centric API Performance Testing Framework represents the primary artefact of this study. It was developed, applied in a real organizational context, and refined based on practical observations.

Using DSR ensures that the framework is grounded in both empirical practice and relevant literature. This approach supports the dual aim of the study: providing a usable solution for organisations and contributing a structured knowledge management perspective to API performance testing research.

2.4 Research Gap and Positioning

Existing API performance testing frameworks predominantly focus on technical execution by developers and QA engineers. This study extends prior work by explicitly incorporating non-technical roles (e.g., Business Analysts and Product Owners) into the performance testing lifecycle. The framework provides these roles with structured visibility and responsibility across planning, governance, and knowledge capture activities, thereby repositioning performance testing as a cross-functional organisational process rather than a purely technical task.

Table 2: Position of a Knowledge-Centric Framework through the lenses of the existing research

Aspect	Existing Performance Testing Frameworks	KM in Software Testing	A Knowledge-Centric Framework
Focus	Technical execution	Knowledge reuse	Integrated technical + governance + KM
Knowledge handling	Implicit / weak	General (not performance-specific)	Embedded in testing lifecycle
Reusability	Limited	Conceptual	Operational (scripts, SLOs, dashboards)
Governance	Weak	Not central	Core component
Target context	Mature orgs	Generic	Low-maturity orgs

This study extends KM literature by demonstrating how knowledge capture can be embedded into operational processes, rather than implemented as a parallel activity:

- With the tacit-to-explicit knowledge transformation perspective, it embeds knowledge codification directly into performance testing workflows rather than treating it as a separate KM activity.
- It integrates feedback loops (Plan–Execute–Reflect–Refine), enabling continuous refinement of testing practices.
- It represents a Level 2 design artefact (method) that contributes prescriptive guidance for organisations introducing performance testing in low-maturity contexts.

3. Research Methodology

In line with DSR principles, the research process in this study comprised the following stages:

- **Problem Identification and Motivation.** The initial step involved identifying the practical problem: API performance testing being conducted in an ad hoc, person-dependent manner with limited governance and knowledge reuse. Empirical observations in a global IT organization provided additional evidence of fragmented practices, tacit knowledge, and weak performance ownership.
- **Definition of Objectives for a Solution.** Based on the problem analysis, the study defined four main objectives for the solution:

1. to establish a structured and repeatable API performance testing process;
2. to transform testing into a knowledge-creation and knowledge-sharing activity followed by extended knowledge repository;
3. to strengthen cross-functional collaboration and performance ownership; and
4. to link testing outcomes with governance mechanisms such as SLOs, risk management, and continuous improvement.

- **Design and Development of the Artefact.** The framework was designed as the main artefact of the study. Based on the literature and case context, three core dimensions were identified: technical, governance, and learning. These dimensions guided the design of six framework components: Scope & SLOs, Environment Setup, Data Preparation, Execution & Metrics, Analysis & Reporting, and

Knowledge Capture & Sharing. The framework's three-layer architecture and governance cycle (Plan-Execute-Reflect-Refine) were iteratively refined using practitioner feedback and insights from early testing activities.

- **Demonstration in a Real-World Context.** The framework was applied in a global IT organization during an enterprise initiative to validate API performance after a critical data source change.
- **Evaluation and Validation.** In accordance with early-stage DSR, evaluation relied on qualitative and observational methods rather than statistical experiments.
- **Communication of Results.** This paper presents the DSR outcomes in four parts: the problem context, the framework design, the case study, and the evaluation with conclusions and future work.

By following this DSR process, the study ensures that the proposed framework is both practically relevant and theoretically grounded. The artefact responds directly to an observed organizational problem while contributing a knowledge-centric perspective on API performance testing to the information systems and software engineering literature.

4. Design and Development of the Knowledge-Centric API Performance Testing Framework

4.1 Purpose and Design Logic

The purpose of the framework is to help organizations transition from ad hoc, fragmented API performance testing practices to a structured, transparent, and repeatable process. It integrates technical activities with knowledge management principles. It reframes performance testing not only as a technical activity but as a knowledge creation process. This helps organisations reduce complexity, manage risks, and build long-term capability. Without such structure, testing remains tacit, person-dependent, and error-prone - leading to repeated mistakes and hidden risks.

4.2 Design Principles

The framework was developed following Design Science Research (DSR) principles, ensuring alignment between the identified problem, the defined objectives, and the structure of the artefact. Iterative build-evaluate-refine cycles were used to adjust the framework based on literature insights and practitioner feedback.

4.3 Design Requirements

Analysis of literature and case observations revealed three necessary dimensions for introducing a sustainable performance testing practice:

- Technical Layer: *Components:* Environment Setup; Data Preparation; Execution & Metrics, *Purpose:* Ensure reliable and reproducible test execution.
- Governance Layer: *Components:* Scope & SLOs; Analysis & Reporting, *Purpose:* Define performance targets, decision criteria, and accountability.
- Organizational Learning Layer: *Component:* Knowledge Capture & Sharing, *Purpose:* Convert testing outcomes into reusable organizational artefacts.

This three-layer architecture treats performance testing as an integrated organisational process rather than an isolated technical activity. The technical layer enables consistent execution, the governance layer structures decision-making, and the learning layer supports reuse and long-term capability development.

The framework operates through a simple **governance cycle**:

- Plan - Define scope, SLOs, and required data.
- Execute - Run tests and collect metrics.
- Reflect - Analyze results and identify insights.
- Refine - Update documentation, scripts, and repository artefacts.

Two feedback mechanisms connect the layers:

- Upward flow: test results and lessons learned are codified into shared artefacts.
- Downward flow: accumulated knowledge informs future planning and threshold definition.

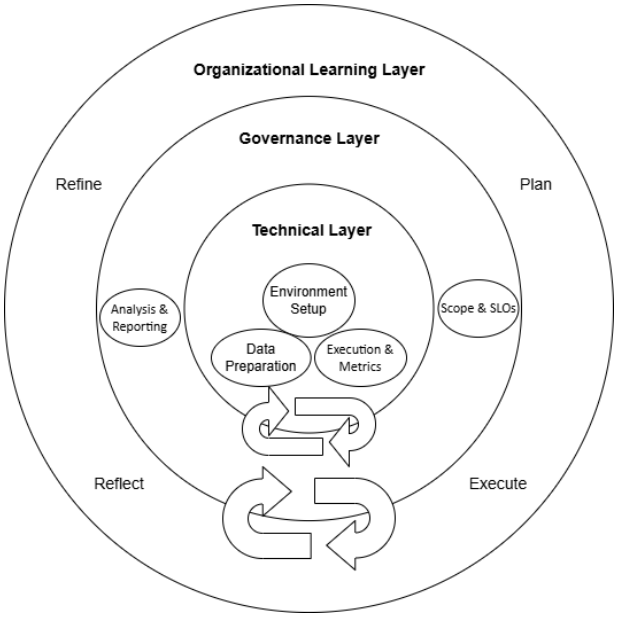


Figure 1: The Framework: Knowledge-Centric API Performance Testing

This cycle supports continuous improvement while reinforcing repeatability and knowledge reuse.

4.4 Expected Outcomes

Application of the framework produces outcomes at two levels:

Technical outcomes	Organizational outcomes
1. Reproducible test execution	1. Reusable scripts and documentation
2. Stable environment configuration	2. Reduced onboarding effort
3. Standardized metric definitions	3. Clearer cross-functional roles
4. Clear performance targets (SLOs)	4. Improved confidence in performance-related decisions

By embedding structured knowledge capture into performance testing, the framework supports the transition from one-off validation activities to a repeatable organizational capability.

5. Case study: Application of the Framework in an Enterprise API Performance Initiative

The case study describes the organisation's first structured attempt to introduce API performance testing. The goal was to move from an ad hoc activity to a governed, knowledge-driven process. The framework was derived and refined through this implementation.

5.1 The Context

The Knowledge-Centric API Performance Testing Framework was applied in a global IT organization that had no prior structured approach to API performance testing. No shared procedures, repositories, metrics, or documentation existed. The implementation took place during an enterprise initiative to validate API performance following a critical data source change. As the organization transitioned toward API-based integrations, ensuring that system changes did not degrade performance became increasingly important.

5.2 Framework Application

Each framework component guided the team through a structured sequence - from defining scope to capturing reusable knowledge. Business Analysts and Product Owners contributed to scope definition, SLO formulation, and interpretation of performance results, ensuring alignment with business priorities and governance requirements.

Table 3: The framework components and their details

Framework Component	Key artefacts produced	Primary roles involved	Example from Case
1. Scope & SLOs	Performance testing strategy; endpoint selection criteria; SLO definition template	PO, BA, QA, QA Lead, Security	Selected endpoints by call volume and response time; executed Normal/Peak/Soak tests; used average P95 across runs + 20% buffer to set initial SLOs.
2. Environment Setup	Documented production-like test environment	Developers, DevOps, QA, Infrastructure, Security	Database resources aligned with production capacity and configuration
3. Data Preparation	Data generation, validation procedures	PO, BA, QA, DevOps, DBA, Legal, Security	Realistic datasets prepared while preserving performance-relevant patterns
4. Execution & Metrics	Standardised test execution plan	DevOps, QA	Core metrics defined: average latency, P95/P99 latency, max latency, throughput, error rate
5. Analysis & Reporting	Structured reporting templates	QA, DevOps, DB teams	Two reporting types: SLO definition (pre- and post-migration) and SLO validation
6. Knowledge Capture & Sharing	Central repository of artefacts	Infrastructure, QA, cross-functional teams	Scripts, configurations, logs, and lessons learned stored for reuse

Through this structured approach, testing moved from irregular and undocumented activities to a reproducible process. Performance discussions expanded beyond QA and DevOps, involving developers, database specialists, and business analysts.

5.3 The Outputs

The framework produced a set of tangible artefacts that did not previously exist in the organization:

- Defined scope and SLO documents
- Standardized test scenarios and execution plans
- Realistic test datasets and data anonymization procedures
- Metrics dashboards (latency, throughput, errors, resource usage)
- Identified performance bottlenecks and improvement recommendations
- Lessons-learned documentation and troubleshooting notes
- Reusable JMeter scripts and environment configurations
- A central knowledge repository for performance testing

These artefacts represent explicit organizational knowledge that can be reused across projects.

5.4 The Observed Effects

The application of the framework resulted in observable changes at both technical and organizational levels.

Technical improvements

- Test results became reproducible and comparable across runs.
- Environment configuration was stabilized and documented.
- Metric definitions were standardized and governed.

Organizational improvements

- The first documented set of SLOs for critical endpoints was established.
- Cross-team collaboration increased.
- Tacit know-how was captured explicitly for the first time.
- A reusable set of scripts reduced setup time for new tests.
- The knowledge repository became a shared reference point for decisions.

Performance testing shifted from an individual activity to a coordinated, multi-role process supported by shared artefacts.

5.5 Lessons Learned

Several lessons emerged from introducing performance testing in a low-maturity context:

- Start small and document consistently. Even small testing activities generate valuable knowledge when captured systematically.
- Treat testing artefacts as reusable assets. Scripts, dashboards, and documentation quickly become core organizational resources.
- Integrate governance early. Without a structured Plan-Execute-Reflect-Refine cycle, teams risk reverting to ad hoc practices.
- Allow flexibility within structure. Components can be adapted to local needs, provided the overall process remains consistent.

In addition to the positive outcomes, several unexpected challenges were observed. First, despite structured documentation, initial adoption was uneven, as some technical team members perceived knowledge capture activities as overhead. This required additional alignment and communication efforts. Second, early SLO definitions proved unstable and required multiple iterations, highlighting the difficulty of translating empirical performance data into governance thresholds.

6. Evaluation and Validation

The evaluation assessed whether the framework achieved its objectives: improving repeatability, enabling knowledge reuse, strengthening collaboration, and supporting decision-making. In Design Science Research (DSR), evaluation focuses on assessing the usefulness and applicability of the artefact in addressing the identified problem (Hevner et al., 2004).

Because the framework was introduced in an organization with no prior structured testing practice, qualitative evaluation methods were appropriate. The assessment used observations, artefact inspection, and practitioner feedback. The focus was on practical use and observable process changes, not statistical measurement. (Table 4)

Table 4: The evaluation criteria and corresponding evidence

Objective	Before	After	Evaluation Focus	Evidence from case
1. Repeatable process	No structured testing process, ad hoc	Defined workflow (Plan–Execute–Reflect–Refine)	Existence of a structured workflow that can be reused	Strategy template, execution checklist, defined test types (Normal/Peak/Soak)
2. Knowledge capture and reuse	Tacit, undocumented	Repository	Artefacts documented and accessible for future use	Repository containing scripts, configurations, data preparation notes, and reporting templates
3. Cross-functional collaboration	QA-only	Cross-functional involvement (QA lead, architects)	Participation beyond QA	Involvement of DevOps, DB, Security, BA/PO in scoping, data preparation, and analysis
4. Decision support	Undefined responsibilities	Defined responsibilities across the teams and stakeholders	Results used in governance discussions	SLO definition and validation reports shared with stakeholders
5. Metric standardisation	Inconsistent	Standardized	Consistent interpretation and reporting of results	Defined latency percentiles (P95/P99), throughput, error rate, and structured reporting format

Following the objectives stated in the Section 1, the table 5 presents the results obtained:

Table 5: The objectives, evidence and achieved results

Objective	Evidence	Achieved
Repeatability	Structured templates, reusable scripts, execution workflows	Yes
Knowledge reuse	Repository with scripts, reports, and lessons learned	Partial
Collaboration & Decision support	Multi-role involvement across QA, DevOps, BA, PO, architects, team leads	Yes

The evaluation results indicate that all primary design requirements - repeatability, knowledge capture, collaboration, and governance integration - were addressed. While knowledge reuse remains partially achieved, the presence of a structured repository and reusable artefacts provides a foundation for future improvement. A key implication of this study is that performance testing should not be treated solely as a technical validation activity but as a cross-functional organisational capability supported by structured knowledge flows.

7. Conclusion, Limitations, and Future Work

This paper addressed the question of how an organization with no established API performance testing practice can introduce a repeatable process while retaining knowledge for reuse. It presented the Knowledge-Centric API Performance Testing Framework, which integrates technical execution, governance structure, and systematic knowledge capture. Developed using the Design Science Research (DSR) approach, the framework structures performance testing into six components: Scope & SLOs, Environment Setup, Data Preparation, Execution & Metrics, Analysis & Reporting, and Knowledge Capture & Sharing.

The case study showed that structured workflows and shared artefacts can replace ad hoc practices. This makes performance testing more repeatable and transparent. The findings show that embedding knowledge capture in testing supports reuse, cross-functional coordination, and consistent decision-making.

Several limitations must be acknowledged. First, the framework was derived and evaluated in a single organizational context, which limits generalizability. Additional applications across different industries and technical environments would strengthen external validity. Second, evaluation relied on qualitative evidence, including artefact inspection and practitioner observation. While appropriate for early-stage DSR, future research could complement these findings with quantitative performance indicators or comparative studies. Third, the case organization was at an early stage of testing maturity; further investigation is needed to assess applicability in highly automated or advanced DevOps settings.

Future research can extend the framework in three directions. First, replication in additional organizations would enable refinement and validation across contexts. Second, more detailed guidance on repository design, template standardization, and tool integration could support deeper operationalization. Third, expanding the framework toward continuous performance testing and performance engineering practices may contribute to a broader organizational model of reliability and learning.

Overall, the study contributes to a structured approach for introducing API performance testing in low-maturity contexts and frames performance testing outputs as reusable organizational knowledge assets rather than isolated technical results.

Ethics declaration: This research did not require formal ethical approval, as it did not involve human subjects, personal data, or sensitive information. The study was conducted using organisational processes and artefacts, ensuring no identifiable individuals or confidential data were disclosed.

AI declaration: ChatGPT was used to enhance the structure and refine the language of the paper.

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Regional Knowledge Potential and Tourism Innovation in Poland: A Multi-criteria Analysis

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Abstract: The paper investigates the knowledge-based determinants of tourism innovation potential in Polish regions and their relevance for smart tourism development. The primary objective is to assess how regional knowledge resources, learning capabilities, and information-processing conditions influence innovation readiness within the tourism sector. Tourism innovation potential is conceptualized not only as a set of infrastructural or technological indicators but also as a component of regional knowledge ecosystems that enable the creation, diffusion, and practical application of knowledge in tourism-related activities. The analysis is based on statistical data from the Polish Central Statistical Office, including indicators related to the information society, research and experimental development, and enterprise innovation activity, complemented by selected tourism-related variables. Together, these indicators form an operational framework for assessing how regions accumulate, manage, and utilize knowledge resources relevant to tourism innovation. To measure this potential, the study applies a multi-criteria decision-making approach combining Hellwig's method and the TOPSIS method. Eleven diagnostic variables were selected, including ten stimulants and one destimulant. Both methods generate standardized synthetic measures of knowledge-based tourism potential within the range [0,1]. Based on these measures, Polish regions were classified into four typological groups representing different levels of knowledge maturity, absorptive capacity, and innovation readiness. A further stage of the analysis examines the relationship between knowledge-driven innovation potential and actual tourism performance. Two indicators of tourist movement were used: the density of tourist movement (WG) and Schneider's tourism intensity index (WS). Spearman's rank correlation analysis indicates a strong positive relationship (rs = 0.90–0.95), suggesting that regions more effective in mobilizing and utilizing knowledge resources tend to attract higher tourist flows. At the same time, several regions with only moderate knowledge potential record relatively high tourism activity, which may reflect effective knowledge-management practices, institutional learning mechanisms, or strong regional cooperation networks. The findings reveal significant regional disparities in the creation and utilization of knowledge within the Polish tourism sector and highlight the importance of strengthening regional knowledge-management systems-such as digital infrastructure, innovation networks, and mechanisms of knowledge exchange - to enhance regional competitiveness and support smart tourism development.

Keywords: Knowledge management, Tourism, Innovation potential, Multi-criteria analysis

1. Introduction

In recent years, the growing importance of knowledge as a strategic resource has significantly reshaped the understanding of regional development processes, particularly in sectors characterized by high levels of service intensity and innovation, such as tourism. Contemporary approaches emphasize that regional competitiveness is increasingly determined not only by tangible assets, but also by the ability to generate, absorb, and utilize knowledge within complex socio-economic systems (Cooke et al., 2007). In this context, tourism is undergoing a transformation towards knowledge-driven and innovation-oriented models, where intellectual capital, absorptive capacity, and network-based knowledge exchange play a critical role in shaping development trajectories (Gürlek, 2020; Wu, 2020; Raisi et al., 2020). At the same time, the emergence of smart tourism highlights the growing relevance of digital technologies, data ecosystems, and learning processes as key enablers of innovation and value creation in tourism destinations (Ye et al., 2020). Despite the increasing recognition of these factors, there remains a need for comprehensive empirical approaches that integrate knowledge-based determinants with measurable indicators of tourism performance at the regional level. Therefore, the main objective of this study is to assess the role of regional knowledge potential as a determinant of tourism innovation in Poland, using a multi-criteria analytical framework that captures both structural and functional dimensions of knowledge systems. The study contributes to the existing literature by linking the concept of regional knowledge ecosystems with tourism innovation potential and by providing an empirical assessment of spatial disparities in knowledge-driven development processes.

2. Literature Review: Knowledge-based Determinants, Innovation Potential, and Smart Tourism Development

2.1 Knowledge Systems and Innovation Processes in Tourism

The growing importance of knowledge as a strategic resource has significantly reshaped the theoretical foundations of tourism development. Within the knowledge-based economy framework, knowledge is no longer perceived as a complementary factor but rather as a core determinant of innovation and competitive advantage. Regional development is thus increasingly driven by the capacity to generate, integrate, and utilize knowledge resources, rather than by the mere availability of material assets (Cooke et al., 2007).

In this context, regional knowledge potential reflects a system's ability to combine competencies, learning processes, and network relationships that enable the diffusion and application of knowledge, particularly in sectors such as tourism, where innovation is often intangible and experience-based. Tourism development is strongly embedded in local knowledge systems, as the uniqueness of tourism products frequently derives from place-specific resources and cultural contexts. Consequently, learning and knowledge adaptation processes play a crucial role and are inherently co-evolutionary, emerging from interactions among actors and continuous adjustments to institutional and environmental conditions (Cristofaro et al., 2020; Dias et al., 2023).

A central component of knowledge-based development is intellectual capital, encompassing human, structural, and relational dimensions. Human capital, encompassing employees' knowledge, skills, and competencies, represents a fundamental factor shaping innovation in tourism, particularly in the context of entrepreneurship and the development of new business models (Chou et al., 2020). In tourism, intellectual capital is particularly significant due to the centrality of service quality and customer experience. Human capital provides the competencies necessary for innovation, relational capital facilitates access to external knowledge and supports value co-creation, while structural capital ensures the organizational infrastructure for knowledge management (Gürlek, 2020; Liu, 2020). Their interaction enhances firms' adaptive capacity and innovation performance (Khalique et al., 2020; Liu et al., 2017).

The effective use of knowledge resources is closely linked to absorptive capacity, defined as the ability to acquire, assimilate, and apply external knowledge (Binder, 2018). In tourism, where innovation often results from combining diverse knowledge sources, absorptive capacity plays a pivotal role. It is embedded in organizational routines and learning mechanisms (Ponce-Espinosa et al., 2020) and acts as a mediator between intellectual capital and innovation outcomes (Wu, 2020).

At the regional level, knowledge transfer and diffusion processes underpin innovation systems. Knowledge circulates through formal and informal networks, fostering innovation and new business models (Raisi et al., 2020). In the fragmented tourism sector, collaborative networks are particularly important, as they facilitate access to diverse knowledge sources and enhance innovation capacity (Arcese et al., 2021). These processes foster the creation of innovation and the diversification of economic activities, which is particularly significant in the context of the development of new tourism products and initiatives based on cross-sectoral collaboration (Schuhbert et al., 2020).

2.2 Tourism Innovation Potential: Drivers and Assessment

Tourism innovation potential can be conceptualized as a systemic capacity to generate, absorb, and implement innovations within a regional context. Innovation extends beyond observable outputs and reflects broader capabilities related to learning and adaptation (Wu, 2020). This perspective aligns with the resource–capability–performance framework, in which knowledge resources and intellectual capital shape organizational capabilities that determine innovation outcomes.

The determinants of tourism innovation are multidimensional, encompassing both internal organizational factors and external environmental conditions. Key drivers include intellectual capital, organizational capabilities, and collaborative networks, which jointly influence the ability to generate and implement innovations (Gürlek, 2020; Khalique et al., 2020). Access to external knowledge and participation in networks further enhance innovation performance by increasing the diversity and intensity of knowledge flows (Binder, 2018; Raisi et al., 2020).

Tourism enterprises play a central role in these processes, acting as agents that transform knowledge into innovative products and services. Their innovation capacity depends on both internal resources, such as intellectual capital and absorptive capacity, and external conditions, including access to digital technologies and

knowledge infrastructures. The development of ICT and digital platforms enables new business models and service personalization (Ye et al., 2020), while collaboration with research institutions supports knowledge transfer and innovation implementation (Dias et al., 2023).

The measurement of tourism innovation potential remains challenging due to its intangible and multidimensional nature. Empirical studies typically rely on composite indicators capturing aspects such as ICT development, research and development (R&D) intensity, and firms' innovation activity (Ye et al., 2020; Suryandaru, 2020). However, these measures should be complemented by qualitative dimensions, including organizational capabilities, network relationships, and learning processes, to fully capture the complexity of innovation systems.

2.3 Digital Transformation and the Emergence of Smart Tourism

The transition towards smart tourism represents a natural evolution of knowledge-based and innovation-driven development. Smart tourism is defined by the integration of digital technologies, data, and knowledge to enhance decision-making processes, service quality, and user experiences. Smart destinations leverage advanced ICT solutions to facilitate stakeholder interactions and optimize resource management (Ye et al., 2020).

Digital technologies and data form the foundation of smart tourism ecosystems, characterized by interconnected networks of enterprises, institutions, and users that co-create value through continuous information exchange. In these ecosystems, data function as a strategic resource, enabling innovative business models, operational efficiency, and adaptability to changing market conditions (Liu, 2020; Wu, 2020).

Smart tourism is also embedded in knowledge ecosystems that support the creation, diffusion, and application of knowledge across multiple actors. These ecosystems rely on dynamic interactions and collaborative processes that foster innovation and value co-creation (Raisi et al., 2020). Intellectual capital and absorptive capacity remain critical enablers, as they allow organizations to integrate diverse knowledge sources and translate them into innovative solutions (Gürlek, 2020; Ponce-Espinosa et al., 2020).

From a regional perspective, smart tourism contributes to both competitiveness and sustainability. Regions that effectively leverage digital technologies and knowledge resources are better positioned to develop innovative tourism products and achieve superior economic performance (Ye et al., 2020). At the same time, smart tourism supports sustainable development through more efficient resource management and reduced environmental impact (Cristofaro et al., 2020).

3. Methodology

The objective of the present study was to assess how regional knowledge resources, learning capabilities, and information-processing conditions influence innovation potential within the tourism sector in Poland. The analysis was conducted using newly released statistical datasets from the Polish Central Statistical Office, including Information Society in Poland (Central Statistical Office, 2024), Research and Experimental Development in Poland (Central Statistical Office, 2023b), Innovation Activity of Enterprises (Central Statistical Office, 2023a), as well as additional indicators from the Local Data Bank identified as stimulants of tourism development in Poland (Central Statistical Office, 2024). Based on these datasets, the key components constituting the tourism innovation potential were identified.

The research applied a multi-criteria decision-making framework integrating Hellwig's (1968) taxonomic method and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). As noted by Hwang and Yoon (1981), TOPSIS represents a methodological extension of Hellwig's approach. Both techniques enable the linear ordering of spatial units according to their respective levels of tourism innovation potential, thereby supporting a comprehensive and comparative statistical evaluation.

In both analytical frameworks, a consistent notation scheme was applied. The parameter m denotes the number of observed units, corresponding in this study to the territorial regions of Poland. The parameter n represents the number of diagnostic variables, classified as either stimulants or destimulants affecting the level of tourism innovation development. Both methodological approaches yield synthetic indicators that enable the linear ordering of regions according to their tourism innovation potential. The resulting rankings were subsequently compared with indicators of tourist traffic density and intensity, conceptualized in accordance with Schneider's definitions. The overall research procedure was adopted from the methodological framework developed by Synówka-Bejenka (2017).

Hellwig's taxonomic method was employed to compute a synthetic development measure, producing values on a normalized scale from 0 to 1. Within this interval, a value of 0 reflects the weakest similarity to the ideal development pattern, whereas a value of 1 indicates the strongest similarity. In parallel, the TOPSIS method was used to derive a synthetic indicator representing the tourism potential of each region. The resulting values also ranged from 0 to 1, with 0 corresponding to the lowest potential and 1 to the highest.

The degree of association between the two rankings derived from the aforementioned synthetic measures was assessed using Spearman's rank correlation coefficient (r_s). This non-parametric statistic assumes values within the interval [−1, 1] and is defined by the following formula:

$$r_s = 1 - \frac{6\sum_{i=1}^{m} o_i}{m(m^2-1)}$$

where:

o_i - denotes the difference between the positions occupied by the i-th region in the two rankings under comparison

m – represents the total number of regions.

The coefficient r_s measures the strength and direction of the monotonic relationship between the rankings, with values approaching 1 indicating a strong positive correlation, values near −1 indicating a strong negative correlation, and values close to 0 suggesting the absence of a monotonic association.

The Hellwig's method

a) Standardization of variables

$$z_{ij} = \frac{x_{ij} - \bar{x}_j}{s_j}$$

i =1,2,…,m

j= 1,2,…,n

b) Determining the value of the development pattern

$$z_j^+ = \begin{cases} \max\limits_i \{z_{ij}\} \\ \min\limits_i \{z_{ij}\} \end{cases}$$

max= variable X_j is the stimulant

min= variable X_j is the destimulant

c) Determining the distance of Euclidean objects from the development pattern

$$d_i^+ = \sqrt{\sum_{j=1}^{n} \left(z_{ij} - z_j^+\right)^2}$$

i =1,2,…,m

j= 1,2,…,n

d) Determining a taxonomic measure of development

$$d_i^H = 1 - \frac{i_i^+}{\bar{d} + 2s_d}$$

where: $\bar{d} = \frac{1}{m}\sum_{i=1}^{m} d_i^+$ and $s_d = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(d_i^+ - \bar{d}\right)^2}$

The TOPSIS method

a) normalization of variables

$$= \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$

i =1,2,…,m

j= 1,2,…,n

b) Determination of the value of the ideal object z^+ (from the Hellwig's method) and the anti-ideal object z^-

$$z_j^- = \begin{cases} \max\limits_i \{z_{ij}\} \\ \min\limits_i \{z_{ij}\} \end{cases}$$

$\max\limits_i \{z_{ij}\}$ *when variable Xj is the stimulant*

$\min\limits_i \{z_{ij}\}$ *when variable Xj is the destimulant*

c) Determining the distance of Euclidean objects from an ideal and non-ideal solution

$$d_i^+ = \sqrt{\sum_{j=1}^{n} \left(z_{ij} - z_j^+\right)^2} \qquad d_i^- = \sqrt{\sum_{j=1}^{n} \left(z_{ij} - z_j^-\right)^2}$$

i =1,2,…,m

j= 1,2,…,n

d) Determining the synthetic index

$$d_i^T = \frac{i_i^-}{i_i^+ + i_i^-}$$

i =1,2,…,m

4. Selection of Diagnostic Variables

For the purposes of the comparative statistical analysis, a total of eleven diagnostic variables were selected. Of these, ten were classified as stimulants, indicating that they exert a positive influence on the measured outcome. In contrast, variable X4 was designated as a destimulant, reflecting its negative effect on the outcome. Among the available statistical data, the authors selected the following determinants of regional knowledge potential specifically oriented toward fostering tourism innovation in Poland:

X_1 - share of net revenues from sales of innovative products in total net revenues from sales in 2022

X_2 – percentage of innovative service enterprises in the years 2020–2022

X_3 – innovative enterprises that cooperated in terms of innovation activity in % of total enterprises in 2023

X_4 – registered unemployment rate in 2024

X_5 – expenditures on innovation activities in service enterprises - per 1000 inhabitants in 2023

X_6 – enterprises with high and very high level of the digital intensity index in 2023

X_7 – The Bank Millenium "eco index" 2024

X_8 – intramural expenditure on R&D by voivodships in 2023 (current prices)

X_9 – number of lodging facilities per 100 km²

X_{10} – length of tourist trails per 100 km² (km)

X_{11} – gastronomic enterprises with more than 9 employees per 100 km²

The selection of variables was guided by two principal criteria: their relevance to the innovation potential of the tourism sector and a sufficiently high coefficient of variation. For each variable included in the analysis, we

calculated key descriptive statistics, including minimum and maximum values, arithmetic means $\bar{x}_j$, standard deviations S_j, and classical coefficients of variation V_j. All computed values are presented in detail in Table 1.

Table 1: Descriptive characteristics of the diagnostic variables

Specification	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}
Minimum	0.00	10.60	2.60	3.00	11.56	10.70	29.00	0.14	66.63	8.76	1.82
Maximum	4.70	41.40	17.60	8.70	3104.69	31.20	61.00	6.24	657.88	57.01	21.54
$\bar{x}_j$	1.73	28.74	7.03	5.79	487.05	18.39	45.50	1.62	258.63	24.52	6.61
S_j	1.21	9.82	4.37	1.73	734.03	4.86	8.46	1.77	199.96	12.45	5.58
V_j	0.70	0.34	0.62	0.30	1.51	0.26	0.19	1.09	0.77	0.51	0.84

Source: Own calculations based on the Central Statistical Office (2022a, 2022b, 2023a, 2023b, 2024a, 2024b) and Bank Millenium (2024) report.

5. Regional Classification of Polish Regions by Knowledge Potential Supporting Tourism Innovation

The values of the taxonomic measures derived from Hellwig's method and the TOPSIS procedure—calculated on the basis of the eleven selected diagnostic variables—served as the foundation for constructing the ranking of the analyzed regions and are presented in Table 2.

Table 2: Synthetic measures and their regional ranges across polish voivodeships

Region	The Hallwig's method d_i^H	Ranking position R_H	Change of the ranking position	Ranking position R_T	TOPSIS d_i^T
Lower Silesia	0.5224795	2	1	1	0.147863957
Kuyavia-Pomeranian	0.2796473	6	8	14	0.122589395
Lublin Voivodeship	0.1885717	12	1	11	0.124260214
Lubusz Voivodeship	0.2517231	9	3	12	0.123544956
Łódź Voivodeship	0.2635930	7	1	6	0.128233500
Lesser Poland	0.4899253	3	1	2	0.140361788
Masovia	0.5521146	1	2	3	0.135416701
Opole Voivodeship	0.1630040	14	1	13	0.122995090
Subcarpathia	0.2509942	10	2	8	0.126112684
Podlaskie Voivodeship	0.1678331	13	3	10	0.124437622
Pomerania	0.3952826	5	0	5	0.132019856
Silesian Voivodeship	0.4090261	4	0	4	0.131387298
Holy Cross Voivodeship	0.0864152	15	1	16	0.117030386
Warmian-Masurian Voivodeship	0.0856267	16	1	15	0.119523073
Greater Poland	0.1988857	11	4	7	0.127900641
West Pomerania	0.2576487	8	1	9	0.124921801

Source: Own calculations based on the Central Statistical Office (2022a, 2022b, 2023a, 2023b, 2024a, 2024b) and Bank Millenium (2024) report.

A statistical analysis was carried out using eleven diagnostic variables to evaluate the tourism innovation potential of Polish regions. Descriptive statistics for each variable – including minimum and maximum values, arithmetic means, standard deviations, and classical coefficients of variation – are presented in Table 2. The coefficient of variation (V_j) illustrates the relative dispersion of each diagnostic variable. The highest variability is observed for X_5 – expenditures on innovation activities in service enterprises per 1,000 inhabitants (V_j=1.51), followed by X_8 - intramural R&D expenditures at the voivodeship level (V_j=1.09), and X_{11} – the density of gastronomic enterprises with more than nine employees per 100 km² (V_j=0.84). In contrast, variables such as X_7

– the Bank Millennium "Eco Index" 2024 (V_j=0.19) and X_6 – the share of enterprises with high or very high levels of the Digital Intensity Index (V_j=0.26) display relatively low variability.

To assess regional differences, the study employed Hellwig's method and the TOPSIS technique to compute taxonomic measure values for each voivodeship. These synthetic measures formed the basis for ranking the regions according to their tourism innovation potential. The resulting values and rankings are provided in Table 2. According to Hellwig's method, the Masovian Voivodeship ranks first (d_i^H = 0.552), indicating the strongest tourism innovation potential, followed by Lower Silesia (d_i^H = 0.522) and Lesser Poland (d_i^H = 0.490). The lowest potential is recorded for the Warmian-Masurian and Holy Cross Voivodeships (both d_i^H =0.086).

The TOPSIS results reveal a slightly different ordering. In this case, Lower Silesia occupies the top position (d_i^T = 0.148), followed by Lesser Poland (d_i^T = 0.140) and the Masovian Voivodeship (d_i^T = 0.135). The voivodeships with the lowest tourism innovation potential according to TOPSIS are Holy Cross (d_i^T = 0.117) and Warmian-Masurian (d_i^T = 0.119).

In Table 3, a detailed classification of the regions into four typological groups, based on their tourism innovation potential, is presented. According to Hellwig's method, regions assigned to the "very high" potential category (Class I) include Masovia, Lower Silesia, and Lesser Poland. Regions exhibiting "high" potential (Class II) comprise the Silesian Voivodeship and Pomerania. The "medium" potential group (Class III) encompasses the Kuyavia–Pomeranian Voivodeship, Łódź Voivodeship, Lubusz Voivodeship, West Pomerania, Subcarpathia, Greater Poland, Lublin Voivodeship, and Opole Voivodeship. Finally, the "low" potential category (Class IV) includes the Holy Cross Voivodeship and the Warmian–Masurian Voivodeship.

Table 3: Taxonomic classification of the investigated regions

Measure values $d_i^{H/T}$	Class	Tourism potential	Region
According to the value of Hellwig's development measure			
$d_i^H \geq 0.4278$	I	Very high	Masovia, Lower Silesia, Lesser Poland
$0.4278 > d_i^H \geq 0.2852$	II	High	Silesian Voivodeship, Pomerania,
$0.2852 > d_i^H \geq 0.1426$	III	Medium	Kuyavia-Pomerania, Łódź Voivodeship Lubusz Voivodeship, West Pomerania, Subcarpathia, Greater Poland, Lublin Voivodeship, Opole Voivodeship
$d_i^H < 0.1426$	IV	Low	Holy Cross Voivodeship, Warmian-Masurian Voivodeship
According to the value of the synthetic TOPSIS meter			
$d_i^T \geq 0.1357$	I	Very high	Lower Silesia, Lesser Poland
$0.1357 > d_i^T \geq 0.1280$	II	High	Masovia, Pomerania, Silesian Voivodeship, Łódź Voivodeship
$0.1280 > d_i^T \geq 0.1204$	III	Medium	Greater Poland, Subcarpathia, West Pomerania, Podlaskie Voivodeship, Lublin Voivodeship, Lubusz, Opole Voivodeship, Kuyavia-Pomerania,
$d_i^T < 0.1204$	IV	Low	Warmian-Masurian Voivodeship, Holy Cross Voivodeship

Source: Own calculations based on the Central Statistical Office (2022a, 2022b, 2023a, 2023b, 2024a, 2024b) and Bank Millenium (2024) report.

A comparable four-group classification was also produced using the TOPSIS method. According to this approach, regions with "very high" potential are Lower Silesia and Lesser Poland. The "high" potential group (Class II) consists of Masovia, Pomerania, the Silesian Voivodeship, and the Łódź Voivodeship. Regions classified as having "medium" potential (Class III) include Greater Poland, Subcarpathia, West Pomerania, the Podlaskie Voivodeship, Lublin Voivodeship, Lubusz Voivodeship, Opole Voivodeship, and the Kuyavia–Pomeranian Voivodeship. The "low" potential regions identified by the TOPSIS method are the Warmian–Masurian Voivodeship and the Holy Cross Voivodeship.

Although some differences occur in the specific ranking positions and group allocations between the two methods, a notable consistency is evident in identifying both the highest- and lowest-performing regions. Lower Silesia, Lesser Poland, and Masovia repeatedly appear among the top-ranking regions, albeit with slight positional shifts, while the Holy Cross and Warmian–Masurian Voivodeships consistently occupy the lowest positions across both classifications. The "Change of the ranking position" column in Table 3 further illustrates these discrepancies, indicating the relative movement of regions between the Hellwig and TOPSIS rankings. Altogether, these findings provide a comprehensive overview of regional disparities in tourism innovation potential within Poland.

Figures 1 and 2 summarise the classification results. Figure 1 ranks the voivodeships by the two synthetic measures and their typological class, while Figure 2 shows the spatial distribution of the classes across Poland, making the regional disparities directly comparable between the Hellwig and TOPSIS approaches.

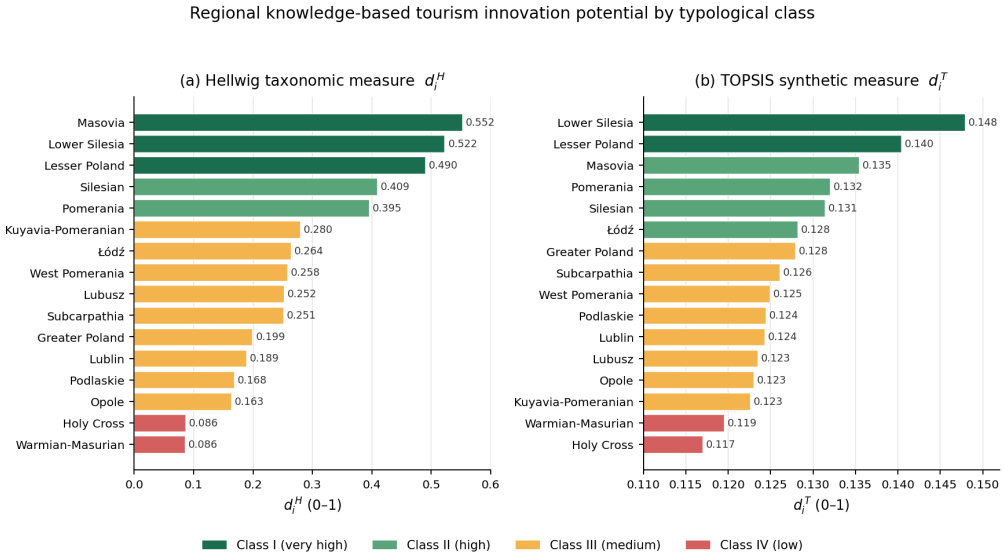


Figure 1: Regional knowledge-based tourism innovation potential by typological class — Hellwig taxonomic measure (d_i^H) and TOPSIS synthetic measure (d_i^T)

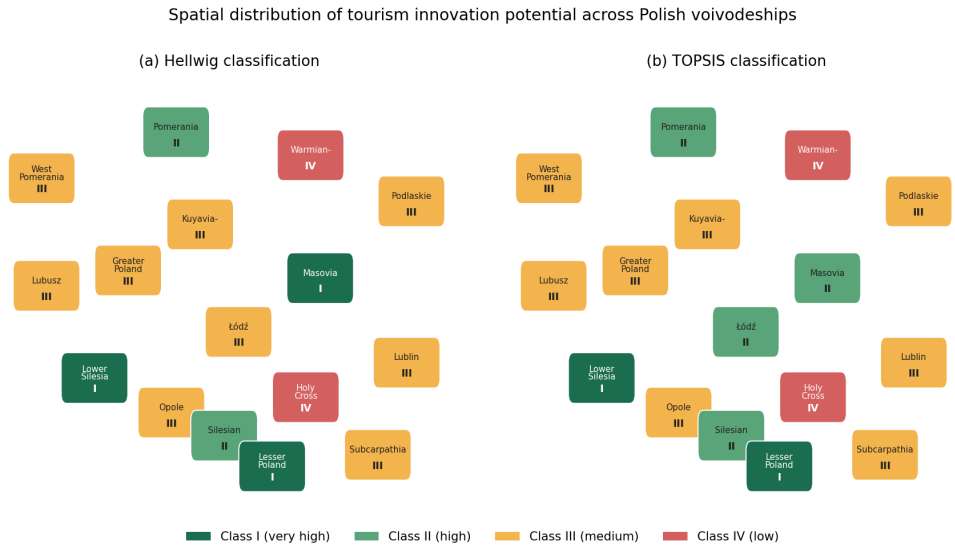


Figure 2: Spatial distribution of tourism innovation potential across Polish voivodeships under the Hellwig and TOPSIS classifications

6. Results and Discussion: Tourism Innovation Potential and Tourist Traffic

To further assess how effectively the regions translated their innovation potential into actual tourism activity, the results were compared with indicators reflecting the number of individuals using accommodation services

in 2023. Based on data from the Polish Central Statistical Office (Central Statistical Office, 2024), two indicators were applied: tourist traffic density (WG), defined as the number of persons using accommodation services during the year per square kilometre of area, and tourist traffic intensity according to Schneider (WS), defined as the ratio of individuals using accommodation services during the year to the total number of inhabitants.

Table 4: Movement density indicator and Schneider indicator

Region	Movement density indicator W_G	Ranking position R_G	Change of the ranking position	Ranking position R_S	Schneider indicator W_S
Lower Silesia	210.39	3	1	4	145.75
Kuyavia-Pomeranian	78.88	7	0	7	71.02
Lublin Voivodeship	47.42	13	3	10	59.23
Lubusz Voivodeship	4640	14	6	8	66.56
Łódź Voivodeship	71.67	8	4	12	55.27
Lesser Poland	376.16	1	1	2	166.53
Masovia	176.19	5	0	5	113.69
Opole Voivodeship	36.66	15	1	16	36.83
Subcarpathia	66.85	9	2	11	57.59
Podlaskie Voivodeship	28.72	16	1	15	50.93
Pomerania	189.22	4	1	3	146.83
Silesian Voivodeship	220.84	2	7	9	63.04
Holy Cross Voivodeship	53.56	11	2	13	53.68
Warmian-Masurian Voivodeship	53.23	12	6	6	94.76
Greater Poland	62.45	10	4	14	53.40
West Pomerania	149.41	6	5	1	209.60

Source: Own calculations based on the Central Statistical Office (2022a, 2022b, 2023a, 2023b, 2024a, 2024b) and Bank Millenium (2024) report.

Table 4 presents actual tourist traffic in 2023. The Lesser Poland and Silisian Voivodeships exhibit the highest density of tourist movement (WG), whereas Podlaskie and Opole record the lowest values. West Pomerania demonstrates the highest tourism intensity (WS) relative to its population, while Opolskie and Holy Cross rank lowest in this respect. Changes in regional rankings, such as the advancement of West Pomerania in terms of WS, reflect differences in the effectiveness with which regions capitalize on their tourism potential.

To assess the strength of tourism innovation potential utilization, Spearman's rank correlation coefficient (r_s) was recalculated. The analysis indicates a high degree of concordance between rankings obtained using both taxonomic methods, based on the WG and WS indicators. The values of these indicators are reported in Table 5. The results reveal a very strong (0.90–0.95) and positive correlation between innovation potential (as measured by the Hellwig and TOPSIS methods) and actual tourist traffic (WG, WS), suggesting that regions with higher tourism innovation potential tend to attract a larger number of tourists.

Table 5: The Spearman's rank correlation coefficients

Coefficients	d_i^H	d_i^T
W_G	$r_s = 0.95$	$r_s = 0.94$
W_S	$r_s = 0.93$	$r_s = 0.90$

Source: Own calculations based on the Central Statistical Office (2022a, 2022b, 2023a, 2023b, 2024a, 2024b) and Bank Millenium (2024) report.

Based on a comprehensive analysis of regional innovation potential in tourism – integrating results derived from the Hellwig and TOPSIS methods with tourist traffic indicators – several key conclusions can be drawn. A strong and highly consistent positive relationship is observed between a region's tourism innovation potential and its tourist movement indicators, namely the density of tourist movement (WG) and the intensity of tourist movement according to Schneider (WS).

The exceptionally high values of Spearman's rank correlation coefficient (ranging from ranging from rs = 0.90 to 0.95) indicate a substantial degree of concordance, demonstrating that regions characterized by higher levels of innovation potential in tourism tend to exhibit greater tourist activity. This finding suggests that investments in tourism innovation are effectively translated into measurable increases in tourist flows.

Despite the strength of these correlations, an examination of individual regional rankings reveals important nuances in the extent to which regions effectively exploit their innovation potential. For example, although Masovia consistently occupies leading positions in terms of innovation potential (1st according to the Hellwig method and 3rd based on TOPSIS), it ranks only 5th with respect to both tourist movement density (WG) and Schneider's tourism intensity indicator (WS). In contrast, West Pomerania, characterized by a moderate level of innovation potential (8th in Hellwig and 9th in TOPSIS), attains the top position in terms of Schneider's intensity indicator (WS). This discrepancy suggests that factors beyond innovation potential – such as effective destination marketing, natural endowments, or geographical advantages – may play a significant role in shaping tourist traffic patterns.

Regions consistently exhibiting high levels of innovation potential, such as Lower Silesia, Lesser Poland, and Masovia, also tend to demonstrate strong tourist movement indicators. In contrast, regions characterized by lower innovation potential, including Holly Cross and Warmian-Masurian, consistently record lower levels of tourist activity. These findings provide robust evidence that the development of tourism innovation constitutes a critical pathway for enhancing tourist flows and strengthening regional competitiveness. Accordingly, policy interventions should prioritize investments in key stimulant variables (X1–X3, X5–X11), while simultaneously addressing the negative effects of destimulants, particularly unemployment (X4). The results offer a solid empirical foundation for the design of targeted, evidence-based strategies aimed at unlocking and fully exploiting tourism innovation potential across all Polish regions.

7. Conclusions

The selected determinants discussed in this article, particularly those relating to Regional Knowledge Potential and Tourism Innovation, play a critical role in understanding how destinations develop competitive advantages in an increasingly dynamic tourism environment. Innovations constitute a central driver of tourism development, enabling the creation of new products and services that respond to evolving consumer expectations while strengthening market positioning. Contemporary solutions - especially those associated with smart tourism ecosystems - have become essential for optimizing destination management, personalizing visitor experiences, and enhancing the efficiency of resource allocation.

An analysis of regional knowledge potential reveals a strong positive relationship between a region's innovation capacity and the volume of tourist traffic it attracts. This finding suggests that investments in knowledge-based assets and innovation-oriented activities translate directly into higher levels of tourism activity. However, a closer examination of regional disparities shows that not all areas fully capitalize on their knowledge potential. Some regions characterized by substantial innovation capabilities demonstrate only moderate tourist flows, while others with relatively lower innovation potential still manage to attract visitors effectively - likely due to factors such as strong branding, targeted marketing strategies, or favourable infrastructural conditions. Regions that consistently exhibit high regional knowledge potential tend to record equally robust indicators of tourist traffic, implying successful integration of innovation into their tourism offer. In contrast, regions with lower levels of innovation capacity generally show reduced density and intensity of tourist activity, underscoring the broader importance of knowledge-driven innovation as a determinant of regional tourism attractiveness.

These findings indicate that strengthening tourism innovation grounded in regional knowledge potential is essential for enhancing both tourist flows and overall regional competitiveness. Policy interventions should therefore prioritize investment in the drivers of regional knowledge creation and innovation, while simultaneously addressing the barriers that inhibit their diffusion. The varying degrees of correlation between knowledge potential and tourism performance highlight the need for region-specific, adaptive development strategies that reflect local socio-economic and institutional contexts.

The study's limitations include a relatively narrow set of diagnostic variables and the cross-sectional character of the analysis, which may not fully capture the dynamic evolution of tourism markets. Although strong correlations between knowledge potential and tourist activity were observed, the exclusive reliance on quantitative measures restricts deeper insight into the mechanisms through which knowledge assets shape innovative performance. Future research should expand the analytical framework by incorporating broader variable sets, applying longitudinal approaches, and employing mixed-methods designs. Such methodological advancements would provide a more comprehensive understanding of how regional knowledge potential influences tourism innovation and would strengthen the empirical basis for evidence-informed policy development.

Ethics Declaration: We didn't need ethical clearance for the research referred to in this paper.

AI Declaration: We didn't use an AI tool in the development of the paper.

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Generative AI as a Knowledge Governance Mechanism: The Role of Digital Trust and Information Security

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Abstract: The rapid diffusion of generative artificial intelligence (GAI) is transforming organizational knowledge processes, yet existing research offers limited insight into its governance implications. This study addresses this gap by conceptualizing GAI as a mechanism of knowledge governance and examining its relationship with digital trust, information security maturity, and decision quality. Data from 300 firms across Poland, Germany, and Spain were collected using a CAWI survey of top management teams. Structural equation modeling (SEM) and multilevel analysis were applied to test relationships between AI-mediated knowledge practices, digital trust, information security maturity, and perceived decision quality. The results show that AI use significantly increases digital trust, which in turn improves decision quality. Digital trust acts as a mediator, while information security maturity moderates this relationship. The findings indicate that the impact of generative AI on decision-making depends on governance conditions rather than technology alone.

Keywords: Generative artificial intelligence, Knowledge governance, Digital trust, Information security

1. Introduction

In the contemporary digital economy, the rapid advancement and diffusion of generative artificial intelligence (GAI) is fundamentally transforming how knowledge is created, interpreted, and governed within organizations. Unlike earlier forms of artificial intelligence, generative systems operate not only as analytical tools but as autonomous agents capable of producing novel content, shaping interpretations, and influencing decision-making processes (Bresciani et al. 2021). As a result, organizations increasingly rely on algorithmically generated knowledge, which challenges traditional assumptions about epistemic authority, knowledge ownership, and managerial cognition. These developments signal a shift from human-centered knowledge paradigms toward hybrid epistemic systems in which human and non-human actors co-produce organizational knowledge.

This transformation introduces a critical need to reconceptualize knowledge governance. While prior research has extensively explored knowledge management systems, organizational learning, and AI adoption, existing frameworks remain largely grounded in anthropocentric epistemologies and do not sufficiently address the governance implications of algorithmically mediated knowledge processes. In particular, the integration of generative AI raises fundamental questions regarding trust, reliability, accountability, and security in knowledge-intensive environments (Żywiołek et al. 2025a). Consequently, knowledge governance must be redefined to incorporate both technological infrastructures and socio-organizational mechanisms that regulate the production, validation, and use of AI-generated knowledge.

Two interrelated constructs—digital trust and information security—emerge as central to this new governance landscape. Digital trust reflects the extent to which organizational actors are willing to rely on algorithmically generated knowledge in decision-making processes, while information security ensures the integrity, confidentiality, and controllability of data and knowledge flows. Together, these dimensions form the foundation for the legitimacy and stability of AI-mediated knowledge systems (Almustafa and Kalash 2025). Without sufficient levels of digital trust, managers may resist or underutilize AI outputs, whereas inadequate information security can undermine organizational resilience and expose firms to new forms of epistemic and operational risk (Hussain et al. 2024).

The intersection of generative artificial intelligence, knowledge governance, and information security has begun to attract scholarly attention; however, existing studies tend to focus either on technological capabilities or on isolated organizational outcomes (Żywiołek et al. 2025c). At the team level, it transforms coordination mechanisms, collective validation processes, and knowledge-sharing practices. At the organizational level, it introduces new forms of synthetic memory, algorithmic dependency, and governance complexity (Khan et al. 2026).

Building on these considerations, this study conceptualizes generative artificial intelligence as a new regime of knowledge governance that restructures epistemic processes across multiple organizational levels. By integrating perspectives from knowledge management, information systems, and organizational theory, the research develops a comprehensive framework linking AI-mediated knowledge practices with digital trust, information security maturity, and decision quality (Alavi and Leidner 2001). Empirically, the study draws on a

large-scale, multi-country dataset collected from top management teams in knowledge-intensive firms, enabling the examination of cross-level relationships using advanced analytical techniques (Żywiołek et al. 2025b).

Despite the growing body of research on artificial intelligence in organizational contexts, important gaps remain in understanding its implications for knowledge governance. First, existing studies are rarely anchored in knowledge governance theory and tend to focus on technological capabilities rather than on the structures that regulate knowledge creation, validation, and use. Second, limited attention has been given to digital trust as a mediating mechanism that conditions whether AI-generated knowledge is incorporated into managerial decision-making. Third, there is a lack of multilevel empirical evidence capturing how AI-mediated knowledge processes simultaneously affect individual cognition, team dynamics, and organizational governance structures.

To address these gaps, this study conceptualizes generative artificial intelligence as a mechanism of knowledge governance that reshapes epistemic processes across organizational levels and examines its relationship with digital trust, information security maturity, and decision quality (Tsai et al. 2022).

For analytical clarity, several key constructs are defined. Knowledge governance is understood as the set of formal and informal mechanisms that regulate the creation, validation, distribution, and use of knowledge within organizations. Digital trust refers to the extent to which organizational actors are willing to rely on AI-generated knowledge in decision-making processes. Epistemic authority denotes the perceived legitimacy of a source—human or algorithmic—in shaping knowledge claims and guiding judgment. Synthetic organizational memory describes the accumulation and use of AI-generated knowledge artifacts that are stored, recombined, and reused within organizational systems independently of direct human cognition. This study builds on these definitions to examine how generative artificial intelligence reconfigures knowledge governance and influences decision-making outcomes in contemporary organizations (Modgil et al. 2026).

Existing research on artificial intelligence in organizations has primarily focused on technological capabilities, adoption processes, and performance outcomes, with limited integration into knowledge governance theory. While knowledge management literature provides robust frameworks for understanding knowledge creation and sharing, it remains largely grounded in human-centered assumptions and does not fully account for the role of algorithmic agents in shaping epistemic processes. As a result, the governance implications of AI-mediated knowledge remain underdeveloped.

Moreover, prior studies have addressed trust in AI mainly as a factor of user acceptance or technology adoption, rather than as a mediating mechanism linking AI-generated knowledge with decision-making outcomes. Similarly, existing research tends to examine AI effects at a single level of analysis, overlooking the interconnected dynamics between individual cognition, team processes, and organizational structures.

This study addresses these limitations by integrating perspectives from knowledge management, AI research, and governance theory into a unified framework. It conceptualizes generative AI as a mechanism of knowledge governance, examines digital trust as a mediating construct, and provides multilevel empirical evidence based on cross-country data.

2. Materials and Methods

This study adopted a quantitative research design to investigate the role of generative artificial intelligence (GAI) as a mechanism of knowledge governance and its impact on digital trust, information security, and decision-making processes within organizations. Data were collected using the Computer-Assisted Web Interviewing (CAWI) method, which enabled the efficient acquisition of standardized responses from senior executives operating in knowledge-intensive industries. The primary objective of the empirical analysis was to examine cross-level relationships between AI-mediated knowledge practices, digital trust, information security maturity, and perceived decision quality.

The research was conducted across three European countries—Poland, Germany, and Spain—to ensure a comparative and cross-national perspective. These countries were selected due to their similar levels of digital transformation, regulatory alignment within the European Union, and increasing adoption of artificial intelligence in organizational contexts. The study focused on top management teams (TMTs), as they play a critical role in shaping strategic decisions, knowledge governance structures, and the adoption of emerging technologies such as generative AI.

In the second phase, a large-scale CAWI survey was conducted in 2024. A total of 300 firms participated in the study, with respondents drawn from senior executive positions, including CEOs, CIOs, CTOs, and other members of top management teams. The sampling strategy ensured representation across knowledge-intensive sectors

such as finance, information technology, consulting, and advanced manufacturing. The multi-country design allowed for the analysis of contextual similarities and differences in AI-driven knowledge governance practices.

The study employed a purposive sampling strategy targeting senior executives from knowledge-intensive firms that actively use or experiment with artificial intelligence solutions. A database of firms operating in Poland, Germany, and Spain was used to identify potential respondents, and invitations to participate in the survey were distributed electronically.

A total of 319 questionnaires were distributed, of which 300 valid responses were obtained, resulting in a response rate of approximately 88%. Only fully completed questionnaires from top management representatives were included in the final dataset. This ensured that respondents possessed sufficient knowledge of organizational decision-making processes and AI adoption practices.

The survey instrument consisted of a structured questionnaire divided into four sections. The first section captured demographic and organizational characteristics, including firm size, industry, respondents' managerial roles, and experience with artificial intelligence technologies. The second section focused on AI-mediated knowledge practices, measuring the extent to which generative AI is used in knowledge creation, interpretation, and decision support. The third section assessed digital trust and information security maturity, capturing managerial perceptions of trust in AI-generated outputs, data reliability, and the robustness of security frameworks. The fourth section evaluated perceived decision quality and governance outcomes, including changes in epistemic authority, knowledge ownership, and organizational risk exposure.

The questionnaire was pre-tested with a group of academic experts and industry practitioners to ensure clarity, reliability, and content validity. All constructs were measured using multi-item scales adapted from prior literature in knowledge management and information systems research and adjusted to the context of generative artificial intelligence. Responses were recorded on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree).

AI-mediated knowledge practices were measured using [5] items capturing the extent to which generative AI supports knowledge creation, interpretation, and decision-making processes. A sample item is: "Generative AI tools are regularly used to support managerial decision-making." Digital trust was measured using [5] items reflecting the perceived reliability, credibility, and usability of AI-generated knowledge. A sample item is: "I trust the outputs generated by AI systems when making decisions."

Information security maturity was assessed using [5] items capturing the robustness of organizational security practices. A sample item is: "Our organization has well-established procedures to ensure the security of AI-related data." Decision quality was measured using [5] items reflecting perceived effectiveness and accuracy of decisions supported by AI. A sample item is: "Decisions supported by AI are of higher quality than those based solely on human judgment."

To analyse the data, structural equation modeling (SEM) and multilevel analytical techniques were employed. SEM was used to test the relationships between key constructs and to assess the mediating role of digital trust in the relationship between AI-mediated knowledge practices and decision quality. Multilevel modeling enabled the examination of cross-level effects, capturing how individual-level perceptions aggregate into team-level dynamics and organizational-level governance outcomes. The reliability and validity of the measurement model were assessed using standard procedures. Internal consistency was confirmed through Cronbach's alpha and composite reliability (CR), with all values exceeding the recommended threshold of 0.70. Convergent validity was evaluated using average variance extracted (AVE), with all constructs exceeding the threshold of 0.50.

Discriminant validity was assessed using the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT). In all cases, the square root of AVE exceeded inter-construct correlations, and HTMT values remained below the recommended threshold of 0.85. The structural model demonstrated a satisfactory fit to the data. The fit indices were within acceptable ranges (CFI = 0.94, TLI = 0.93, RMSEA = 0.05, SRMR = 0.04), indicating that the proposed model adequately represents the observed data.

Figure 1 presents the research design and process, illustrating the sequential stages of the study—from conceptual model development, through survey design and data collection, to advanced statistical analysis and interpretation of results. This structured approach ensures a comprehensive examination of how generative artificial intelligence functions as a new regime of knowledge governance and how it reshapes organizational processes through the interplay of digital trust and information security.

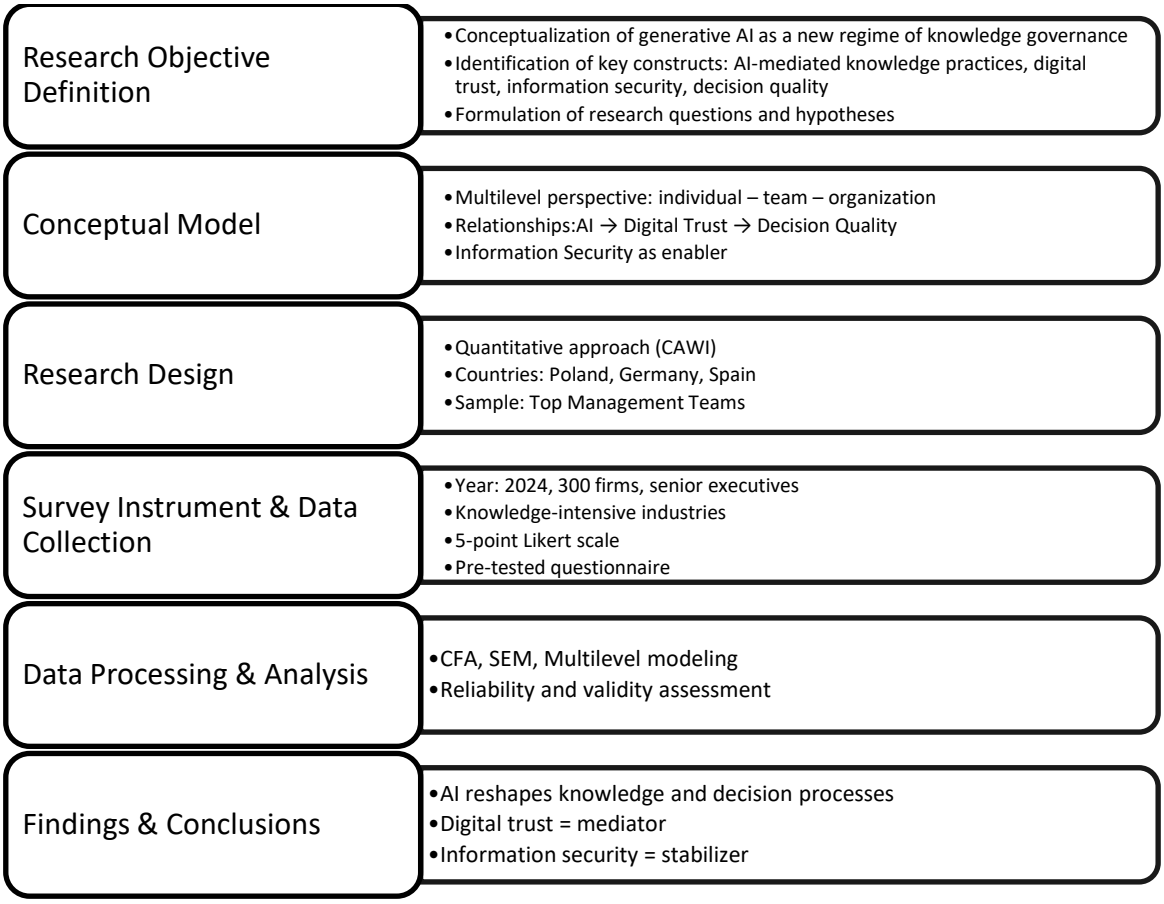


Figure 1: Research procedure

Figure 1 presents a structured overview of the research process, encompassing the stages from conceptualizing generative artificial intelligence as a knowledge governance mechanism, through the development of the multilevel research model and survey design, to data collection and advanced statistical analysis. This systematic approach enables a comprehensive examination of how AI-mediated knowledge practices, digital trust, and information security interact across individual, team, and organizational levels. The following section presents the empirical findings, providing insights into the role of generative AI in reshaping epistemic authority, enhancing or constraining decision quality, and redefining governance mechanisms within contemporary organizations. To assess the potential impact of common method bias, Harman's single-factor test was conducted. The results indicated that a single factor did not account for the majority of the variance, suggesting that common method bias is unlikely to be a serious concern. Additionally, procedural remedies such as ensuring respondent anonymity and careful questionnaire design were applied to minimize potential bias.

3. Results

The results of the study provide empirical evidence on how generative artificial intelligence operates as a new regime of knowledge governance, reshaping epistemic processes across individual, team, and organizational levels. The analysis focuses on the relationships between AI-mediated knowledge practices, digital trust, information security maturity, and perceived decision quality. Particular attention is given to the reconfiguration of epistemic authority, managerial sensemaking, and knowledge ownership in environments where algorithmically generated knowledge increasingly complements and, in some cases, substitutes human cognition.

The empirical analysis provides strong support for the proposed model of generative artificial intelligence as a mechanism of knowledge governance. The results of the structural equation modeling (SEM) indicate that AI-mediated knowledge practices have a significant positive effect on digital trust ($\beta = 0.62$, $p < 0.001$), confirming that the increased use of generative AI in knowledge processes is associated with higher levels of managerial reliance on algorithmically generated outputs. The structural model explains a substantial proportion of variance in the key endogenous constructs. The R^2 value for digital trust is 0.38, while the model explains 0.47 of the

variance in decision quality, indicating moderate to strong explanatory power. Effect sizes (f^2) indicate that AI-mediated knowledge practices have a large effect on digital trust ($f^2 = 0.62$), while digital trust has a substantial effect on decision quality ($f^2 = 0.41$). The moderating effect of information security maturity is moderate ($f^2 = 0.18$). Confidence intervals (95%) obtained using bootstrapping confirm the stability of the estimates, with all key relationships remaining statistically significant within the interval bounds.

Digital trust, in turn, demonstrates a strong positive relationship with perceived decision quality ($\beta = 0.54$, $p < 0.001$), supporting its role as a key mediating construct. The indirect effect of AI-mediated knowledge practices on decision quality through digital trust is statistically significant ($\beta = 0.33$, $p < 0.001$), indicating that trust conditions the effectiveness of AI in organizational decision-making.

Information security maturity shows a significant moderating effect on the relationship between digital trust and decision quality ($\beta = 0.27$, $p < 0.01$). Organizations with higher levels of security maturity exhibit more stable and reliable outcomes of AI-driven decision processes, suggesting that security frameworks enhance the legitimacy and controllability of AI-mediated knowledge systems.

To examine cross-level effects, a hierarchical linear modeling (HLM) approach was applied. The data structure consisted of three levels: individual-level perceptions (Level 1), team-level aggregation within top management teams (Level 2), and organizational-level characteristics (Level 3). The results indicate that AI-mediated knowledge practices significantly influence epistemic authority at the individual level ($\beta = 0.48$, $p < 0.001$), while at the team level they affect knowledge validation processes ($\beta = 0.41$, $p < 0.01$). At the organizational level, AI adoption is associated with increased governance complexity ($\beta = 0.36$, $p < 0.05$).

Descriptive statistics further support these findings. A majority of respondents (68%) indicate moderate to high reliance on AI-generated knowledge in decision-making processes, while 57% report concerns regarding the transparency and interpretability of AI outputs. Additionally, 61% of firms assess their information security maturity as medium, suggesting that many organizations are still in the process of adapting their security frameworks to AI-driven environments.

Overall, the results confirm that generative artificial intelligence significantly reconfigures knowledge governance by reshaping trust dynamics, decision processes, and epistemic structures across multiple organizational levels.

Table 1: Descriptive statistics and reliability

Construct	Mean	SD	Cronbach's α
AI-mediated knowledge practices	3.87	0.74	0.89
Digital trust	3.65	0.81	0.91
Information security maturity	3.54	0.77	0.88
Decision quality	3.92	0.69	0.90
Epistemic authority (individual level)	3.71	0.73	0.86
Team knowledge validation	3.68	0.76	0.87
Organizational governance complexity	3.59	0.71	0.85

The descriptive statistics presented in Table 1 indicate that all examined constructs exhibit moderate to high mean values, suggesting a relatively advanced adoption of AI-mediated knowledge practices and associated governance mechanisms within the analyzed organizations. The reliability coefficients (Cronbach's α) exceed the recommended threshold of 0.70, confirming the internal consistency of the measurement scales and supporting the validity of further analysis.

These results provide a solid empirical foundation for examining the relationships between constructs. To further explore the strength and direction of associations between variables, a correlation analysis was conducted.

Table 2: Correlation matrix

Variable	1	2	3	4
1. AI practices	1.00			
2. Digital trust	0.62***	1.00		
3. Info security maturity	0.48***	0.55***	1.00	
4. Decision quality	0.51***	0.54***	0.49***	1.00

The correlation matrix presented in Table 2 reveals statistically significant and positive relationships between all key variables. In particular, AI-mediated knowledge practices show a strong correlation with digital trust ($r = 0.62$, $p < 0.001$), indicating that increased reliance on generative AI is associated with higher levels of trust in algorithmically generated knowledge. Similarly, digital trust demonstrates a strong correlation with decision quality ($r = 0.54$, $p < 0.001$), highlighting its central role in shaping effective decision-making processes.

While correlation analysis confirms the existence of significant relationships, it does not provide insights into causality or the structural dependencies between variables. Therefore, structural equation modeling (SEM) was applied to test the proposed research model and examine both direct and indirect effects.

Table 3: Structural model results (SEM)

Path	β	t-value	p-value
AI practices → Digital trust	0.62	9.87	<0.001
Digital trust → Decision quality	0.54	8.94	<0.001
AI practices → Decision quality (direct)	0.21	3.12	<0.01
Info security → Decision quality	0.33	5.21	<0.001
Interaction (Trust × Security) → Decision quality	0.27	2.98	<0.01

Indirect effect = 0.33 ($p < 0.001$)

The results of the structural equation modeling presented in Table 3 provide strong support for the hypothesized relationships. AI-mediated knowledge practices have a significant positive effect on digital trust ($\beta = 0.62$, $p < 0.001$), confirming that the use of generative AI strengthens managerial confidence in algorithmically generated knowledge. Digital trust, in turn, significantly influences decision quality ($\beta = 0.54$, $p < 0.001$), validating its role as a key mediating construct.

The direct effect of AI practices on decision quality remains significant but weaker ($\beta = 0.21$, $p < 0.01$), indicating partial mediation. Furthermore, information security maturity exerts both a direct effect and a moderating influence on decision quality, reinforcing its role as a stabilizing factor within the emerging knowledge governance regime.

To provide a clearer visualization of these relationships and the overall structure of the model, Figure 3 presents the structural equation model with standardized path coefficients.

Figure 3 presents the structural equation model and confirms the validity of the proposed relationships between AI-mediated knowledge practices, digital trust, information security maturity, and decision quality. The model provides empirical support for the argument that generative artificial intelligence should be understood not merely as a technological instrument, but as an emerging mechanism of knowledge governance that reconfigures epistemic processes within organizations.

The strongest path identified in the model is the relationship between AI-mediated knowledge practices and digital trust ($\beta = 0.62$, $p < 0.001$). The second key relationship, between digital trust and decision quality ($\beta = 0.54$, $p < 0.001$), further reinforces the central role of trust in AI-mediated governance systems. This coefficient shows that trust significantly determines whether AI-generated outputs are incorporated into managerial reasoning in ways that improve strategic and operational decision-making. The result suggests that organizations do not benefit from generative AI simply because the technology is available; rather, the positive effects of AI on decision processes depend on whether managers regard its outputs as credible, intelligible, and sufficiently

reliable to enter the domain of organizational judgment. This is highly relevant for contemporary organizations, where decisions are increasingly informed by synthetic, predictive, and generative forms of knowledge that cannot always be fully verified in real time.

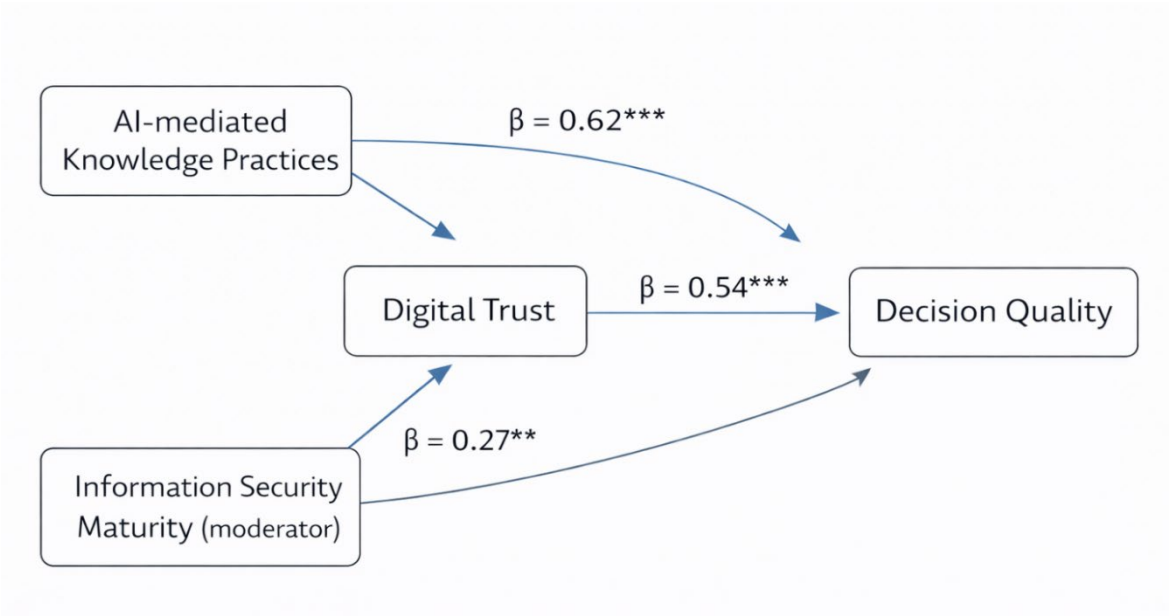


Figure 3: Structural Equation Model

The model also reveals a direct effect of AI-mediated knowledge practices on decision quality ($\beta = 0.21$, $p < 0.01$), although this relationship is weaker than the indirect path through digital trust. This finding indicates partial mediation and confirms that generative AI influences decision quality in two ways. First, it directly supports managerial processes by accelerating access to information, broadening the cognitive scope of decision-makers, and enabling faster synthesis of complex inputs. Second, and more importantly, it affects decisions indirectly by shaping the degree of trust managers place in algorithmically generated knowledge. The relative weakness of the direct effect compared with the indirect one highlights an essential theoretical point: the organizational consequences of generative AI are not determined solely by functional efficiency, but by interpretive and governance conditions that mediate how AI outputs are accepted, contested, or ignored.

A further important result concerns the role of information security maturity, which exerts a significant moderating effect on the relationship between digital trust and decision quality ($\beta = 0.27$, $p < 0.01$). This finding demonstrates that information security is not merely a technical background condition, but an active stabilizer of the emerging regime of AI-based knowledge governance. In organizations with higher information security maturity, trust in AI-generated knowledge is more likely to translate into effective decisions because the broader governance environment provides mechanisms of control, traceability, and risk limitation. By contrast, in low-maturity environments, even relatively high trust may not result in robust decision outcomes because algorithmically generated knowledge remains vulnerable to manipulation, leakage, distortion, or misinterpretation. Thus, information security maturity enhances the legitimacy and operational reliability of AI-mediated cognition by embedding it within structures of accountability and control.

Taken together, the structural model supports the broader argument of the article that generative artificial intelligence reconfigures knowledge governance across organizational levels. At the individual level, the model implies a transformation of managerial cognition, as executives increasingly rely on non-human systems to frame problems, generate alternatives, and support judgment. At the team level, the significance of digital trust suggests that collective acceptance of AI outputs becomes a condition for shared sensemaking and coordinated action. At the organizational level, the moderating role of information security maturity confirms that the governance effects of generative AI are contingent upon formal infrastructures capable of regulating epistemic risk. In this sense, the model not only explains decision quality but also reveals the institutional conditions under which generative AI can become a legitimate and resilient component of organizational knowledge systems.

The findings also carry important theoretical implications. First, they support the view that generative AI should be conceptualized as an epistemic actor rather than as a neutral support tool. The significant paths in the model indicate that AI participates in the production of organizationally relevant knowledge and shapes the conditions

under which that knowledge is trusted and operationalized. Second, the model expands existing knowledge governance theory by demonstrating that trust and security are not peripheral concerns but constitutive dimensions of algorithmically mediated knowledge systems. Third, the partial mediation observed in the model suggests that the governance of generative AI requires attention not only to performance outcomes, but also to the socio-cognitive mechanisms through which AI outputs gain epistemic legitimacy.

From a managerial perspective, the results underscore that successful implementation of generative AI requires more than technological deployment. Organizations need to cultivate digital trust through transparency, explainability, and consistent interaction with AI systems, while simultaneously strengthening information security maturity to ensure integrity, controllability, and resilience. Without these complementary governance mechanisms, AI adoption may intensify epistemic uncertainty rather than reduce it. Managers may either over-rely on synthetic outputs without adequate control or reject potentially valuable AI-generated knowledge due to mistrust and perceived risk. Both scenarios weaken the capacity of organizations to leverage generative AI as a productive governance mechanism.

In summary, Figure 3 provides strong empirical evidence for the proposed model and demonstrates that the relationship between generative AI and decision quality is neither simple nor purely technological. It is shaped by the interplay between AI-mediated knowledge practices, digital trust, and information security maturity. This configuration confirms that generative artificial intelligence constitutes a new regime of knowledge governance—one that transforms how knowledge is produced, validated, and used in organizations, while simultaneously generating new demands for trust, security, and institutional control.

4. Discussion and Conclusions

The findings support the view that generative artificial intelligence should be understood not only as a technological tool, but as an epistemic actor within knowledge governance systems. This extends knowledge management theory by showing that organizational knowledge is increasingly shaped through interaction between human decision-makers and algorithmic systems (Salah and Ayyash 2024). A key theoretical contribution of this study is the identification of digital trust as a mediating mechanism between AI-mediated knowledge practices and decision quality. Trust is therefore not only a matter of user acceptance, but a condition that determines whether AI-generated knowledge becomes part of organizational reasoning. The study also shows that information security maturity plays a governance role. It supports the reliability, traceability, and controllability of AI-mediated knowledge, and should therefore be treated as part of knowledge governance rather than as a purely technical function (Mantulenko et al. 2024). From a practical perspective, organizations implementing generative AI should focus on three areas. First, they should strengthen explainability so that managers can understand and evaluate AI-generated outputs. Second, they should develop information security maturity through clear procedures for data protection, access control, and system monitoring. Third, they should manage dependency on AI by maintaining human oversight and establishing procedures for validating AI recommendations.

The study has several limitations. Its cross-sectional design does not capture how trust and governance mechanisms evolve over time. In addition, the focus on firms from Poland, Germany, and Spain may limit the generalizability of the findings to other institutional contexts. Future research should use longitudinal designs, include broader geographical samples, and further examine how human and algorithmic cognition interact in organizational decision-making (Tarasova 2024; Steiber and Alvarez 2024).

In conclusion, the study shows that the effectiveness of generative AI depends not only on technological adoption, but also on governance conditions. Digital trust and information security maturity are central mechanisms through which AI-generated knowledge becomes usable, credible, and controllable in organizational decision-making.

Ethics Declaration: Ethics approval was not required.

AI Declaration: AI tools were not used to create this article.

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Immersive Knowledge Transfer Through VR Glasses: Designing and Using Instructional Video-based Microlearning for Customer Self-repair and Technical Support

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Abstract: The growing complexity of technical products and increasing customer expectations for fast and autonomous problem resolution are driving the need for new approaches to knowledge transfer beyond traditional service channels. Virtual reality (VR), combined with immersive video-based microlearning, offers new possibilities for delivering procedural knowledge directly to end users. This study investigates the effectiveness of immersive, video-based microlearning delivered through VR glasses in supporting customer self-repair and technical support. The study adopts a quantitative research design based on a large-scale CAWI survey conducted among 11,318 users of technical products across three European countries. The analysis focuses on key constructs, including usability, learning effectiveness, task complexity reduction, customer confidence, and reduction in service interactions. The results indicate that immersive instructional content significantly enhances procedural understanding, reduces perceived task complexity, and increases customer confidence in performing basic maintenance and repair tasks. The findings also suggest a partial reduction in reliance on traditional service channels. This study contributes to the literature by extending immersive learning research to customer self-service contexts and by empirically validating relationships between usability, learning effectiveness, and customer confidence in VR-supported environments. The results offer practical implications for organizations seeking to redesign technical support models through immersive learning technologies.

Keywords: Virtual reality, Immersive learning, Customer knowledge transfer, Self-service innovation

1. Introduction

The increasing technological complexity of contemporary industrial products, combined with rising customer expectations for rapid and autonomous problem resolution, is transforming traditional approaches to technical support and knowledge transfer. Customers are no longer passive recipients of service but are becoming active participants in maintenance and repair processes. This shift creates a growing demand for accessible, effective, and user-centered forms of instructional support that go beyond conventional manuals and standard video tutorials (Żywiołek 2025a; Pandey et al. 2023).

In response to these challenges, immersive technologies—particularly virtual reality (VR)—are emerging as promising tools for enhancing the transfer of procedural and tacit knowledge. VR glasses, when combined with instructional video-based microlearning, enable users to engage with content in a highly contextualized and interactive manner. Unlike traditional learning formats, immersive environments can simulate real-world tasks, guide users step by step, and provide a sense of presence that facilitates deeper understanding and retention of knowledge (Żywiołek 2025b). This is especially relevant in the context of customer self-repair, where clarity of instruction and user confidence are critical factors determining successful task completion.

Despite growing interest in extended reality, research on its use in customer self-service and technical support remains limited. Most studies focus on training contexts, with little attention to empowering end users. There is also a lack of empirical evidence on how immersive microlearning affects user experience, task complexity, and knowledge transfer in real settings. This study addresses this gap by investigating the use of VR glasses as a medium for delivering instructional microlearning aimed at supporting customer self-repair in a manufacturing environment. The study adopts a quantitative research approach based on survey data collected from users of technical products (Sterbak et al. 2022; Zhong 2020). The study evaluates key dimensions such as usability, learning effectiveness, user engagement, and the impact of immersive guidance on reducing reliance on traditional service channels.

The main contributions of this research are threefold. First, it provides empirical insights into the effectiveness of immersive video-based learning in enhancing procedural knowledge and customer autonomy. Second, it identifies the practical benefits and limitations associated with implementing VR-supported self-repair systems in an industrial context. Third, it offers managerial implications for manufacturing firms seeking to redesign their technical support models by integrating immersive learning technologies, with the aim of improving customer experience while reducing service costs.

The remainder of the paper is structured as follows: the next section reviews the literature on immersive learning, virtual reality, and customer knowledge transfer. The subsequent section presents the research methodology (Koohang et al. 2023). This is followed by the presentation and analysis of empirical findings. The discussion section interprets the results in relation to existing research, and the final section concludes with practical implications and directions for future research.

2. Review of Literature

This section presents the theoretical background of immersive knowledge transfer, focusing on the use of virtual reality (VR) and video-based microlearning in the context of customer self-repair and technical support. It discusses the evolution of immersive learning technologies, the role of microlearning in procedural knowledge acquisition, and the growing importance of customer knowledge empowerment in industrial environments.

2.1 Immersive Technologies and Virtual Reality in Knowledge Transfer

Immersive technologies, particularly virtual reality, have gained increasing attention as tools for enhancing learning and knowledge transfer processes. VR enables users to interact with simulated environments in a way that closely resembles real-world experiences, thereby supporting experiential learning and improving cognitive engagement (Shang et al. 2024). Unlike traditional instructional formats, immersive environments allow users to perform tasks in a controlled yet realistic setting, which is particularly valuable for acquiring procedural and tacit knowledge.

Research indicates that immersion plays a critical role in learning effectiveness, as it increases user attention, reduces cognitive overload, and enhances memory retention. VR-based training has been widely applied in fields such as healthcare, aviation, and industrial operations (Żywiołek et al. 2025), where accurate task execution is essential. However, most existing applications focus on employee training, with relatively limited attention given to end users such as customers performing independent maintenance or repair tasks.

2.2 Video-based Microlearning and Procedural Knowledge Acquisition

Microlearning refers to short, focused learning units designed to deliver specific knowledge or skills in a concise and accessible format. In recent years, video-based microlearning has become particularly popular due to its ability to present complex procedures in a clear and visually guided manner. This approach aligns well with the concept of "just-in-time" learning, where users access information exactly when it is needed (Yordanova 2025).

In the context of technical tasks, video-based instruction has been shown to improve comprehension and task performance compared to text-based manuals. By breaking down procedures into manageable steps and combining visual and auditory cues, microlearning supports faster knowledge acquisition and reduces the likelihood of errors. When integrated with immersive technologies such as VR, video-based microlearning can further enhance learning outcomes by embedding instructional content within a realistic task environment (Khan et al. 2023).

2.3 Customer Self-Service, Self-Repair and Knowledge Empowerment

The increasing availability of digital technologies has contributed to the growing importance of customer self-service models. Customers are increasingly expected to perform basic maintenance and troubleshooting tasks independently, particularly in industries characterized by complex technical products. This shift reflects a broader trend toward customer empowerment, where users are equipped with the knowledge and tools necessary to manage products without direct assistance from service personnel (Żywiołek 2024).

Effective knowledge transfer is a key enabler of successful self-repair. Traditional support channels, such as printed manuals, call centers, or standard video tutorials, often fail to provide sufficient clarity or contextual guidance, leading to user frustration and increased reliance on service desks. In contrast, interactive and immersive forms of instruction have the potential to bridge this gap by delivering more intuitive and user-centered learning experiences (Gupta et al. 2019).

2.4 Research Gaps and Emerging Trends in Immersive Customer Support

Despite the growing interest in immersive learning technologies, several research gaps remain. First, existing studies have predominantly focused on VR applications in formal training settings, with limited empirical evidence on their effectiveness in customer-facing contexts. Second, there is a lack of research examining how immersive instructional content influences key outcomes such as user confidence, perceived task complexity, and independence in problem-solving.

Furthermore, the integration of VR with microlearning approaches in real industrial environments has not been sufficiently explored. Most studies rely on experimental or laboratory settings, which do not fully capture the complexity of real-world usage scenarios. There is also a need to better understand the organizational implications of implementing immersive support systems, including their impact on service efficiency and cost reduction.

In response to these gaps, this study investigates the application of VR-based instructional microlearning in a real manufacturing context, focusing on its role in supporting customer self-repair and transforming traditional technical support models.

The proposed research model is grounded in established theoretical perspectives on technology adoption and experiential learning. In particular, the relationships between usability, learning effectiveness, and customer confidence can be explained by the Technology Acceptance Model (TAM) and self-efficacy theory. Usability reflects perceived ease of use, which influences both learning outcomes and user confidence. At the same time, immersive learning environments support experiential learning processes, enhancing procedural understanding and reducing perceived task complexity. These theoretical foundations provide a basis for the formulation of the research hypotheses.

3. Research Model and Hypotheses

Based on the literature on immersive learning, usability, and customer self-service, a research model was developed to examine the relationships between key constructs influencing customer self-repair supported by VR-based microlearning.

The model assumes that the usability of VR solutions positively affects learning effectiveness, which in turn reduces perceived task complexity and increases customer confidence. Higher confidence is expected to reduce reliance on traditional service interactions.

The following hypotheses are proposed:

H1: Usability positively influences learning effectiveness.

H2: Learning effectiveness positively influences task complexity reduction.

H3: Task complexity reduction positively influences customer confidence.

H4: Learning effectiveness positively influences customer confidence.

H5: Usability positively influences customer confidence.

H6: Customer confidence positively influences reduction in service interactions.

Figure 1 presents the proposed research model.

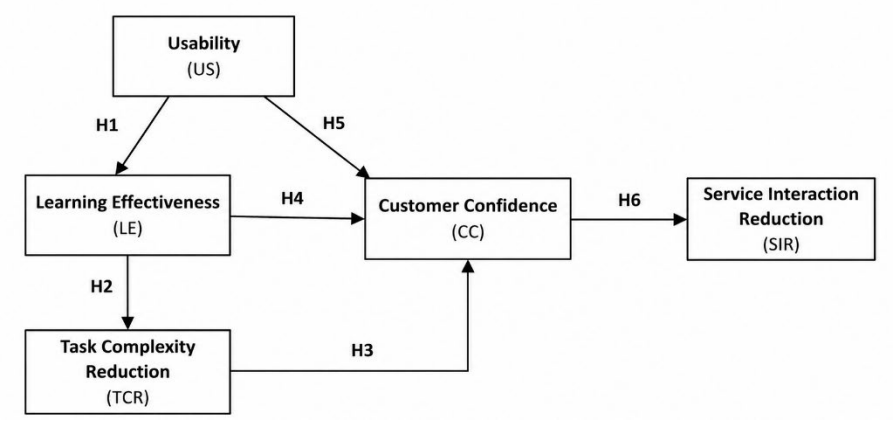


Figure 1: Research model

The proposed model reflects the interdependencies between usability, learning effectiveness, and customer confidence in VR-supported environments. It enables a structured examination of how immersive microlearning influences user autonomy and reduces reliance on traditional technical support.

4. Materials and Methods

This study adopts a quantitative research design to examine the role of immersive, video-based microlearning delivered through VR glasses in supporting customer self-repair and technical support. Data were collected using the CAWI method among respondents from Poland, Norway, and Portugal.

The study is based on quantitative data, enabling statistical analysis of relationships between key constructs using SEM-PLS. A total of 11,318 participants took part in the survey. The research instrument was a structured questionnaire with 26 items measured on a 7-point Likert scale, covering usability, learning effectiveness, task complexity reduction, customer confidence, and service interaction reduction.

Data were analyzed using PLS-SEM in SmartPLS, selected for its suitability in examining relationships between latent variables. The research process included four stages: literature review, questionnaire development, data collection, and statistical analysis. Figure 2 presents the stages of the research process.

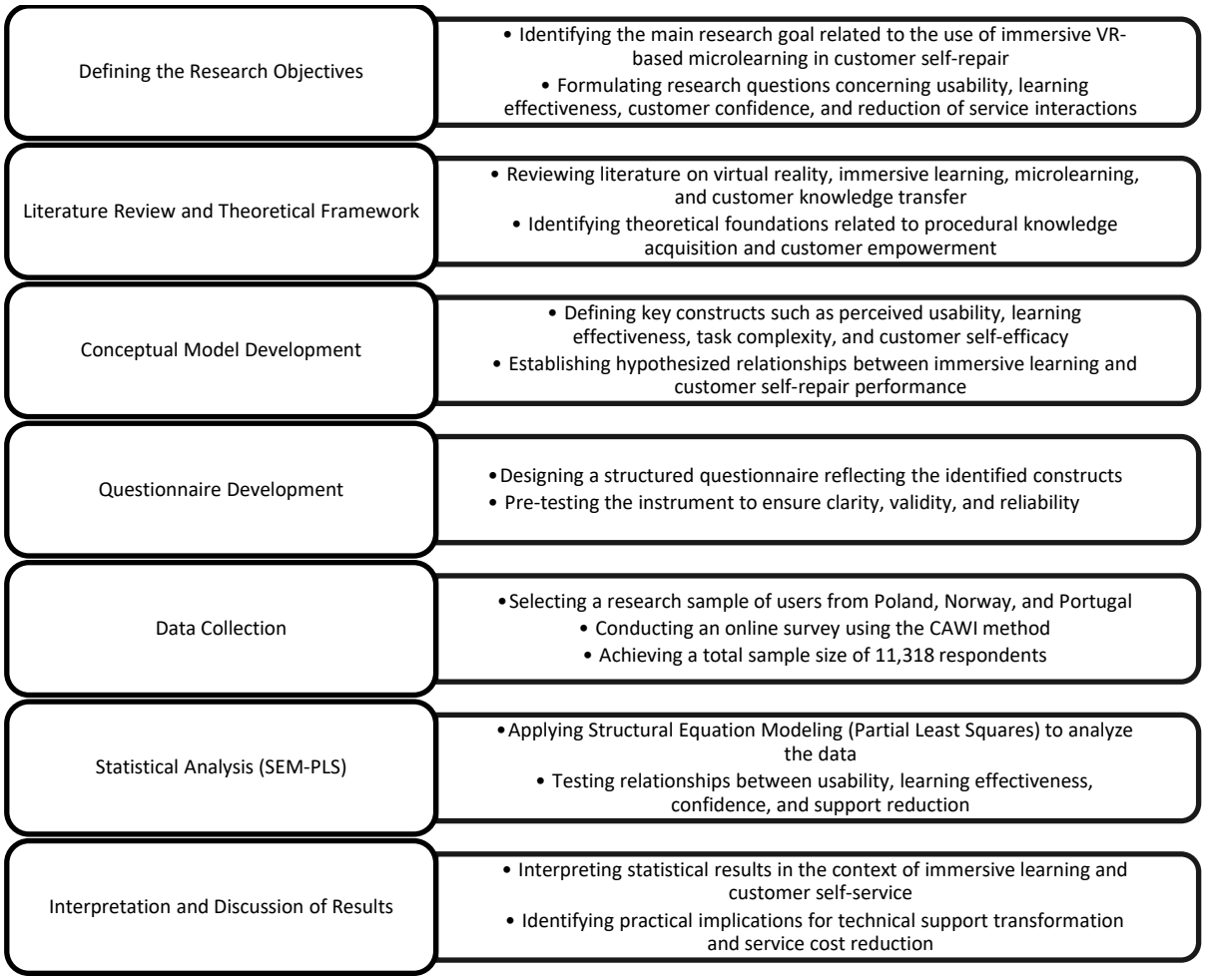


Figure 2: Research Steps

Figure 2 presents the stages of the research process, from problem identification to results interpretation. The empirical study was conducted on a large and diverse sample from Poland, Norway, and Portugal, with Table 1 summarizing the key characteristics of the respondents.

Table 1: Description of the research group

Category	Subcategory	Distribution (%)
Gender	Male	68%
	Female	32%
Age	18–29 years	21%
	30–39 years	26%

Category	Subcategory	Distribution (%)
	40–49 years	23%
	50+ years	30%
Education	Secondary education	46%
	Higher education	54%
Professional position	Technical specialists	34%
	Managers	27%
	Operational staff	23%
	Business owners / self-employed	16%
Experience with immersive / digital technologies		

The analysis confirms high demographic and professional diversity, providing a reliable basis for examining perceptions of immersive learning technologies. The sample consisted of 68% men and 32% women, with most respondents aged 30–49, representing active users of technical products. A notable share of participants was also aged 50+, capturing varying levels of technological familiarity. The sample was balanced in terms of education (54% higher, 46% secondary). Technical specialists formed the largest group (34%), followed by managers (27%), operational staff (23%), and business owners (16%), reflecting strong representation of users engaged in technical processes. Experience with digital technologies varied: 44% reported general familiarity with digital tools, 39% had knowledge of immersive technologies, and 17% had practical experience with VR. This allows for assessing both expectations and actual usability perceptions.

The questionnaire covered familiarity with VR, usability, clarity of instruction, learning effectiveness, task complexity, and customer confidence. It also examined the impact on service interactions and attitudes toward adoption, enabling the identification of key drivers and barriers to using VR-based support tools.

From a methodological perspective, the analysis was conducted with a high level of statistical rigor, applying a significance level of 0.01 and a maximum estimation error of d = 1%. The study was intentionally carried out in three European countries—Poland, Norway, and Portugal—representing different levels of digital maturity and technological adoption, which strengthens the comparative dimension of the research.

The statistical analysis was performed using Microsoft Excel, Statistica, and SmartPLS software. In particular, SmartPLS was used to conduct Structural Equation Modeling (SEM-PLS), allowing for the examination of complex relationships between latent variables such as perceived usability, learning effectiveness, customer confidence, and reduction in reliance on traditional support channels. This approach enabled robust validation of the research model and provided detailed insights into the role of immersive microlearning in supporting customer self-repair.

A quantitative approach was considered appropriate due to the study's objective of examining relationships between latent variables and testing a structured research model. The use of SEM-PLS enables the analysis of complex interdependencies between constructs such as usability, learning effectiveness, and customer confidence

5. Empirical Results

This section presents the empirical findings on the effectiveness of immersive, video-based microlearning delivered through VR glasses in customer self-repair and technical support. The analysis focuses on key constructs, including usability, learning effectiveness, task complexity reduction, customer confidence, and reduction in service interactions. Relationships between these variables are examined using SEM-PLS, with attention to differences across respondent groups. Table 2 presents mean values and Cronbach's alpha coefficients, confirming the reliability of the measurement scales. The results indicate that Learning Effectiveness achieved the highest evaluation ($M = 5.34$; $\alpha = 0.92$), suggesting that respondents perceive immersive video-based instruction as highly effective in supporting the understanding of procedural tasks. Participants emphasized that step-by-step guidance presented in a VR environment significantly improved their ability to follow and replicate maintenance and repair activities.

Similarly, Customer Confidence scored highly ($M = 5.08$; $\alpha = 0.89$), indicating that immersive learning not only enhances knowledge acquisition but also strengthens users' belief in their ability to independently perform

technical tasks. This finding is particularly relevant in the context of self-repair, where confidence directly influences user engagement and task completion.

The construct Reduction of Task Complexity also received a strong evaluation (M = 4.96; α = 0.87), demonstrating that VR-based instructional content helps simplify the perception of complex procedures. By visualizing actions in a realistic environment, users reported a clearer understanding of task sequences and reduced cognitive effort.

Perceived Usability of VR solutions was rated positively (M = 4.72; α = 0.90), indicating that respondents generally found immersive systems intuitive and accessible. However, the slightly lower score compared to learning-related constructs suggests that usability challenges—such as device comfort or initial adaptation—may still exist for some users.

The lowest mean value was observed for Reduction in Service Interactions (M = 4.18; α = 0.85). While still positively evaluated, this result indicates that although immersive learning supports user independence, it does not entirely eliminate the need for traditional technical support. This may reflect the limitations of VR solutions in addressing more complex or unexpected technical issues.

Overall, the findings confirm that immersive, video-based microlearning delivered through VR glasses significantly enhances procedural understanding, reduces perceived task difficulty, and increases customer confidence. At the same time, the results suggest that further development of usability aspects and integration with existing support systems is necessary to fully realize the potential of immersive technologies in transforming technical service models.

Table 2: Mean values and Cronbach's α coefficient

Variable	Mean	Cronbach's Alpha
Learning Effectiveness	5.34	0.92
Customer Confidence	5.08	0.89
Reduction of Task Complexity	4.96	0.87
Perceived Usability of VR Solutions	4.72	0.90
Reduction in Service Interactions	4.18	0.85

Table 3 presents the analyzed factors, including mean values and reliability coefficients (Cronbach's alpha), related to immersive, video-based microlearning in customer self-repair. The variables cover key dimensions such as usability, learning effectiveness, task complexity reduction, customer confidence, and reduction in service interactions. The analysis also includes user engagement, clarity of guidance, and overall satisfaction, enabling the examination of relationships between usability, learning outcomes, and behavioral intentions toward VR-based support tools. To ensure the methodological rigor of the study, Cronbach's alpha coefficients were calculated for all constructs, confirming a high level of internal consistency and reliability of the measurement scales. This approach strengthens the validity of the results and supports further analysis of dependencies between variables within the proposed research model.

Table 3: Relationships between factors

	Usability	Learning Effectiveness	Task Complexity Reduction	Customer Confidence	Service Interaction Reduction
Usability	1	0.64	0.58	0.61	0.47
Learning Effectiveness	0.64	1	0.66	0.72	0.53
Task Complexity Reduction	0.58	0.66	1	0.68	0.55
Customer Confidence	0.61	0.72	0.68	1	0.59
Service Interaction Reduction	0.47	0.53	0.55	0.59	1

The analysis of the survey results provides empirical insight into the effectiveness of immersive, video-based microlearning delivered through VR glasses in supporting customer self-repair and technical assistance processes. The study examined five key variables: perceived usability of VR solutions, learning effectiveness, reduction of task complexity, customer confidence, and reduction in service interactions. All variables were measured using a 7-point Likert scale, and internal consistency was verified using Cronbach's Alpha coefficients.

Among the analyzed dimensions, the highest average score was recorded for Learning Effectiveness (M = 5.34; α = 0.92), indicating that respondents perceive immersive instructional content as highly effective in facilitating the understanding of procedural tasks. The combination of visual guidance and contextual immersion significantly enhances users' ability to follow and replicate repair activities. Similarly, Customer Confidence achieved a high score (M = 5.08; α = 0.89), confirming that improved understanding directly translates into greater self-efficacy in performing technical tasks independently.

The variable Reduction of Task Complexity also received a strong evaluation (M = 4.96; α = 0.87), suggesting that immersive environments help simplify the perception of complex procedures by presenting them in a clear and structured manner. Perceived Usability of VR systems was rated positively (M = 4.72; α = 0.90), indicating that users generally find such solutions intuitive, although some barriers related to initial adaptation and device handling may still exist. The lowest average score was observed for Reduction in Service Interactions (M = 4.18; α = 0.85). While still above the neutral midpoint, this result suggests that immersive learning supports user independence but does not fully replace traditional technical support, particularly in more complex or unforeseen situations.

Correlation analysis revealed strong and statistically significant relationships among the examined variables. In particular, Learning Effectiveness was strongly correlated with Customer Confidence (r = 0.72) and Reduction of Task Complexity (r = 0.66), indicating that effective knowledge transfer directly enhances both user competence and perceived ease of task execution. Furthermore, Usability demonstrated meaningful relationships with both Learning Effectiveness (r = 0.64) and Customer Confidence (r = 0.61), confirming that the intuitive design of immersive systems plays a critical role in achieving positive learning outcomes. Moderate correlations were also observed between Customer Confidence and Reduction in Service Interactions (r = 0.59), suggesting that increased user autonomy contributes to a decreased reliance on external support. Overall, the results highlight that the effectiveness of immersive knowledge transfer depends not only on the quality of instructional content but also on system usability and user experience. The findings support the assumption that VR-based microlearning can significantly improve procedural understanding, enhance user confidence, and partially transform traditional technical support models.

The relationships between the analyzed constructs were further examined using Structural Equation Modeling (SEM-PLS). The following figure presents the estimated research model along with the path coefficients, illustrating the strength and direction of relationships between usability, learning effectiveness, customer confidence, and service interaction reduction (table 4).

Table 4: Results of the SEM-PLS analysis

Hypothesis / Relationship	Path coefficient (β)	t-value	p-value	Result
H1: Usability → Learning Effectiveness	0.64	18.72	< 0.001	Supported
H2: Learning Effectiveness → Task Complexity Reduction	0.66	19.85	< 0.001	Supported
H3: Task Complexity Reduction → Customer Confidence	0.68	20.43	< 0.001	Supported
H4: Learning Effectiveness → Customer Confidence	0.72	22.11	< 0.001	Supported
H5: Usability → Customer Confidence	0.61	17.36	< 0.001	Supported
H6: Customer Confidence → Service Interaction Reduction	0.59	16.94	< 0.001	Supported

To examine relationships between constructs, SEM analysis using PLS-SEM was conducted. The model tested the effects of usability and learning effectiveness on customer confidence, as well as the impact of confidence on reducing service interactions. The results show that learning effectiveness has the strongest positive effect on customer confidence (β = 0.72), indicating that immersive instruction significantly improves users' ability to perform repair tasks independently. Usability of VR Solutions also demonstrates a significant positive effect on both Learning Effectiveness (β = 0.64) and Customer Confidence (β = 0.61). This suggests that intuitive system design, ease of navigation, and overall user comfort are critical factors that support both the learning process

and the willingness of customers to engage with self-repair tasks. In other words, even highly effective content may not achieve its full potential if the technological interface is perceived as difficult or unintuitive.

Furthermore, Learning Effectiveness strongly contributes to the Reduction of Task Complexity (β = 0.66), which in turn has a significant positive effect on Customer Confidence (β = 0.68). This indirect pathway indicates that immersive learning simplifies the perception of technical tasks, making them more accessible and manageable for users without specialized expertise.

The model also confirms that Customer Confidence has a meaningful impact on the Reduction in Service Interactions (β = 0.59), suggesting that users who feel more capable are less likely to rely on traditional technical support channels. However, the strength of this relationship indicates a partial rather than complete substitution effect, meaning that immersive solutions complement rather than fully replace conventional service models.

The coefficient of determination (R^2) values further support the explanatory power of the model. Learning Effectiveness reaches an R^2 of 0.41, Task Complexity Reduction 0.44, Customer Confidence 0.55, and Service Interaction Reduction 0.35, indicating moderate to strong levels of explained variance across the constructs.

The findings from the structural model demonstrate that the effectiveness of immersive VR-based microlearning is not solely dependent on the technology itself, but rather on the interaction between usability, instructional quality, and user perception. While technological accessibility is important, the primary driver of successful self-repair remains the ability of users to understand and confidently apply procedural knowledge. The results emphasize that user-centered design and knowledge-oriented implementation are crucial, beyond technology alone. Organizations should focus on clarity, usability, and alignment with user capabilities.Overall, the model confirms that immersive microlearning enhances customer autonomy, improves learning outcomes, and supports the shift toward more efficient, self-service-oriented support models.

6. Discussion and Conclusion

From a theoretical perspective, the study extends immersive learning research to customer self-service contexts and validates a model linking usability, learning effectiveness, and customer confidence in VR environments.

The findings confirm that immersive microlearning supports procedural understanding, reduces perceived task complexity, and increases customer confidence in performing repair activities (Zhou et al. 2024).

The strongest effects concerned learning effectiveness and customer confidence, showing that immersive instructional content supports the acquisition and application of procedural knowledge. This aligns with experiential learning theory, which stresses the value of contextualized interaction for knowledge retention. Unlike manuals or standard videos, VR instruction enables users to engage with simulated tasks, improving cognitive processing and learning outcomes (Hu and Zhao 2024).

The results highlight the critical role of usability in the success of immersive learning solutions. Despite advanced VR capabilities, effectiveness depends on intuitive and accessible design. The positive relationship between usability, learning effectiveness, and customer confidence confirms the importance of user-centered design in technology adoption.

The study also shows that immersive learning reduces perceived task complexity, acting as a mediator between knowledge acquisition and user confidence. By presenting procedures as clear, step-by-step visual instructions, VR-based microlearning makes technical tasks more accessible for non-expert users, extending prior research by demonstrating enhanced effectiveness within immersive environments (Dwivedi et al. 2022).

However, the results indicate that the reduction in service interactions, although significant, is not complete. This suggests that immersive solutions should complement rather than replace traditional technical support. In more complex situations, users may still require expert assistance, highlighting the need for hybrid support models integrating immersive and conventional channels.

From a broader perspective, the study contributes to the literature by shifting the focus of immersive technologies from employee training to customer-oriented knowledge transfer. It provides empirical evidence of VR's effectiveness in empowering end users beyond organizational settings, extending the concept of knowledge management toward more distributed and user-driven models.

From a managerial standpoint, the findings suggest that organizations aiming to implement VR-based support systems should prioritize three key areas. First, they should invest in the development of high-quality instructional content that is tailored to user needs and specific technical tasks. Second, ensuring usability and

accessibility of VR solutions is essential to maximize adoption and effectiveness. Third, companies should integrate immersive learning into existing service ecosystems, creating hybrid support models that balance automation with human expertise (Onwubiko 2015).

This study examined the effectiveness of immersive, video-based microlearning delivered through VR glasses in supporting customer self-repair and technical support. The findings indicate that immersive learning enhances procedural understanding, reduces perceived task complexity, and increases customer confidence in performing basic maintenance tasks. The results also suggest a partial reduction in reliance on traditional service channels, supporting more autonomous and cost-efficient support models.

The study has several limitations. Although conducted across three European countries, the findings may not be fully generalizable to other contexts. The use of self-reported data may reflect subjective perceptions rather than actual performance. Additionally, the focus on relatively simple tasks limits applicability to more complex technical scenarios.

Future research should incorporate experimental designs to assess actual task performance and error rates. Qualitative approaches, such as interviews or user observations, could provide deeper insights into user experience and adoption barriers. Longitudinal studies would further help to evaluate the long-term impact of VR-based learning on user competence and reliance on technical support. In conclusion, immersive microlearning represents a promising direction for customer support and knowledge transfer. However, its effectiveness depends not only on technology, but also on usability, instructional design, and integration with existing support systems.

Ethics Declaration: Ethics approval was not required.

AI Declaration: AI tools were not used to create this article.

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PhD Research Papers

Understanding Healthcare Professionals' Adoption and Sustained Use of AI Medical Technologies in Saudi Arabia's Vision 2030 Context

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Abstract: Despite Saudi Arabia's Vision 2030 AI strategies, a significant gap remains between policy measures and the sustained clinical integration of AI in healthcare. This research employs a sequential exploratory mixed methods design to investigate the transition from initial adoption to continuous usage among practitioners. Currently, the qualitative phase is complete, with thematic analysis underway for interviews conducted with physicians, radiologists, and nurses across the Kingdom. Emerging findings reveal that trust in autonomous AI is not a static construct but evolves through distinct phases: from initial distrust to hesitant reliance, and finally to trustful integration. Preliminary data further suggests that workflow complexity and organisational readiness pose more significant barriers to sustained use than the technical performance of the AI itself. Theoretically, this study proposes a framework for "Adaptive Clinical Integration" that identifies key acceptance factors and explores how Agile project management practices can be adapted to manage the unique complexities of AI-Based Medical Devices (ABMDs). By bridging individual acceptance models with agile science, this research provides a context-specific roadmap for Saudi policymakers to ensure the successful, sustained assimilation of high-stakes healthcare AI.

Keywords: Artificial intelligence in healthcare, Technology adoption, Clinical decision support, AI-assisted robotic surgery, UTAUT2, Saudi Arabia

1. Introduction

In Saudi Arabia, healthcare is undergoing a radical transformation driven by Vision 2030, with a strategic mandate to leverage Artificial Intelligence (AI) for systemic improvement. Economic projections suggest AI could generate between $15 and $27 billion in value for the country's healthcare sector by 2030 (AlBasri et al., 2022). Currently, 77 per cent of Saudi healthcare leaders report active AI use a nearly twofold increase from the previous year and 96 per cent intend to expand their investments (Philips, 2023). However, this surge in investment and leadership optimism masks a critical implementation gap. Despite the rapid deployment of AI-Based Medical Devices (ABMDs), evidence suggests that high-level technological performance does not automatically translate into clinical utility. In Saudi Arabia specifically, while infrastructure is rapidly maturing, the transition from institutional acquisition to frontline practitioner integration remains precarious (Handayani et al., 2018; Cangelosi et al., 2025).

This gap is particularly acute in high-stakes autonomous technologies, such as robotic surgery and Clinical Decision Support Systems (CDSS). Unlike generic IT, these systems demand deep alignment with professional identity, complex clinical workflows, and significant organisational adaptation (Asan et al., 2020; Wenderott et al., 2024).

This research aims to investigate the key factors influencing selected medical professionals' acceptance of specific AI-Based Medical Devices adoption in Saudi Arabia's healthcare sector, centred on agile project management approaches tailored for AI-driven initiatives. To achieve this, the study addresses the following research questions:

RQ1: What key factors influence medical professionals' acceptance of AI-Based Medical Devices adoption in Saudi Arabia's healthcare sector?

RQ2: How do identified factors interact and contribute to the successful adoption of AI-Based Medical Devices in healthcare settings?

RQ3: How can agile project management practices be adapted to effectively manage AI-Based Medical Devices adoption in Saudi Arabia's healthcare sector?

2. Literature Review and Theoretical Background

2.1 AI Medical Technologies in Healthcare

AI technologies have proven their worth in various fields of medicine. According to Rajpurkar et al. (2022), much progress has been achieved in analysing medical images in radiology, pathology, gastroenterology, and ophthalmology. Topol (2019) claims that artificial intelligence can help optimise health care systems' functioning and predict patients' fates by adding to rather than substituting doctors' skills. On the other hand, Briganti and Le Moine (2020) cite some successes in detecting arrhythmias and analysing images; however, they correctly note the lack of sound design and external validation of many studies.

In Saudi Arabia, AI-based diagnostic technologies are in active clinical use (Philips, 2023), and this study focuses on two fields of technology that informed the selection of participant medical professionals.

Table 1: AI-Based Medical Devices and target sample

Technology Category	Target Healthcare Professionals	Clinical Role & Interaction	Interaction Rationale for Study Inclusion
Autonomous Systems (AI assisted robotic surgery)	Surgeons	Primary Operators: Direct, real-time interaction where the AI provides precision guidance and automates specific surgical tasks	High stakes dependency; adoption hinges on the balance between AI autonomy and the surgeon's professional identity/control
AI Clinical Decision Support Systems (CDSS)	Physicians, Nurses, Radiologists	Interpretive & Advisory Users: Use AI for diagnostic imaging (radiologists) or therapeutic suggestions and patient monitoring (physicians/nurses)	CDSS integrates into daily cognitive workflows; successful adoption depends on how AI-driven insights are trusted and validated by the clinical team

The most spoken about AI-based medical technologies globally and in Saudi Arabia are shown in Table 1 (Faisal, 2024). Firstly, the field of autonomy involves robotics systems with AI assistance being used for surgical operations to conduct minimally invasive procedures more accurately. Secondly, the utilisation of CDSS in Saudi Arabia is significantly on the rise to increase diagnostic accuracy, reduce medication errors, and improve adherence to treatment guidelines (Alqahtani et al., 2016).

2.2 Technology Acceptance in Healthcare Contexts

The adoption of healthcare technology depends on a complex interplay of user, organisational, and technological factors. The Technology Acceptance Model (TAM) and its successor, TAM2, established perceived usefulness and ease of use as primary determinants (Davis, 1989), with meta-analyses confirming their robustness across diverse fields (Granić & Marangunić, 2019). While TAM2 improved explanatory power by incorporating social influence and cognitive processes (Venkatesh & Davis, 2000), these generic frameworks often lack the granularity required for high-stakes clinical environments.

The Unified Theory of Acceptance and Use of Technology (UTAUT) attempted to harmonise these perspectives (Venkatesh et al., 2003), yet research highlights significant structural omissions. For instance, Dwivedi et al. (2017) found that UTAUT overlooks the central mediating role of attitude. Furthermore, while UTAUT2 introduced consumer-centric variables such as hedonic motivation and habit (Venkatesh et al., 2012), it remains insufficient for clinical AI. Critically, none of these models inherently account for trust the most vital predictor of adoption in medical decision-making where errors have dire consequences (Kaplan et al., 2023).

Recent evidence suggests that Generic models fail to capture clinical nuances such as professional identity, workflow complexity, and organisational readiness (Shachak et al., 2019; Dwivedi et al., 2020), with workflow integration identified as a primary barrier in radiology AI (Wenderott et al., 2024). Clinician-centred models like TrAAIT confirm that trust alone explains 36% of AI acceptance variance (Stevens and Stetson, 2023). These factors form an interrelated socio-technical layer: trust establishes the psychological condition for delegation, professional identity shapes its perceived boundaries, and organisational readiness determines whether individual acceptance can be sustained at the organisational level (Shachak et al., 2019; Kaplan et al., 2023).

The conceptualisation of trust as a dynamic, stage-like process has gained increasing traction in the human–automation literature. Madhavan and Wiegmann (2007) established, through an integrative review, that trust in automated systems operates through mechanisms distinct from interpersonal trust, evolving in response to performance cues and operator experience rather than the social reciprocity characteristic of human–human relationships. More recently, phase-oriented accounts have elaborated this trajectory. McGrath et al. (2025) propose the CHAI-T process framework, which situates trust evolution within collaborative human–AI teaming cycles and advocates active management of trust across performance phases rather than treating initial acceptance as a stable endpoint. In clinical settings specifically, Naiseh et al. (2022) demonstrate that the class and quality of explanation provided by AI systems materially affects clinicians' capacity to calibrate trust in CDSS tools, highlighting the importance of transparency mechanisms for enabling appropriate reliance rather than blanket scepticism. Notwithstanding this growing body of process-oriented work, existing phase models have been developed predominantly in Western, experimental, or general automation contexts; none has been empirically grounded in the lived experience of healthcare practitioners within a high-context, hierarchical, rapidly digitalising non-Western health system. This study's identification of a three-stage trajectory initial distrust, hesitant reliance contingent on perceived system performance, and trustful integration characterised by confident delegation responds to this gap by offering a contextually embedded account of how Saudi clinicians construct and move through sequential trust states during actual AI deployment.

While UTAUT2 focuses on adoption as a static, one-time event, this research employs agile project management as a conceptual bridge to address the dynamic, iterative processes required for sustained clinical integration.

2.3 Synthesis of Prior Research

A summary of key research on AI adoption in healthcare is presented in Table 1. They are derived from high-quality sources (Q1/Q2 in Scimago Journal Rank; 3/4 in ABS ranking). Some clear trends emerge. Performance Expectancy and Perceived Usefulness often influence intentions to adopt technology across different settings (Kim et al., 2024; Prakash and Das, 2021; Pan et al., 2019). Trust is seen both as an independent predictor and a mediator (Stevens and Stetson, 2023; Cornelissen et al., 2022; Kim et al., 2024). The impact of facilitating conditions and social influence varies by setting. According to Zhai et al. (2021), social influence predicts behaviour quite strongly among Chinese oncologists, but according to Cornelissen et al. (2022), it plays no role at all for Dutch physicians. Very few studies focus on sustained usage or analyse the specific context of Gulf healthcare.

Table 2: Synthesis of Key Studies on AI Adoption in Healthcare

Study	Context	Region	Key Variables	Main Findings	Limitation
Prakash and Das (2021)	Healthcare AI (CDSS)	India	UTAUT, Trust, Resistance	Performance expectancy and trust; resistance significant	Pre-adoption focus
Zhai et al. (2021)	Radiation oncology	China	UTAUT, Social Influence	Social influence and facilitating conditions are strongest	Single centre; age bias
Cornelissen et al. (2022)	Care pathways	Netherlands	UTAUT, Professional Identity	Medical performance expectancy is dominant; gender moderates	Online volunteer sample
Jones et al. (2022)	CDSS	USA	UTAUT	Eight dominant themes were identified such as Alert fatigue, Automation and Redundancy	inpatient only. trauma population
Stevens et al. (2023)	Oncology	USA	UTAUT, IS Success, Trust	Trust explains 36% of variance; system performance is critical	Single centre
Aljarboa and Miah (2023)	CDSS	Saudi Arabia	UTAUT + TTF	13 factors identified as influencing CDSS acceptance, including: Performance expectancy, effort expectancy, facilitating conditions, task-technology fit.	Qualitative only; GP-focused
Wenderott et al. (2024)	Radiology	Germany	TAM, Workflow Integration	Positive attitudes: workflow barriers dominate	Single department
Kim et al. (2024)	Medical AI	South Korea	UTAUT, Trust Mediation	Trust mediates UTAUT factors and acceptance	Age-limited sample
Alsudairy et al. (2025)	Primary care AI	Saudi Arabia	TAM/UTAUT	31% using AI tools; 54% lack training; 49.2% cite high costs; 48% concerned about human touch erosion.	Primary care only; mixed awareness levels
Shao et al. (2026)	DeepSeek LLM-CDSS	China	UTAUT + Perceived Risk Theory	Performance expectancy, effort expectancy and facilitating conditions reduce perceived risk.	Single hospital; convenience sample; emerging technology (LLM)

Some key trends have been identified from this synthesis. Trust and workflow integration emerge consistently as highly relevant but less researched concepts within varying national settings. Research tends to concentrate on adoption intentions and not on the continued use of AI applications after the implementation phase.

2.4 Project Management Practices in AI Healthcare Projects

Traditional project management methods, designed for stable requirements, are poorly suited to AI healthcare projects. Agile approaches offer benefits through iterative development and ongoing value delivery (Kokol et al., 2022), though adoption remains limited. Technology acceptance and user behaviour influence implementation (Shetty and Joshi, 2024), while workflow integration and AI complexity demand flexible, adaptive strategies rather than fixed plans (Nair et al., 2024; Koçak et al., 2025).

2.5 Agile Principles for AI Healthcare Implementation

Agile principles offer a fitting framework for implementing AI in healthcare because they handle the uncertainty and complexity of AI projects. Unlike the traditional waterfall approach, agile methods encourage iterative development, ongoing stakeholder engagement, and flexibility in adjusting to changing needs (Kokol et al., 2022). In this study, agile principles serve as the implementation framework that operationalises the theoretical constructs of the extended UTAUT2 model. The success of agile AI projects depends on user acceptance and

behavioural factors, which shows the importance of implementation methods that meet stakeholder needs (Shetty & Joshi, 2024). Specifically, agile project management contributes to AI adoption by fostering trust through iterative, small-scale deployments that allow clinicians to validate system performance before full-scale use. It further ensures sustained use by providing the structural flexibility needed to refine clinical workflows continuously as professional knowledge and AI capabilities evolve. Research highlights that successful AI implementation requires flexible methods to tackle workflow integration issues, improve processes, and adapt to organisational changes (Nair et al., 2024; Koçak et al., 2025). Agile methods also promote continuous learning and improvement through regular feedback, which boosts clinical value and aids effective change management (Leuba & Piricz, 2024; Nihi et al., 2025). In the context of Saudi Arabia's Vision 2030, agile principles like flexibility in implementation, stakeholder involvement, and continuous adaptation will likely play a key role in supporting AI adoption across healthcare organisations with varying levels of digital maturity.

Critically, the qualitative phase of this study has identified specific Agile-aligned patterns that emerged consistently across participant accounts and may offer potential directions for extending the UTAUT2 model. These emerging themes point to a recognised structural limitation of UTAUT2: its exclusive focus on individual-level variance, which leaves unexplained the team-level and process-level dynamics through which individual intention is or is not translated into sustained clinical use. Further exploration of these themes, including potential operationalisation and their relationships within the broader theoretical model, will be reported in a subsequent manuscript following completion of the full thematic analysis. The present paper signals this as a theoretical direction under active investigation.

2.6 Issues Surrounding Knowledge in AI Healthcare Adoption

Trust in clinical AI is an epistemic process through which practitioners collectively refine tacit knowledge about system reliability (Nonaka and Takeuchi, 1995), not merely a psychological disposition. Established frameworks such as UTAUT and TAM treat knowledge acquisition as an individual event, underestimating collective sensemaking through which institutional trust is built (Tamilmani et al., 2021; Shachak et al., 2019). Knowledge creation is geographically embedded: Western findings may not reflect Saudi Arabia's steeper hierarchies, collectivist culture, and directive policymaking (Argote and Miron-Spektor, 2011), with regional studies sparse (Nasseef et al., 2022; Aljarboa and Miah, 2023). Most studies measure initial acceptance but neglect double-loop learning (Argyris, 1977) through which practitioners revise assumptions during deployment; workarounds constitute acts of tacit knowledge creation and knowledge sharing that, if captured, can drive iterative improvement.

2.7 Research Gaps

The first gap is that of context specificity. While social influence has been determined as a key variable affecting the process of adoption among Chinese oncologists (Zhai et al., 2021), it has been insignificant among Dutch oncologists (Cornelissen et al., 2022). This inconsistency suggests the need for studying contextual aspects to determine which variables function in certain contexts.

The second gap concerns inadequate attention paid to the stage of transitioning from intention to integration. It has been noted that most studies concentrate on intentions rather than the continuity of use (Prakash and Das, 2021; Kim et al., 2024). The process of transitioning from intention to implementation is critical for those technologies that require gradual skill acquisition.

Thirdly, the organisational and implementation dimensions of AI adoption need further theoretical exploration. Whereas there is sufficient literature on the acceptability dimensions for individuals, there are not enough studies on the organisational processes by which individual acceptability is leveraged to facilitate organisational adoption through implementation processes, adaptive implementation, and training programs (Kokol et al., 2022; Nair et al., 2024).

3. Methodology

A sequential exploratory mixed-methods research design is used in this study, whereby the qualitative phase precedes the quantitative generalisation phase (Creswell & Clark, 2017). The initial qualitative phase utilizes semi-structured interviews to capture the unique cultural nuances of the Saudi context. These qualitative insights will then inform a quantitative survey designed to empirically validate the interaction of these factors and assess the effectiveness of Agile management practices in facilitating organisational integration.

3.1 Qualitative Phase

Seventeen semi-structured interviews were conducted with healthcare professionals across major Saudi cities, recruited through purposive expert sampling supplemented by snowball referrals. Participants were selected based on direct clinical experience with either AI-assisted robotic surgery (surgeons) or Clinical Decision Support Systems (physicians, radiologists, and nurses), ensuring diversity of role and specialisation. The protocol covered thematic areas aligned with UTAUT2 constructs including performance expectancy, effort expectancy, social influence, facilitating conditions alongside the additional constructs such as trust proposed by this study, and was pilot tested with two clinicians prior to data collection.

3.2 Data Analysis

Reflexive thematic analysis (Braun and Clarke, 2006) was applied through six inductive coding stages using NVivo. Saturation was monitored iteratively: new conceptual categories ceased to emerge by interview 15, with interviews 16 and 17 serving to confirm and enrich existing themes, distinguishing code from meaning saturation. Trustworthiness was ensured through member-checking, whereby Arabic transcripts were returned to participants for verification (Birt et al., 2016), and English translations were independently reviewed by two bilingual colleagues.

3.3 Quantitative Phase

Qualitative findings will inform a survey instrument deployed across Saudi health institutions, with each theme operationalised as a latent construct using validated scales where available and new items for constructs specific to the Saudi clinical context. The instrument will undergo cultural validation by Saudi healthcare experts, cognitive interviews to identify comprehension issues, and pilot testing (n=15–20) to assess psychometric properties. Common method bias will be assessed using Harman's single factor test and controlled via a common latent factor approach. Moderating variable's professional role, years of experience, and institutional type were selected based on qualitative evidence that adoption trajectories vary across these dimensions. The target sample of 200–300 respondents was determined through power analysis (GPower: minimum 176), parameter-to-case ratios (Jackson, 2003), and Monte Carlo simulation, accounting for 15–20% non-response (Kline, 2016). Data will be analysed using PLS-SEM (Hair et al., 2019).

4. Initial Conceptual Thinking and Proposed Framework

The proposed framework integrates insights from the literature and early interview data into a theory-based model that goes beyond traditional adoption theories, differentiating between individual adoption and clinical integration as related but distinct outcomes. Each process requires different forms of organisational support and encounters different obstacles, examined here across three interrelated dimensions. Among individual-level variables are performance expectancy, effort expectancy, and trust, which foster initial willingness to use AI-based technology. Trust, for instance, is an outcome of a series of experiences ranging from initial scepticism to trusting use of the AI-based decision-making process. First, there is doubt followed by hesitant reliance on perceived system performance, until trust finally leads to use in making clinical decisions (Stevens and Stetson, 2023).

At the organisational level, organisational readiness, leadership support, training quality, and flexibility in adapting workflows are critical to whether an individual's positive attitude translates into the effective use of clinical technology. Theoretically, these variables operate through a socio-technical logic where individual intent is moderated by the organisational environment. High-quality training and leadership communication act as vital catalysts that transform a practitioner's initial positive attitude into sustained clinical usage. This relationship is inherently iterative; as practitioners achieve integration, their frontline experiences feed back into organisational policy, allowing for the continuous, data-driven refinement of workflows and safety governance.

The Adaptive Clinical Integration Framework (ACIF), presented in Figure 1, is structured around three propositions: P1 holds that individual-level factors mediated by Trust generate Behavioural Intention toward organisational enablers; P2 posits that organisational-level factors drive Sustained Use; and P3 captures the iterative feedback loop through which Sustained Use informs continuous Organisational refinement. This differs from static "Go-Live" models by treating implementation as a non-static, Agile co-evolution between technology and the clinical workforce over time. The qualitative data further indicate that additional Agile-aligned constructs, yet to be formally operationalised, play a meaningful role in facilitating this co-evolution. The complete development and empirical validation of the proposed theoretical framework will be outlined in separate manuscripts.

Figure 1 illustrates the proposed Adaptive Clinical Integration framework, linking individual acceptance constructs with organizational level.

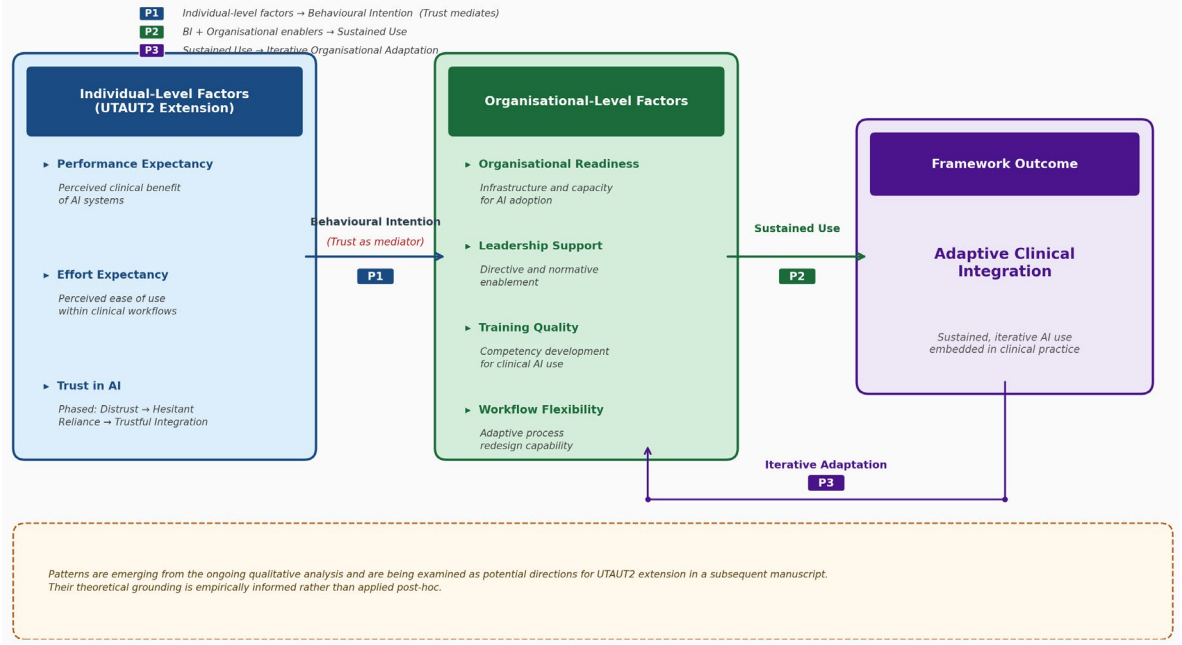


Figure 1: Initial Conceptual Thinking

5. Study Progress and Preliminary Insights

At the time of writing, data collection for the qualitative phase is almost done. Semi-structured interviews have been conducted with participants from hospitals and healthcare institutions across several major regions of Saudi Arabia.

The process of data analysis has started already. Some trends have been identified. Firstly, trust toward AI systems appears to emerge in distinct phases from distrust to cautious use and eventual trustful integration; as one participant noted, "I trust it at a high rate, maybe about 85%. But I still review every alert or suggestion before applying it" (P17). Secondly, issues with workflow integration appear to pose larger obstacles compared to problems of technology; as P04 described, "It took a while at the beginning, but it didn't last long; it was between one and two months." A third pattern concerns organisational support as a moderating factor; P10 captured the gap between institutional encouragement and actual provision: "The hospital encourages but does not adequately provide the necessary resources for education and training." These are summarised in Table 3 below.

Table 3: Preliminary Themes from Early Interview

Emerging Theme	Illustrative Insight	Theoretical Relevance
Trust Development Phases	Trust evolves through distinct stages from skepticism to confident integration	Extends static trust models to dynamic processes
Workflow Integration Priority	Workflow concerns outweigh technical capability worries	Aligns with Task-Technology Fit (TTF) and implementation science
Organisational Support Moderation	Training and leadership quality influence the acceptance-sustained use link	Extends UTAUT facilitating conditions

These are early observations rather than final conclusions. Thematic analysis is still in progress, and the final conceptual framework will be refined based on it.

6. Expected Contributions and Areas for Development

6.1 Theoretical Contribution

The contribution of this study to the technology acceptance literature can be viewed in three ways. First, by focusing on long-term clinical use rather than mere acceptance, this research fills the gap in understanding how AI is integrated into daily medical practice over time. Second, by including professional identity and autonomy as key concepts, this study builds on previous models to address the specific realities of clinical practice with autonomous systems. Third, by presenting adaptive clinical integration as an organisation-level concept that connects individual acceptance and implementation outcomes, the theoretical framework ties technology acceptance research to implementation science in a way that meets the challenges of autonomous AI in healthcare.

6.2 Practical Contribution

This study supports healthcare organisations and policymakers in Saudi Arabia in developing evidence-based strategies for a positive, sustained AI implementation process, in alignment with Vision 2030 objectives.

6.3 Methodological Contribution

This design is effective for exploring complex adoption questions in relatively unstudied regions. By creating surveys informed by insights from qualitative research, the current study ensures that future surveys can measure constructs and their relationships pertinent to Saudi Arabian health care practitioners.

7. Conclusion

This paper has presented the rationale, theoretical foundation, and methodology for a mixed-methods study on AI adoption among Saudi healthcare providers, motivated by several unresolved issues in the field. These issues include the neglect of the adoption process for medical professionals, lack of understanding concerning how adoption turns into sustainable usage, and a lack of studies in the Gulf region.

Feedback Sought

Feedback is welcomed on two areas: (1) the coherence of Agile principles as the implementation mechanism bridging individual acceptance and organisational integration, particularly how specific Agile practices are identified and linked to adoption constructs through the qualitative data in RQ3; and (2) the planned transition from qualitative themes to survey instrument development, particularly how identified themes will shape the survey questions and overall instrument structure.

Acknowledgements

The author sincerely acknowledges the contributions, guidance and support of Dr Maksym Koghut and Dr Roula Michaelides as members of the supervisory team.

Ethics Declaration: Ethics clearance for the study was received from the Manchester Metropolitan University's Research Ethics Committee prior to data collection. Informed consent was obtained from the subjects before conducting the interview session. Data confidentiality is maintained by securing and anonymising the information collected from the respondents. The study adheres to the guidelines set forth in the Declaration of Helsinki.

AI Declaration: The author confirms that no AI tools were used in drafting, analysing, or preparing this manuscript. All content reflects the original work of the research.

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The Adoption of Green Knowledge Management in Startups: A Comparative Landscape

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Abstract: In the context of the global twin transition towards digitalisation and sustainability, startups increasingly rely on Green Knowledge Management (GKM) to integrate environmental objectives into their core operations. Although GKM is widely recognised as a relevant enabler of sustainability-oriented entrepreneurship, the existing academic literature remains fragmented. It is often limited to single-country empirical settings and frequently treats GKM as a monolithic construct rather than a complex set of distinct organisational routines. This study addresses this critical gap by providing a comparative analysis of GKM adoption between startups operating in China and Europe. Grounded in Institutional Theory and the Dynamic Capabilities View, the study conceptualises GKM as a multidimensional construct comprising five sub-dimensions: green knowledge acquisition, storage, sharing, application, and creation. To examine whether these dimensions exhibit comparable patterns across the two distinct regions, the study utilises a cross-sectional survey of 679 startups, comprising 302 firms in China and 377 in Europe, employing measurement invariance assessment to ensure robust cross-group comparability. The findings indicate statistically significant differences across all five sub-dimensions, with Chinese startups reporting consistently higher average maturity scores than their European counterparts. Crucially, these results should not be interpreted as universal performance hierarchies. Rather, they highlight region-specific baseline profiles that may reflect differences in institutional environments, support structures, and entrepreneurial ecosystems. While the observed pattern is consistent across all knowledge dimensions, the study acknowledges the descriptive nature of these capability gaps without claiming strict causal identification of the underlying drivers. This study contributes by establishing an initial comparative benchmark for multidimensional GKM across contrasting institutional contexts. Furthermore, it provides an empirical foundation for future work to investigate the mechanisms linking institutional pressures and GKM development using advanced structural modelling. From a practical perspective, the findings suggest that sustainability support for startups should be tailored to regional conditions and to the specific knowledge processes that require strengthening.

Keywords: Green knowledge management, Sustainable entrepreneurship, Startups, Comparative analysis, Institutional theory, Dynamic capabilities

1. Introduction

In the contemporary global economy, the dual imperatives of digitalisation and sustainability, often referred to as the "twin transition", have fundamentally reshaped the competitive landscape. Startups, characterised by their agility and innovative potential, are increasingly recognised as pivotal actors in driving this technological and ecological evolution (George, Merrill and Schillebeeckx, 2021; Lee et al., 2025). However, operating under severe resource constraints, these emerging ventures face significant challenges in integrating complex environmental objectives into their core operations. To navigate this demanding landscape, startups must cultivate robust internal capabilities to capture, process, and deploy environmentally relevant information. This imperative has been further intensified by the rapid diffusion of Artificial Intelligence (AI), which is fundamentally transforming how organisations acquire, store, and apply knowledge at scale, particularly in the environmental domain (Cai et al., 2025; Genty et al., 2026). Consequently, Green Knowledge Management (GKM) has emerged as a critical strategic asset that enables organisations to translate environmental awareness into tangible sustainable performance (Ulhaq et al., 2024; Fadillah, Hadijah and Gunawan, 2025).

While the theoretical importance of knowledge management (KM) in driving corporate sustainability is widely acknowledged, the existing literature exhibits notable limitations. A substantial body of research has investigated traditional KM processes, often highlighting specific routines such as knowledge acquisition, sharing, and application as essential antecedents to green innovation and sustainable performance (Nasir et al., 2024; Nguyen et al., 2025). Building on this foundation, recent scholarship has increasingly shifted its focus toward the specialised domain of GKM (Khan, Mehmood and Kwan, 2024). Notably, the emergence of AI-powered tools, such as large language models and predictive analytics, has begun to reshape each of these knowledge routines in ways that are particularly consequential for startups (Kudryavtsev et al., 2024; Kusetogullari et al., 2025). However, despite this conceptual evolution, many empirical studies still tend to treat GKM as a monolithic concept, overlooking the highly nuanced and multidimensional nature of environmental knowledge routines. To accurately capture an organisation's capability profile, it is imperative to deconstruct this broad construct. According to the foundational scale development by Yu et al. (2022), the operationalisation of GKM typically encompasses a spectrum of distinct sub-dimensions, primarily including green knowledge

acquisition, green knowledge storage, green knowledge sharing, green knowledge application, and green knowledge creation.

Furthermore, the prevailing research heavily relies on single-country empirical settings or specific industrial contexts, such as the manufacturing sectors in Pakistan (Abbas and Sağsan, 2019) or the traditional small and medium-sized enterprise (SME) sector in Malaysia (Nasir et al., 2024). Crucially, this existing body of literature is overwhelmingly concentrated on established, resource-rich corporations or mature conventional firms, leaving a notable empirical gap regarding high-growth startups. Given that startups operate with unique organisational agility yet extreme resource scarcity, GKM paradigms validated in large enterprises cannot be directly transplanted into the entrepreneurial context. This narrow geographic, sectoral, and organisational focus fails to account for the profound impact of varying institutional environments and firm life-cycle stages on entrepreneurial behaviour and capability development, an omission that contradicts the core tenets of Institutional Theory (Bruton, Ahlstrom and Li, 2010).

The institutional contexts of emerging economies and developed markets present vastly different regulatory pressures, market incentives, and cultural norms regarding sustainability (Lozano and Martínez-Ferrero, 2022). Organisations do not develop ecological capabilities in a vacuum; rather, their strategic allocation of resources is deeply conditioned by the "rules of the game" dictated by their institutional environments (North, 2012; Vatn, 2005). While the institutional landscapes of China and Europe differ in their regulatory frameworks and market incentives, how these distinct environments shape the baseline adoption of GKM in startups remains an empirical void. There is a distinct absence of rigorous cross-cultural comparative studies investigating whether startups across these regions suffer from uniform operational deficits or context-specific capability bottlenecks within their GKM sub-dimensions.

To address this research gap, this study conducts a comparative analysis of GKM adoption between startups in China and Europe. Grounded in Institutional Theory and the Dynamic Capabilities View, the paper decomposes the GKM construct into five sub-dimensions and provides an initial mapping of regional capability profiles. Employing Partial Least Squares Structural Equation Modelling (PLS-SEM) and the Measurement Invariance of Composite Models (MICOM) procedure, the study first examines cross-cultural measurement invariance and then uses independent samples t-tests to compare baseline differences across the two regions. The paper is therefore positioned as a comparative, descriptive study rather than a full causal model. Specifically, it makes three contributions: (1) it quantitatively compares multidimensional GKM profiles across two distinct institutional contexts; (2) it provides empirical support for the cross-cultural applicability of the GKM scale within this startup sample; and (3) it identifies the specific knowledge routines where regional adoption gaps are most pronounced, establishing an empirical benchmark for understanding context-dependent capability development.

The remainder of this paper is structured as follows: Section 2 outlines the theoretical background. Section 3 details the methodology, including data collection and the MICOM procedure. Section 4 presents the results of the comparative analysis. Finally, Section 5 discusses the theoretical and managerial implications, alongside concluding remarks.

2. Theoretical Background

2.1 Green Knowledge Management: From the Knowledge-based View to Dynamic Capabilities

The theoretical foundation for understanding how startups leverage environmental capabilities follows a clear evolutionary trajectory from the Resource-Based View (RBV) to the Knowledge-Based View (KBV), and ultimately to the Dynamic Capabilities View (DCV). The RBV initially posited that organisations achieve sustained competitive advantage by accumulating resources that are valuable, rare, inimitable, and non-substitutable (Barney, 1991). Building upon this static framework, the KBV emphasised that knowledge is the most strategically significant and difficult-to-replicate resource of an organisation (Grant, 1996). However, in highly turbulent environments such as the "twin transition", possessing static knowledge is insufficient. The DCV extends these theories by emphasising a firm's ability to systematically integrate, build, and reconfigure internal and external competences to address rapidly changing environments. For green startups, which typically lack massive physical capital and established supply chains, the dynamic capability to continuously effectively manage intellectual and environmental assets becomes a primary determinant of survival.

Situated within this dynamic capabilities framework, GKM represents a specific, environmentally focused variation of traditional KM principles. Theoretically, GKM is fundamentally conceptualised as the systematic organisational process of integrating environmental considerations into the handling of knowledge assets to

foster eco-innovation and mitigate ecological footprints (Sahoo, Kumar and Upadhyay, 2023; Ulhaq et al., 2024). While early research frequently treated GKM as a singular, aggregated construct, recent methodological advancements emphasise that treating green knowledge as a monolithic entity masks the intricate operational realities of a firm. To accurately capture the true capability maturity of an organisation, scholars must decompose GKM into distinct, sequential sub-dimensions. Addressing this empirical necessity, the comprehensive scale development and validation by Yu et al. (2022) provides a robust multidimensional framework tailored to evaluate specific environmental knowledge routines. Following this validated taxonomy, this study conceptualises GKM as a multidimensional construct comprising five core routines, as summarised in Table 1.

Table 1: Dimensions of Green Knowledge Management (GKM) and their definitions

Dimension	Core meaning
Green Knowledge Acquisition (KAc)	Identifying and absorbing external environmental information, regulations, and clean technologies.
Green Knowledge Storage (KSt)	Codifying, structuring, and retaining environmental knowledge in organisational memory.
Green Knowledge Sharing (KSh)	Facilitating internal and external exchange of green practices and insights.
Green Knowledge Application (KAp)	Using stored and shared knowledge to improve operations, compliance, and strategy.
Green Knowledge Creation (KC)	Generating novel environmental solutions and green innovations.

By treating these sub-dimensions independently, this research can pinpoint the exact capability bottlenecks of startups. This shifts the academic discourse from merely asking whether a startup is "green" to identifying which specific knowledge process represents the main constraint on sustainable growth.

2.2 Institutional Context and Capability Development

While internal resource theories explain how capabilities function, Institutional Theory offers the essential theoretical lens to understand why external environments dictate the specific development pathways of these green capabilities. According to this perspective, the cultivation of green routines rarely occurs in isolation. Rather than merely acting as a passive backdrop, institutions exert powerful coercive, normative, and cognitive pressures that actively shape organisational behaviour and resource allocation (DiMaggio and Powell, 1983; Scott, 2014). Instead of purely autonomous decision-making, startups strategically adapt their KM behaviour to conform to the prevailing regulatory constraints, market incentive structures, and societal expectations of their specific geographic contexts (Bruton, Ahlstrom and Li, 2010).

The application of institutional theory is particularly critical when comparing the adoption of GKM across diverse economic regions. The European and Chinese institutional landscapes for sustainable entrepreneurship exhibit stark contrasts, generating entirely different configurations of institutional pressures. Europe is characterised by a highly mature, heavily regulated compliance environment driven by stringent top-down coercive pressures, such as the mandates embedded within the European Green Deal. Coupled with deep-rooted normative expectations regarding environmental preservation, startups in this highly institutionalised setting are often compelled to prioritise foundational compliance, rigorous documentation, and secure knowledge storage to meet strict societal and auditing standards (Scott, 2014). This environment effectively transforms foundational green routines into mandatory compliance standards rather than discretionary strategic assets. Conversely, China represents a rapidly evolving institutional environment characterised by aggressive, state-led technology incentivisation and a high-velocity market dynamic. The Chinese government heavily subsidises the digital and green sectors, creating an ecosystem where rapid expansion is rewarded. In such an environment, startups face intense mimetic and competitive isomorphic pressures to rapidly adopt widely recognised "green" signals to secure resources (DiMaggio and Powell, 1983). Chinese startups are pushed toward rapid capability deployment and active knowledge application to capture immediate market subsidies, secure state-backed funding, and establish rapid competitive positioning.

Despite these institutional disparities, there remains a gap in the empirical literature in quantitatively mapping how different environmental pressures relate to baseline maturity levels across the five GKM sub-dimensions. By bridging Institutional Theory with the DCV, this study provides a basis for comparing the GKM capability profiles of European and Chinese startups and for describing how regional contexts shape internal digital-green operations.

Based on the theoretical arguments regarding distinct institutional pressures, this study formally posits the following hypothesis:

> ***Hypothesis (H):*** *The baseline adoption levels across the five GKM sub-dimensions differ between startups in China and Europe.*

3. Methodology

3.1 Data Collection and Sample

To quantitatively assess and compare the adoption of GKM across different institutional contexts, this study employed a cross-sectional survey design. The sample comprises startups operating in two major economic regions: China and a diverse European cohort spanning France, Denmark, Germany, the United Kingdom, Italy, Poland, and Spain. Data were collected through a professional commercial survey panel service via the Qualtrics platform, with contacts sourced directly from the provider's pre-screened proprietary panels of business professionals. Target respondents were restricted to startup founders, senior executives, and managers directly involved in the strategic and operational decision-making of their respective ventures, ensuring that the informants possessed a holistic view of the firm's environmental routines.

Regarding the target population size, the commercial provider compensated respondents on a per-valid-completion basis until predetermined regional quotas were met. Consequently, the exact number of initial survey invitations distributed remains proprietary to the panel provider and is inherently unknown. Standard quality control protocols, including embedded attention checks and deduplication, were implemented proactively by the provider to ensure initial data integrity (Boas, Christenson and Glick, 2020).

While securing knowledgeable informants was crucial, maintaining structural comparability between the two regional cohorts was equally important. Consequently, the sampling criteria strictly targeted ventures that fall within the broadly recognised parameters of startups. Specifically, the selected firms across both regions are constrained by similar firm age and employee headcount boundaries, predominantly reflecting small-to-medium structural configurations. By employing this ex-ante sample restriction, the study controls for the disproportionate influence of vast resource disparities typically found between nascent ventures and large incumbent corporations. This methodological design helps ensure that the observed comparative gaps in GKM capabilities are mainly related to distinct institutional and regional contexts rather than fundamental demographic imbalances.

Given the cross-regional nature of the study, a translation and back-translation protocol was implemented. The original English measurement scales were translated into local languages (e.g., Chinese) by bilingual academic experts and subsequently back-translated into English by independent researchers to ensure semantic equivalence and cross-cultural validity. Before the full-scale distribution, a pre-test was conducted with a small pilot group of startup founders to evaluate the clarity, readability, and relevance of the questionnaire items, leading to minor refinements. Furthermore, to mitigate the risk of Common Method Bias (CMB), several procedural remedies were applied ex-ante (Podsakoff et al., 2003). To prevent response inertia and patterned answering, the presentation order of the questionnaire items was systematically randomised. Additionally, respondents were assured of strict anonymity and confidentiality, and were explicitly informed that there were no right or wrong answers, thereby minimising social desirability bias and respondent defensiveness.

After secondary data screening to eliminate any remaining incomplete responses or unengaged answering patterns, the final valid sample comprised 679 startups. This dataset includes 302 validated responses from Chinese startups and 377 validated responses from European startups. The resulting sample provides a sound empirical foundation for conducting comparative institutional analysis and offers sufficient statistical power for the present study.

3.2 Measurement Scales

To capture the multidimensional nature of organisational capabilities, this study adopted the comprehensive GKM scale developed and validated by Yu et al. (2022). The measurement instrument decomposes GKM into five distinct, interrelated sub-dimensions: Green Knowledge Acquisition (KAc, 5 items), Storage (KSt, 5 items), Sharing (KSh, 6 items), Application (KAp, 5 items), and Creation (KC, 5 items). All items were evaluated on a standard 5-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (5). Minor linguistic adaptations were made to align the phrasing with the specific context of green startups without altering the core theoretical meaning. The complete survey script, detailing the exact phrasing of all measurement items, is presented in Table 2.

Table 2: Measurement items for Green Knowledge Management (GKM)

Item	Wording
Green Knowledge Acquisition (KAc) — 5 items	
KAc1	We regularly acquire information about eco-friendly products or services from external stakeholders (e.g., customers, suppliers).
KAc2	We regularly acquire information about eco-friendly products or services from internal stakeholders (e.g., management, staff).
KAc3	We regularly arrange training sessions for employees to develop their knowledge of eco-friendly products or services.
KAc4	We have a well-developed information system that enables employees to access the eco-friendly information they need.
KAc5	We encourage and support our employees to acquire knowledge about eco-friendly products or services.
Green Knowledge Storage (KSt) — 5 items	
KSt1	We have sufficient information about eco-friendly products or services.
KSt2	We have an effective information system to manage information on eco-friendly products or services.
KSt3	We can easily retrieve information about specific environmental challenges from our information system.
KSt4	We have comprehensive information about our competitors and the impact of their operations on the natural environment.
KSt5	We have procedures to retain departing employees' critical knowledge within our information system.
Green Knowledge Sharing (KSh) — 6 items	
KSh1	We regularly interact internally to discuss environmental developments and share related knowledge.
KSh2	We have a well-organised system (e.g., platforms, routines, or communities) that enables us to share environmental knowledge and learn from each other.
KSh3	We have access to up-to-date equipment and collaboration tools to obtain and share environmental knowledge.
KSh4	We recognise and reward employees who share innovative ideas and information to protect the natural environment.
KSh5	We regularly share the latest environmental knowledge and market trends with employees through emails, training sessions, workshops, etc.
KSh6	We regularly share information and knowledge related to the natural environment with our customers, suppliers, and other external stakeholders.
Green Knowledge Application (KAp) — 5 items	
KAp1	We fully comply with environmental regulations in our operations.
KAp2	We ensure that the acquired knowledge is applied to develop eco-friendly products or services.
KAp3	We use the knowledge obtained from our experiences and mistakes to continuously improve our environmental performance.
KAp4	We use acquired knowledge to shape our eco-friendly business strategies.
KAp5	We are committed to the ongoing implementation and monitoring of eco-friendly initiatives.
Green Knowledge Creation (KC) — 5 items	
KC1	We use existing information to create eco-friendly products or services.
KC2	We encourage debates and discussions at all levels to generate new environmental knowledge.
KC3	We highly appreciate and reward employees who propose new ideas, knowledge, and solutions for sustainability.
KC4	We collaborate with other firms or institutions to co-create eco-friendly products or services.
KC5	We regularly evaluate new green ideas for further refinement.

Note: Items were rated on a 5-point Likert scale. Throughout the scale, "we" refers to the respondent's company.
Source: Adapted from Yu et al. (2022).

3.3 Analytical Strategy: Measurement Invariance and Mean Comparison

Before comparing the GKM adoption levels between Chinese and European startups, it is an important methodological prerequisite to establish that the measurement instrument operates identically across both

cultural groups. Comparing mean scores without establishing invariance can lead to biased conclusions, as differences might stem from diverse cultural interpretations of the survey items rather than actual capability gaps. Therefore, this study uses PLS-SEM to perform the MICOM procedure (Henseler, Ringle and Sarstedt, 2016). The MICOM procedure is a multi-step assessment that checks for configural invariance and compositional invariance. Only after establishing partial measurement invariance through the PLS-SEM algorithm can the study proceed to cross-regional comparisons.

Subsequently, independent samples t-tests were conducted using the Statistical Package for the Social Sciences (SPSS). By using the raw Likert-scale mean scores, this analytical step quantified and compared the baseline capability gaps between the two regional groups. Furthermore, Levene's test for equality of variances was incorporated to adjust the t-values and degrees of freedom, accounting for the varying sample sizes and potential heteroscedasticity between the Chinese and European datasets (Field, 2024).

4. Results

4.1 Measurement Invariance Assessment

Before conducting a cross-regional comparison of organisational capabilities, it is necessary to establish that the measurement instrument operates equivalently across both the Chinese and European startup samples. Step 1 of the MICOM procedure established configural invariance, as both regional groups were evaluated using identical indicators, data treatment, and algorithm settings within the SmartPLS environment. Subsequently, Step 2 assessed compositional invariance by examining the original correlation (c-value) between the empirical composite scores of both groups. The results of the permutation test (based on 5,000 permutations) are detailed in Table 3.

As shown in Table 3, the original correlations (c-values) for all GKM sub-dimensions are very high, ranging from 0.997 to 1.000. While the permutation p-values for Knowledge Acquisition (KAc), Knowledge Sharing (KSh), and Knowledge Application (KAp) fall below the 0.05 threshold, this statistical rejection can be attributed to the heightened sensitivity of the permutation test when applied to large datasets (N = 679). Because the c-values remain near-perfect, established methodological guidelines suggest that the composites are practically identical across the two groups. Thus, practical compositional invariance is successfully established for the present sample. This robust validation provides a reliable methodological foundation for conducting meaningful cross-regional mean comparisons while effectively mitigating the risk of substantial measurement bias.

Table 3: Results of measurement invariance of composite models (MICOM) step 2

Constructs	Original correlation (c)	5.0% Quantile	Permutation p-value	Invariance status
KAc	1.000	1.000	0.015	Practically established
KSt	1.000	0.999	0.570	Fully established
KSh	1.000	1.000	0.017	Practically established
KAp	0.997	0.999	0.000	Practically established
KC	1.000	1.000	0.090	Fully established

Having established partial measurement invariance (Step 2), the methodological prerequisite for cross-group comparison is fulfilled. This validation provides a reasonable foundation for the subsequent use of traditional parametric tests (e.g., independent samples t-tests) to compare the observed construct means, indicating that the identified differences stem primarily from actual capability gaps rather than divergent cultural interpretations of the measurement items. Nevertheless, consistent with the descriptive nature of this study, the findings should still be interpreted as regional baseline differences within this specific sample rather than universally applicable estimates.

4.2 Comparative Analysis of GKM Adoption

An initial assessment of the pooled sample (N=679) indicated moderate to high overall adoption levels across the five GKM dimensions. However, given the theoretical premise that institutional contexts shape capability development, analysing the aggregated data would obscure regional differences. Therefore, building upon the invariant measurement model, independent samples t-tests were conducted to compare the raw Likert-scale mean scores of the five GKM sub-dimensions between the two regions. As Levene's test for equality of variances was significant ($p < 0.001$) across all variables, the t-values and degrees of freedom (df) were adjusted and reported under the assumption of unequal variances. Table 4 presents the comparative statistics.

Table 4: Independent samples T-Test for GKM adoption (China vs. Europe)

Constructs	China (N = 302)	Europe (N = 377)	Mean difference	t-value	df	p-value	Cohen's d
	Mean (SD)	Mean (SD)					
KAc	4.23 (0.74)	3.42 (1.09)	0.813	11.530	661.437	< 0.001	0.855
KSt	4.24 (0.67)	3.44 (0.96)	0.797	12.684	666.133	< 0.001	0.943
KSh	4.25 (0.73)	3.40 (1.10)	0.844	11.971	656.632	< 0.001	0.886
KAp	4.27 (0.70)	3.76 (0.96)	0.507	7.954	672.205	< 0.001	0.594
KC	4.27 (0.67)	3.51 (1.06)	0.766	11.471	644.793	< 0.001	0.845

Note: t-values and degrees of freedom are reported based on equal variances not assumed. SD = Standard Deviation.

The empirical data reveals a clear and statistically significant baseline divergence. Chinese startups reported consistently high self-assessment scores across the entire GKM spectrum, with means ranging from 4.23 to 4.27 on a 5-point scale. Conversely, European startups exhibited a more conservative baseline capability profile, with average scores ranging predominantly from 3.40 to 3.76.

The independent samples t-tests confirmed that the mean differences across all five GKM dimensions are statistically significant ($p < 0.001$). Importantly, the effect size analysis (Cohen's d) supports the practical magnitude of these differences, confirming they are not merely statistical artefacts driven by the large sample size. According to standard benchmarks, the effect sizes for Knowledge Storage ($d = 0.943$), Knowledge Sharing ($d = 0.886$), Knowledge Acquisition ($d = 0.855$), and Knowledge Creation ($d = 0.845$) are large. Knowledge Application ($d = 0.594$) demonstrated a medium-to-large effect size. Together, these results indicate a substantial practical gap in capability adoption, thereby supporting Hypothesis (H) for the present dataset.

5. Discussion and Conclusions

5.1 Discussion of Findings

This study offers an initial comparative analysis of GKM adoption between Chinese and European startups. The empirical results show a statistically significant difference in baseline capability profiles, with Chinese startups reporting consistently higher scores across all five sub-dimensions. These differences suggest that GKM adoption is highly context-dependent and should be interpreted with caution, as the present study observes baseline variances rather than testing a strict causal mechanism. Importantly, these findings introduce a necessary boundary condition, challenging prior literature that implicitly approaches GKM as a universally applicable set of best practices (Abbas and Sağsan, 2019; Nasir et al., 2024). Furthermore, by applying the MICOM procedure, the study provides sample-specific evidence that the multidimensional GKM scale can be robustly used for cross-cultural comparison, laying a foundation for future predictive modelling in global contexts (Henseler, Ringle and Sarstedt, 2016; Hair et al., 2019).

To interpret these regional divergences, Institutional Theory offers a valuable lens. One plausible explanation for the higher scores among Chinese startups is the presence of a strong, state-led support environment. China has heavily incentivised the green technology and digital sectors, creating a high-velocity ecosystem characterised by intensive coercive and mimetic isomorphic pressures that incentivise startups to signal green competence in order to access public subsidies and state-backed resources (DiMaggio and Powell, 1983; Marquis and Qian, 2014; Chen et al., 2018). In such an environment, startups may experience intense mimetic and competitive isomorphic pressures to aggressively deploy green knowledge and generate eco-innovations to capture state support and market share. Consequently, founders might be driven to prioritise higher-order dimensions, which is reflected in their peak absolute scores in Knowledge Application and Creation, perceiving them as immediate competitive advantages (Khan, Mehmood and Kwan, 2024).

By contrast, the lower scores reported by European startups may reflect a vastly different, compliance-oriented regulatory landscape. In Europe, stringent environmental compliance is deeply embedded in the market fabric, driven in large part by overarching regulatory frameworks such as the European Green Deal (Lamenta and Grzybowska, 2023). In such settings, foundational green knowledge routines are often treated as absolute regulatory baselines or essential "hygiene factors" rather than unique strategic assets. This hyper-regulated environment may foster a culture of rigorous, self-critical evaluation, leading European startups to adopt a more

conservative stance when rating their foundational capabilities (Bocken and Geradts, 2020; Baumüller and Sopp, 2022).

Additionally, these findings may also be influenced by cross-cultural response styles. Research on survey methodology has consistently documented that respondents in East Asian and emerging-market contexts tend toward more extreme positive responding on Likert-type scales, while Western European respondents typically exhibit a central-tendency bias that produces more moderate self-assessments (Harzing, 2006). This interpretive caveat adds necessary contextual depth to the descriptive survey data without overstating causality, and future research employing objective performance indicators would help disentangle genuine capability gaps from measurement artefacts.

5.2 Theoretical and Managerial Implications

As an empirical analysis, this study offers initial theoretical insight into the relationship between international entrepreneurship and GKM. By executing the MICOM procedure, the research provides sample-specific evidence for the cross-cultural comparability of the multidimensional GKM scale developed by Yu et al. (2022). The findings suggest that while baseline adoption levels differ, the underlying structure of green knowledge routines remains broadly similar across the two institutional settings. This provides a basis for future, more complex modelling in later work.

From a managerial perspective, these findings caution against a "one-size-fits-all" approach to sustainable digitalisation. For European managers and investors, the data suggests a need to support startups in building stronger digital knowledge storage infrastructures, as digital tools can help manage green knowledge more efficiently (Ulhaq et al., 2024). European policymakers may also encourage founders to move from a compliance-driven mindset towards more proactive innovation. For Chinese stakeholders, the uniformly high self-assessments may indicate a need for closer examination in future research so that genuine capability development can be distinguished from overly optimistic reporting.

5.3 Limitations and Future Research

While this study provides robust comparative insights, it is subject to three main limitations. First, concerning data collection, the reliance on cross-sectional, self-reported data introduces inherent biases, although these were effectively mitigated by the MICOM procedure and ex-ante procedural remedies. Second, at the theoretical measurement level, this study did not quantitatively capture specific macro-institutional variables, such as regional compliance indices or government subsidies. Third, regarding analytical depth, the current research scope is confined to a descriptive baseline exploration of capability differences rather than testing complex causal relationships.

Building upon this baseline exploration, future research should move beyond descriptive comparisons to examine the broader structural relationships between GKM routines and firm outcomes. Specifically, subsequent studies could investigate how these distinct knowledge dimensions influence actual sustainable performance. Furthermore, there is a clear avenue to explore complex mediating mechanisms and the moderating role of digital technologies, such as AI, in translating these regional capabilities into tangible ecological and financial results.

5.4 Conclusion

In conclusion, navigating the twin transition of digitalisation and sustainability requires a contextualised understanding of organisational capabilities. By mapping the multidimensional GKM landscape of 679 startups, this preliminary study shows that regional institutional forces are associated with different patterns of how green knowledge is acquired, stored, shared, applied, and created. Recognising these comparative differences is an early step toward building more context-sensitive sustainable enterprises in the global digital economy.

Acknowledgements

This work has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 101034319 and from the European Union - NextGenerationEU.

Ethics Declaration: No formal ethical approval was required. This study involved a standard, anonymous organisational-level survey of startup managers, without collecting sensitive personal data or involving vulnerable populations.

AI Declaration: AI tools were utilised solely for language refinement and proofreading. The author thoroughly reviewed all AI-assisted content and retains full responsibility for the manuscript's accuracy and originality.

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Organizational Unlearning in Angolan Ports: A Path Toward Digitalization and the Blue Economy

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Abstract: Studies on organizational unlearning show that, although researchers recognize its importance and research on the topic has increased substantially in recent years, significant gaps remain in the literature. Early research neglected its potential as an autonomous organizational capacity, and there is a scarcity of studies in critical infrastructure sectors, such as ports, while the African context remains virtually unexplored. In this regard, the present study analyzes the role of organizational unlearning as a critical factor in the digital transformation of Angolan ports, within the context of the blue economy. The research adopted a quantitative, descriptive, and correlational approach, based on a sample of 248 employees at different hierarchical levels in Angolan ports, who responded to a structured questionnaire. The data were analyzed using descriptive statistics, reliability and validity tests (Cronbach's alpha, AVE, and CR), Pearson's correlation, and linear regression models to test the proposed hypotheses. The empirical results reveal that organizational culture exerts a positive and statistically significant influence on organizational unlearning practices, confirming its role as the primary antecedent of this process.

Keywords: Organizational unlearning, Digitalization, Blue economy, Ports

1. Introduction

The growing complexity of organizational environments and the acceleration of digital transformation processes have required organizations to continuously adapt, learn, and renew their practices. In this context, the concept of organizational unlearning emerges as an essential mechanism for change and innovation, as it allows organizations to abandon obsolete routines, beliefs, and procedures, creating cognitive and operational space for new ways of operating (Becker, 2010; Tsang & Zahra, 2008).

Despite growing academic interest, the literature on organizational unlearning still has theoretical and empirical gaps and is heavily concentrated in European and Asian contexts, with scientific research on African contexts being scarce or even nonexistent.

Most studies treat unlearning as a preliminary stage of organizational learning, rather than as an autonomous strategic capability capable of supporting dig y transformation and organizational sustainability (Wang et al., 2023) and early case studies on unlearning described organizations that failed due to an inability to unlearn, without addressing cases in which organizations successfully unlearned (Sharma & Lenka, 2022). Furthermore, research on the topic remains concentrated in business and industrial contexts, with few studies applied to critical infrastructure sectors, such as the port sector, and virtually no analyses in African contexts.

In the port sector, the need for transformation is particularly urgent. Advances in digital technologies, the demand for logistical efficiency, and international pressures for environmental sustainability have driven the transition to the blue economy paradigm, which aims to balance economic growth with the preservation of marine ecosystems (World Bank, 2022).

Based on the theory of organizational change (Wang et al., 2023), this study presents organizational unlearning as a critical factor in the digital transformation of Angolan ports, within the broader context of the blue economy.

In light of the identified theoretical gaps, this study analyzes the role of organizational unlearning as a critical factor in the digital and sustainable transformation of Angolan ports, within the context of the blue economy.

Specifically, this study seeks to answer the following research question:

How does organizational unlearning influence digital transformation and the transition to the blue economy in Angolan ports, considering the mediating role of organizational culture?

2. Literature Review and Hypothesis Formulation

2.1 Organizational Unlearning

Previous studies define organizational unlearning as "the process of reducing or eliminating pre-existing knowledge or habits" (Akgün et al., 2002), a deliberate attempt to eliminate knowledge, beliefs, or routines (

Hedberg, 1981;), the intentional removal of established knowledge within an organization (Holan and Phillips, 2004), and the discarding of old routines to make way for new ones; (Tsang & Zhara, 2008), a key factor in the success of knowledge transfer (Yildz, 2010), a process that occurs at the individual level and then spreads to the organization as a whole (Wang et al., 2019), a conscious and intentional process of letting go, which does not necessarily imply the permanent destruction of what has been learned, but rather the choice not to use what is stored in memory (Kmieciak, 2020).

In an analysis of the existing literature on unlearning, one can find various concepts used to describe unlearning. In this article, we present it as "conscious elimination" and "intentional " of "beliefs," "routines," "values," "change in action," "unloading," "renunciation," and "discarding" as elements that interconnect them in the literature.

H1: Organizational unlearning practices positively influence digitalization and innovation in Angolan ports.

2.2 Unlearning and Organizational Culture

Empirical studies consider organizational culture to be one of the main drivers of knowledge management, organizational learning mechanisms, and corporate innovation, and have addressed these relationships (Leal-Rodríguez et al., 2019).

In this sense, creating an environment in which outdated and obsolete knowledge is regularly challenged and excluded from organizational memory becomes an imperative duty for organizations. (Chen et al., 2024).

H2: Organizational culture positively influences organizational unlearning practices.

2.3 Unlearning and Organizational Digitalization

Recent studies have deepened our understanding of the mechanisms through which unlearning contributes to organizational transformation. Cegarra-Navarro, Di Chiacchio, and Cubillas-Para (2024) demonstrate that regenerative unlearning enhances innovation performance in ecological processes through knowledge base management, while Cubillas-Para, Cegarra-Navarro, and Vătămănescu (2024) show that regenerative unlearning fosters digital transformation through collaboration with customers and organizational agility.

H3: Digitalization and innovation have a positive impact on the promotion of sustainable practices associated with the blue economy.

3. Method

The research adopted a quantitative, descriptive, and correlational approach, with the aim of empirically testing the proposed relationships between Organizational Unlearning Practices (OUP), Organizational Culture (OC), Digitalization and Innovation (DI), and the Blue Economy (BE).

The study population consists of employees at Angola's ports. Data were collected using a structured questionnaire, developed based on the constructs identified in the literature review and adapted to the Angolan port context. To improve the quality of the questionnaire and the data, the initial questionnaire was reviewed by a professor and three senior port officials to gather feedback before it was administered to the other employees. After incorporating the professor's comments and making further revisions, the final version of the questionnaire was created, explained to the employees who agreed to participate in the study, and subsequently distributed.

The sample was selected for convenience, covering different functional areas; the data collection instrument was a structured questionnaire using Likert-type scales.

The variables were organized into blocks reflecting the factors identified in the literature. The statistical analysis included reliability tests, factor analysis, and multiple regression.

The final sample consisted of 248 employees, spanning different hierarchical levels and functional areas.

Additionally, measures were taken to ensure the reliability of the data.

3.1 Construct Development and Reliability Analysis

Based on our formulated hypotheses, four constructs were defined, namely Organizational Unlearning Practices (OUP), Organizational Culture (OC), Digitalization and Innovation (DI), and Blue Economy (BE).

Given the exploratory nature of the study, a reliability analysis was conducted using Cronbach's alpha (α) to verify whether the items within the constructs exhibited internal consistency and were properly interrelated; the reliability of the instrument will be assessed using Cronbach's alpha (α), with values above 0.70 considered acceptable.

4. Results

Table 1: Reliability Test of the Constructs

Construct	No. of Items	Cronbach's alpha (α)	Factor Loadings (λ)	Composite Reliability (CR)	Average Variance Extracted (AVE)	√AVE
Organizational Unlearning Practices	5	0.759	0.68 – 0.84	0.86	0.58	0.76
Organizational Culture	5	0.737	0.65 – 0.81	0.83	0.56	0.75
Digitalization and Innovation	5	0.764	0.69 – 0.85	0.88	0.61	0.78
Blue Economy	5	0.711	0.63 – 0.80	0.82	0.55	0.74

To assess the internal consistency of the scales used in the questionnaire, a reliability test was conducted using Cronbach's alpha (α). The alpha (α) values presented in Table 1 indicate that all constructs demonstrate good reliability, as they are greater than 0.70, as recommended by (Hair et al., 2019).

The factor loadings (λ) range from 0.63 to 0.85, confirming that the indicators adequately represent their respective constructs. The composite reliabilities (CR) range from 0.82 to 0.88, exceeding the minimum threshold of 0.70 and indicating high internal reliability.

Table 2: Correlation matrix among the constructs

Correlations					
Constructs		**Mean_PDO**	**Mean _CO**	**Average_DI**	**Average_EAzul**
Organizational Unlearning Practices	Pearson Correlation	1	.149*	,094	,145*
	Sig. (2-tailed)		,019	,138	,022
	N	248	248	248	248
Organizational Culture	Pearson Correlation	.149*	1	.083	.461**
	Sig. (2-tailed)	,019		,191	<,001
	N	248	248	248	248
Digitalization and Innovation	Pearson Correlation	.094	.083	1	,122
	Sig. (2-tailed)	,138	,191		,055
	N	248	248	248	248
Blue Economy	Pearson Correlation	.145*	.461**	,122	1
	Sig. (2-tailed)	,022	<,001	0.055	
	N	248	248	248	248
*. Correlation is significant at the 0.05 level (two-tailed).					
**. Correlation is significant at the 0.01 level (two-tailed).					

Table 2 presents the Pearson correlation coefficients between the main constructs analyzed in the theoretical model.

All correlations are positive, suggesting conceptual coherence among the variables and the absence of multicollinearity issues.

Although of varying magnitudes, the observed relationships provide initial empirical support for the proposed model.

Overall, the results partially confirm the proposed theoretical model: Hypothesis H2 was statistically supported, highlighting the role of organizational culture as the primary antecedent of organizational unlearning, while Hypotheses H1 and H3 were not statistically supported, suggesting that the relationships between unlearning, digitalization, and the blue economy in Angolan ports still lack greater maturity and may depend on mediating factors. Nevertheless, the positive coefficients observed in all relationships suggest a trend consistent with the theoretical model, indicating that organizational culture and unlearning play a relevant, albeit still incipient, role in accelerating digital transformation and consolidating the transition to the blue economy in Angolan ports, in line with global sustainability and innovation goals in the maritime-port sector.

Table 3: Linear Regression Results (H1)

Hypothesis 1 – Linear Regression between Organizational Unlearning Practices and Digitalization

ANOVA[a]						
Model		**Sum of Squares**	**Df**	**Mean Square**	**F**	**Sig.**
1	Regression	1.103	1	1.103	2,216	,138[b]
	Residual	122,392	246	,498		
	Total	123,494	247			
a. Dependent Variable: Media_DI						
b. Predictors: (Constant), Media_PDO						

4.1 Hypothesis 1 Test

The first hypothesis (H1) proposed that organizational unlearning practices positively influence the level of digitalization and innovation in Angolan ports. To test this relationship, a linear regression was performed, considering the mean of unlearning practices (PDO) as the independent variable and the mean of digitalization and innovation (DI) as the dependent variable.

The model results indicated a correlation coefficient (R) of 0.094 and an R^2 of 0.009, revealing that the independent variable explains approximately 0.9% of the variation observed in digitalization and innovation. The F-value of 2.216 with $p = 0.138$ ($p > 0.05$) demonstrates that the model is not statistically significant at the 95% confidence level.

This result can be explained by the early stage of digital maturity among Angolan port organizations, which remain heavily rooted in bureaucratic routines and traditional operational practices. As noted by (Wang et al., 2023; Sharma & Lenka, 2022), unlearning is a gradual process that requires favorable organizational conditions—such as an innovative culture, digital leadership, and strategic knowledge management—for its effects to translate into concrete technological gains.

Table 4: Linear Regression Results (H2)

Hypothesis 2 – Linear Regression between Organizational Culture and Unlearning Practices

ANOVA[a]						
Model		**Sum of Squares**	**Df**	**Mean Square**	**F**	**Sig.**
1	Regression	2.628	1	2.628	5.582	.019[b]
	Residual	115,806	246	,471		
	Total	118,434	247			
a. Dependent Variable: Media_PDO						
b. Predictors: (Constant), Media_CO						

The second hypothesis (H2) proposed that organizational culture positively influences organizational unlearning practices in Angolan ports. To test this relationship, a linear regression was performed, with organizational culture (CO) as the independent variable and organizational unlearning practices (PDO) as the dependent variable.

The results show a correlation coefficient (R) of 0.149 and an R^2 of 0.022, indicating that organizational culture explains approximately 2.2% of the variance observed in organizational unlearning practices. The F-value of

5.582 with p = 0.019 (p < 0.05) confirms that the model is statistically significant, supporting the hypothesis that organizational culture exerts a positive and direct influence on organizational unlearning.

These results are consistent with the existing literature, according to which an organizational culture open to innovation, experimentation, and continuous learning encourages the abandonment of routines and obsolete beliefs, thereby stimulating the creation of new knowledge and practices (Büschgens et al., 2013; Leal-Rodríguez et al., 2019).

Therefore, the results empirically confirm Hypothesis H2, demonstrating that organizational culture is a determining factor in promoting organizational unlearning. This finding reinforces the importance of developing a culture of learning and critical reflection, which enables port organizations to abandon obsolete practices and adopt new operational approaches, thereby facilitating the transition to more digital and innovative management models.

Table 5: Results of the Linear Regression (H3)

Hypothesis 3 – Linear Regression between Digitalization, Innovation, and the Blue Economy

ANOVA[a]						
Model		**Sum of Squares**	**Df**	**Mean Square**	**F**	**Sig.**
1	Regression	1.681	1	1,681	3,706	,055[b]
	Residual	111,599	246	,454		
	Total	113,280	247			
a. Dependent Variable: Media_EAzul						
b. Predictors: (Constant), Media_DI						

4.2 Hypothesis 3 Test

The third hypothesis (H3) posits that port digitalization has a positive impact on the promotion of the blue economy in Angolan ports. To test this relationship, a linear regression was performed, considering digitalization and innovation (DI) as the independent variable and the blue economy (EA) as the dependent variable.

The model results indicated a correlation coefficient (R) of 0.122 and an R^2 of 0.015, meaning that digitalization explains approximately 1.5% of the variance observed in the blue economy. The F-value of 3.706 and p-value of 0.055 (p > 0.05) show that the model did not reach statistical significance at the 95% confidence level, although it exhibits a trend close to the conventional significance threshold.

5. Discussion

The empirical results partially confirm the proposed theoretical model, showing that organizational culture exerts a significant influence on organizational unlearning practices, while the relationships between unlearning and digitization (H1) and between digitization and the blue economy (H3) were not statistically significant.

These findings reveal that, in Angolan ports, digital transformation and the transition to a blue economy are still conditioned by cultural, structural, and technological maturity factors. The positive influence of organizational culture on unlearning confirms the literature that argues that cultures open to innovation, collaboration, and continuous learning are essential for eliminating obsolete practices and developing new organizational capabilities (Büschgens et al., 2013; Leal-Rodríguez et al., 2019), which identify organizational culture as one of the main facilitators of innovation, organizational learning, and knowledge management. Similarly, Chen et al. (2024) argue that organizations capable of continuously questioning established practices create environments more conducive to abandoning obsolete knowledge and incorporating new skills. This relationship indicates that culture is the main driver of cognitive and behavioral change necessary for organizational renewal.

On the other hand, the absence of statistical significance in hypotheses H1 and H3 does not allow us to confirm the direct relationships proposed in this linear regression model.

Thus, the results demonstrate that organizational culture emerges as the critical factor that sustains both the unlearning process and the adoption of technological innovations, configuring itself as the link between internal change and external sustainability objectives. This interpretation is reinforced by recent studies on regenerative unlearning (Cegarra-Navarro et al., 2024; Cubillas-Para et al., 2024), which suggest that the effects of unlearning on innovation and digital transformation tend to be mediated by organizational mechanisms such as knowledge

management, stakeholder collaboration, and organizational agility rather than manifesting through direct and linear relationships, which helps explain the lack of statistical significance found in hypotheses H1 and H3 of the present study.

6. Conclusions

This study analyzed the role of organizational unlearning as a critical factor in the digital transformation of Angolan ports, within the context of the blue economy, which in African port contexts is still limited and deeply conditioned by cultural and structural factors.

The empirical results obtained partially confirm the proposed model, highlighting that organizational culture constitutes the main antecedent of organizational unlearning, while the direct relationships between unlearning and digitalization (H1) and between digitalization and the blue economy (H3) did not prove to be statistically significant. Such results reveal that the digital and sustainable transformation process does not only depend on the introduction of technologies, but above all on the organizational capacity to review consolidated beliefs, routines and practices, in other words, to unlearn.

In theoretical terms, the study contributes to expanding the scope of literature by conceiving unlearning as an autonomous strategic capability, and not just as a by-product of organizational learning.

From an empirical point of view, the results reflect the initial stage of digital and institutional maturity of Angolan ports. The lack of statistical significance in some relationships does not confirm hypotheses H1 and H2, that is, digitalization has not yet been fully incorporated into organizational routines, which limits its direct impact on port sustainability and the blue economy. However, the positive coefficients observed suggest that there is an evolutionary trend, and that, as technological investments, public policies and training processes are consolidated, the effects of digitalization on sustainability may become more significant.

6.1 Areas for Future Research

Although this study has contributed to the advancement of the literature on organizational unlearning and port sustainability, certain limitations are acknowledged that open avenues for future research.

Future research may adopt structural equation modeling (SEM) to test indirect relationships between organizational culture, unlearning, digitalization, and sustainability, exploring the mediating role of culture and digital leadership.

We recommend conducting longitudinal studies to capture how unlearning and digitalization evolve over time, especially following the consolidation of *the Single Port Window (JUP)* and blue economy policies.

Comparisons with other African or Portuguese-speaking port contexts (such as Portugal, Mozambique, and Brazil) may offer a more comprehensive view of the cultural and institutional factors that facilitate or inhibit digital and sustainable transformation.

Acknowledgments

We express our gratitude to NECE—Center for Business Studies—for its institutional support and for the conditions it provided for the development of this work, noting that the academic and scientific environment fostered by the center contributes to the consolidation of academic discourse.

We also thank the anonymous reviewers for their constructive and helpful comments.

AI Statement: This paper was edited using ChatGPT 2025 software to improve the clarity of the text and language (since the author of the article is not a native English speaker), as well as to correct grammatical and spelling errors. I hereby declare that this software was not used at any time to create content for the research process. Its use was supervised and carefully reviewed by the author to ensure the accuracy and integrity of the information in this research. Furthermore, it should be noted that the article was reviewed after its completion using the international anti-plagiarism software Turnitin. We declare that we used it transparently, ethically, and responsibly, and we assume full responsibility for the final content. We emphasize that there is no conflict of interest on the part of any other parties involved.

Ethical Statement: We confirm that this article complies with the ethical principles of scientific research and is our own work. Whenever we consulted works published by third parties, these were clearly cited.

We declare that this work and any part thereof have not been previously submitted for any other purpose, whether for evaluation or otherwise.

We further confirm that we obtained informed consent from all individuals involved in the preparation of this article, in accordance with the institution's ethical guidelines;

We confirm that we followed the Code of Conduct for Integrity during the preparation of this manuscript.

Declaration of Conflict of Interest: We declare that there is no conflict of interest.

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Knowledge-based Analysis of Open Data

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Abstract: There is a shortage between the emerging availability of time stamped open data and the capacity of extents in the application sphere to turn it into a reliable source of knowledge without the help of data scientists. Time series now concern every aspect in our daily life, from environmental monitoring to music, or the telemetry of our actions on social media. This struggle of understanding the underlaying data behaviour deepens when considering the heterogeneity problem of the scattered series, that must be handled consistently to produce a reliable source of knowledge. The current approach proposes to target this bottleneck by generating a versatile and domain-neutral representation of data, containing statistics, designed to be consumed both by people (via a brief interaction) and by systems (via a standardized enriched structure). This method has the aim of converting tacit data into explicit artefacts, prioritizing time series knowledge representations. The paper will present a knowledge-based approach to time series interpretation, which takes a dataset from an open data source, without domain assumptions, transforms it into a common format, with semantic enrichment of metadata and includes analytical results. The open data are mapped onto a sub-part of the SemTS (Semantic Time Series) ontology, so that series characteristics can be stored and reused as knowledge artefacts. The final output is a knowledge specialized JSON, partitioned into insightful sections (e.g. dimensions, feature families), plus explanations in natural language, with the aim of reducing comprehension barriers for non-specialists and facilitating subsequent integration into knowledge management flows, like cataloguing, searching or comparing. The proposed format encompasses insights regarding the series, drawing a profile for the series that includes quality indications (e.g. missingness, gaps, outliers), trend patterns, seasonality (cyclicality). The contribution is a practical knowledge aspect for time series analysis, a tool to convert raw time-stamped open data into reusable knowledge artefacts, that could guide downstream decisions in the data discovery procedure. The intent is to assist with accessible diagnostics, rather than to replace analytical expert judgment.

Keywords: Knowledge-based data structure, Open data interoperability, Time series knowledge, Semantic enrichment, Insight extraction, Analytical results

1. Introduction

As a result of digital transformations, open data has changed its purpose, from a transparency initiative to a pillar of knowledge that drives decisions. However, this is not enough because, while the volume of available data continues to pile up, the insight gap between the raw data provided and the usable knowledge widens continuously. Open data sets capture the information into a rigidly syntactic form, without semantical context, sinking the underlaying knowledge (Damagatla and Bossi, 2025). The transition from the simple availability of data to the generation of meaningful value in society and economy remains an uneven process, marked by a divergence between the published information and the actual absorption capacity of the market, mainly caused by heterogeneity and lack of standardization (e.g. different formats, inconsistent metadata, unclear meaning) of data sources (Ortiz-de-Urbina-Criado, Abella and Garcia-Luna, 2023). Without processing, data remains in a stationary state, with no added value, insufficient to sustain complex decision-making. A major challenge in this fast-paced landscape is the need for uniformity of data infrastructure that should ensure not only accessibility, but also interoperability for integrated analytics (Davies et al, 2019).

In this state of constant data volume expansion, the knowledge management (KM) tools must go beyond the role of storing resources and step in, introducing active components that ensure the capacity to absorb data properly (Kamalruzaman, Mohd and Maaz, 2025). The limitations in the current landscape of temporal data management and the lack of widely used standardized models limit the reuse of data and reduces the fusion of results originated from different analytical methods (Moreira, 2024).

This paper seeks to spotlight and remedy aspects of these problems by offering an insight into how data can be transformed from an inert resource into a tool for knowledge sharing. It positions itself within the KM framework by addressing the representation of time series originating from public repositories, converting raw data into structural knowledge, emerging when the data is contextualized, interpreted and semantically organized. This paper is organized as follows: firstly, it positions the study within knowledge management and semantic analysis of open data; we draw the background section acknowledging the open data reuse and ontology-based approach used. Following, the third section frames the method, describing the current state of the research based, proposing a pipeline that turns open-source time series data into semantically structured knowledge. In

section 4, the solution is instantiated on a sustainability-oriented open dataset to assess its practical applicability. Finally, we conclude with a discussion of the empirical results that point the contribution of knowledge capturing, reuse and interoperable capabilities.

2. Background

Hahnel et al. (2026) report reflects a growing transition in the awareness of practicing the FAIR (findable, accessible, interoperable and reusable) guiding principles for scientific data management, that serve as a rulebook to data producers and publishers in their activity. There has been an increase rate of active users that use artificial intelligence (AI) for data processing, transitioning to advanced knowledge management practices.

A possible solution is the integration of an existing ontology into a tool for analysing open data, where the datasets constitute raw data that acquire informational value by structured contextualization and become knowledge when it is interpreted, enabling decision-making actions (Rowley, 2007). Although the open data processing is considered as a technical endeavour, there are premises to transform open data into organizational information and expose the knowledge through an ontology (Kawtar, Hind and Dalila, 2022).

The Semantic Time Series (SemTS) ontology was used in our approach to accommodate the need for semantic structuring of insight derived from multivariate time series studies, blending them with domain specific expertise (Grass et al, 2025). SemTS was conceived to identify and describe segments within time series, defined as specific data points or time intervals, each segment caring its own knowledge characteristics, associated to statistical features, anomalies, patters, etc. or priori information provided by experts in the field. In this ontology, the time series segment class extends classes from the DCAT (Data Catalog) vocabulary to allow segments to be part of other segments, providing a hierarchical structure that reflects the fractal nature of temporal data (Grass et al, 2024). DCAT conforms to RDF (Resource Description Framework) vocabulary that model data interchange on the web, representing the information as a graph.

By adopting the SemTS ontology, the tool proposed in the paper employs knowledge graphs (KG) to present the information in a more accessible manner for semantic searches or automatic reasoning in KM systems (Mohammad, Nachouki and Mohamed, 2025). KG represent more than a static database, but a way to model the expertise and structure of a specific subject, so that a machine can easily subtract the semantics behind the data, while maintain human readability (Grass et al, 2023). KG enable one to represent stored information as a dynamic interpretable knowledge ecosystem by AI systems, providing meaning understanding withing the ontological representation (Peng et al, 2023).

3. Knowledge-based Analysis

3.1 Method

The proposed method spirals around the idea that time series should not only be handled as tabular static structures, but also as resources that could be organized, described and reused, without losing their semantic structure, to achieve the knowledge level. Thus, we chose to explore the capabilities of SemTS ontology, which provides an applicable blueprint for representing time series, exploring their temporal segments, characterizing attributes and the information extracted from analysis. Based on this theory, the work aims to transform a standard time series representation into an explicit semantic form, compliant with SemTS.

To implement this approach for analysing open data, we developed a software tool that integrates the ontology guidelines and applies feature extraction methods into the data manipulation process. Afterwards, the tool was experimentally evaluated on a public dataset, exemplifying a possible solution to demonstrate the practical applicability of the tool and underline the leverage offered by the ontology in structuring knowledge artefacts.

Overall, this method is not limited to a simple conversion of a file from a format to another, but it defines a systematic process that transforms temporal data into semantic information objects enriched with analytical features. Looking from this perspective, the research contribution consists in the semantic formalization of a time series according to the SemTS ontology, whereas integrating a characterization component, with the purpose of representing data as a conglomerate of knowledge artifacts, organized into a knowledge graph. In this light, this approach responds to the need of data analysis, while also achieving the need for knowledge management, aiming for a reusable and interoperable representation.

The method follows the logic of the DIKW (data, information, knowledge, wisdom) hierarchy (Rowley, 2007) and goes through a gradual mechanism, emphasising different levels of processing. Data corresponds to the raw tabular contents without an explicit role, information reveals after establishing the semantics of the columns,

contextualizing the observations and knowledge emerges from the structure build on top of these observations, allowing reasoning.

3.2 Proposed Tool for Open Data Analysis

The data conversion and analysis tool is implemented as a Python CLI (Command-Line Interface) application that loads a time series from a tabular form and a set of running settings, and returns its representation accompanied by the derived analytical features, according to SemTS formalities. From a technical point of view, the tool is projected to process the data flow in sequential phases, from ingesting and formalizing the input presented as a CSV (Comma Separated Values) to generating a serialized graph response, in form of a JSON-LD (JavaScript Object Notation for Linked Data) and representing it as a knowledge graph. This structural approach translated the series data into a knowledge artefact, which can be interrogated or visualized into a hierarchical manner. In addition, the tool incapsulates an inspection mechanism that allows the visualization of the graph structure, so the user can easily understand the relationships between elements and their properties, facilitating a knowledge-oriented data exploration initiative.

To ensure the generality of the solution, while considering the particularities of the input datasets, the tool call is parametrized with a specific configuration to adapts the process to the data needs. The configuration sets key structures on the input data, as the entity identification field, the label field of the entity, the time field, the time interpretation option (the way to represent the time in a uniform manner), the encoding granularity of the records and the presence of the descriptive features resulted from the analysis.

To emphasize the analysis fact, besides the representation of the input data, the result integrates semantic knowledge extracted from numerical transformations over the data. The method integrated an analysis step based on features, inspired from the framework presented in Hyndman et al (2025), converting the series data points into knowledge measures that capture its behaviour. The features extracted using the *tsfeatures* Python package are organized into thematic families, targeting some aspect of the temporal dynamics of the data (such as statistical description – mean, median, variance; autocorrelation; etc.).

3.3 Data to Knowledge Flow

The tool follows a data-to-knowledge flow, in which raw data are semantically formalized and decorated with descriptive features of the time series, generating semantic knowledge objects. This approach supports the transfer of knowledge, because it contains the context information of the studied entity.

In our context, knowledge is defined as semantically structured information, that can be contextualized. The input table values are treated as data, becoming information when associated with the ontology element; knowledge surface when overviewing the whole representation. The time series knowledge is organized into a semantic infrastructure that allows further explorations (queries, comparisons, integrations with other knowledge flows).

Internally, the tool can be described as a sequence of specialized stages (Figure 1), organized as a semantic processing pipeline. Its architecture segregates data loading, structural role configuration, ontological representation according to SemTS, observation encoding, derived knowledge integration and result serialization, followed by visual representation as a knowledge graph.

Data ingestion. The time series is loaded along with the build configuration, and it is normalized so it can be processed uniformly, regardless of the source particularities. In this stage, the tool manages the missing values, based on the policy chosen by the user, either by omitting them or represent them explicitly.

Structural binding. The build configuration is applied to mark the columns that play the role of entity, label and time; the remaining columns are interpreted as series dimensions, supporting the construction of generic schema for semantic structuring.

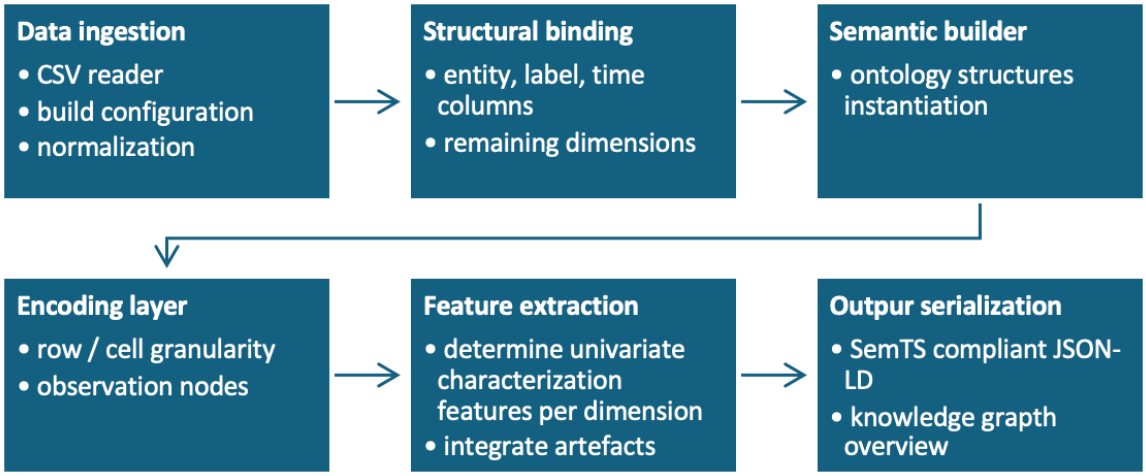


Figure 1: Data flow for knowledge-based analysis

Semantic builder. Based on the previous interpretation, the tool builds ontological structures for the main segment of the series, the temporal segments and the semantic dimensions, using SemTS classes and properties.

Encoding layer. The observations nodes are generated accordingly to the chosen granularity from the raw data and are bonded with the segments.

Feature extraction. If the analytics are enabled, the tool computes univariate features per dimension and integrates them as derived knowledge, along with their provenance.

Output serialization. The resulting structure is serialized as a JSON-LD, which could be auxiliary exported with a graphical representation.

3.4 Semantic Correspondences

The first step in the structuring process is assigning the analysis unit, the time series being decomposed into three structural components: entity, time, and dimensions, laying the support for all subsequent operations. The entity defines the central unit of observation, representing the element that is measured and holds the knowledge. Time constitutes an order reference of the observations and dimensions are the actual variables that characterize the entity at a time. Afterwards, these concepts are instantiated as class objects of SemTS ontology; the equivalence between the elements of the time series and the ontology representation is illustrated in Tabel 1. SemTS provides knowledge at the conceptual level, defining how time series data elements (segments, dimensions, values) can be semantically described.

Before any semantic formalization, the time is converted to a generic format according to the OWL-Time (Web Ontology Language). To ensure a deterministic behaviour of the output, under the same factors, there are defined stable IRIs (Internationalized Resource Identifiers) for the graph nodes.

The main challenge lies in organizing the process of the time series into a hierarchical configuration within the SemTS ontology. A segment (*semts: TimeSeriesSegment*) is defined as a basic unit that can represent either a complete series, a sub-period of it, or even a projection onto a single dimension, an aspect that spots the flexibility to use the class for different level of semantic granularity, different layer, but same meaning.

For each entity in the dataset, one creates a parent segment node, which serves as a container for the entire temporal history that is going to be connected to all dimensions (*semts: segmentDimension*) identified. This architectural approach allows multivariate structured series handling. Observations at a given moment are instantiated as sub-segments, connected to the main segment (via *semts: isPartOf*), and have attached their own temporal index (semts: segmentIndex), attached to a time node (*time: Instant*).

The encoding of the values originated from time series in the semantic graph holds a challenge related to the equilibrium between the expressivity of the output and the performance of the conversion. The tool proposes two strategies regarding the granularity of the result, each with its set of technical and analytical implications.

Table 1: Proposed time series data mapping to SemTS ontology

Input time series element	Proposed semantic role	SemTS correspondent semts: …	SemTS properties semts: …
Structural elements			
Complete series of an entity	Main segment of the series	*TimeSeriesSegment*	*title, segmentDimension, segmentIndex*
Time observation	Time segment of the series	*TimeSeriesSegment*	*isPartOf, segmentIndex, rowIndex, title*
Projection of the series on a single dimension	Segment on a dimension	*TimeSeriesSegment*	*isPartOf, segmentDimension, segmentKnowledge, title*
Analytical indicator / column	Series dimension	*DataDimension*	*title, dimensionPosition*
Relationship between full series and dimensions	Defining multivariate structure	Segment – dimension relationship	*segmentDimension*
Relationship between full series and time observations	Series hierarchy	Relationship between segments	*isPartOf*
Time associated with a segment	Semantic temporal index	Segment index	*segmentIndex*
Content elements			
The complete observation of a row (row granularity)	Knowledge attached to the temporal segment	*SegmentDataCharacteristic*	*segmentKnowledge, hasValue*
An individual value per dimension (cell granularity)	Knowledge point		
The compact value of the observation	Embedded value of the observation	*EmbeddedValue*	*valueString*
The associated individual value	Embedded value of the point		
Extracted features (mean, acf, entropy, trend, etc.)	Derived characteristics of the series	*SegmentDataCharacteristic*	*title, description, hasValue, knowledgeGenerationEntity*
Value of a feature	Embedded value of the feature	*EmbeddedValue*	*valueString*
Knowledge elements			
The complete set of features for a dimension	Main knowledge group	*KnowledgeGroup*	*segmentKnowledge, groupKnowledge, title*
Family of features (stats, acf, stl, etc.)	Thematic knowledge group	*KnowledgeGroup*	*groupKnowledge, title*
Feature calculation method	Methodological provenance	*KnowledgeGenerationMethod*	*title, description*
Relationship between feature and calculation method	Provenance relationship	Knowledge – method relationship	*knowledgeGenerationEntity*

The row granularity design attaches each temporal segment to a single knowledge node (*semts: SegmentDataCharacteristic),* which contains all dimensions in a JSON object serialized as a string (*valueString*); this is recommended for large datasets, since it maintains the cohesion of the observation for a time point, reducing the number of nodes in the graph. The cell granularity expands a segment, a knowledge node and a value node for each individual cell. Even though it offers semantic navigation, this is suitable for small datasets, since it generates extensive elements in the graph.

If the features option is enabled by configuration, the tool determines descriptive features for each dimension of the time series and adds them to the structure. The tool extracts the values over time for each dimension and forms a univariate series, on which one applies feature calculations. To integrate these results into the

representation, it first creates a semantic segment that represents the series projected on a single dimension, then knowledge nodes describing the features are attached to each segment. The structure is managed by *semts: KnowledgeGroup*, each individual feature being represented by *semts: SegmentDataCharacteristic*; the compute method is preserved by *semts: KnowledgeGenerationMethod*.

4. Case Study for Open Data Analysis

4.1 Dataset Preparation

The case study aims to illustrate how the flow projected within the proposed tool transforms a time series into a semantic structure focused on knowledge representation. The example gives a demonstrative instantiation of the ontological model with an explicit configuration, highlighting the use of the ontology classes, properties and the semantic relationships that results between the elements resulted from the formalization of the time series.

The dataset choice has focused on sustainability-related data provided by a recognized source; the search concluded with the finding of a dataset regarding the sustainable development goals (SDGs) from the United Nations (UN) organization. We considered this data suitable to KM analysis since SDGs are used internationally for reporting the state of the sustainability development efforts by each country, so it needs to be standardized to perform correct assessments of comparison and interpretation. Looking forward, this transformation of data into a knowledge-based format allows its visualisation as a graph and querying to identify behaviours in achieving sustainability goals.

From the full database – *SDR2025-data.xlsx* (Sachs et al, 2025), we explored a part of the *Backdated SDK Index* data (columns A to V). The records of each country appear as an annually observed entity, and each record corresponds to a temporal observation described by a set of dimensions. We selected a part of this data set (rows 3627 to 3651), i.e., the series regarding the evolution of the SDG indexes corresponding to Romania, each row representing an annual observation. Before feeding the data to the tool, we extracted the referred piece and converted it into a CSV with the structure presented in Table 2, along with the column's structural role.

Table 2: Input data structure, columns description and structural role in the ontology representation

Tabular columns	**id**	**country**	**year**	**indexreg**	**sdgi_s**	**goal1, …, goal17**
Description	Country code	Country name	Measurements time	Continent identifier	SDG index score	SDG measurements
Structural role	Entity identifier	Entity label	Temporal index	Series dimensions		

By passing this structure through the ontological tool, it gets reinterpreted as a semantic map and each component gain a certain role. Generally, for any time series, an entity identifier, a label and a temporal index are defined, and the remaining columns are handled as dimensions of the series.

Specifically, the tool performs a generic interpretation scheme with a custom user specification, and certain roles are established, guiding the tool how to interpret the initial structure. In this case, the build configuration (Figure 2) provides entity (*id*), label (*country*), time (*year*), granularity type and whether to include features; the remaining columns (*indexreg, sdgi_s, goal1 – goal17*) are interpreted according to a generic mapping rule, as analytical dimensions. The tool is not depended on fixed column names, but on structural roles that are configured or inferred according to a set of processing rules, so this logic could be reused.

```
config = BuildConfig(
    base_iri="https://example.org/kg/semts/sdr2025/",
    entity_col="id",
    label_col="Country",
    time_col="year",
    time_mode="year",
    granularity="row",
    omit_missing=True,
    include_features=True,
    feature_set="extended",
)
```

Figure 2: Example run build configuration

4.2 Results and Discussion

The entire series associated with Romania (Figure 3) is instantiated as a node of type *semts: TimeSeriesSegment*, representing the main segment of the model and functioning as an aggregation point for segments, dimensions and derived segments. For each temporal index (year, in this case), the tool creates a distinct time segment of the same class type, connected to the main node via *semts: isPartOf*, to express the hierarchy between the whole series and its time observations. Each time segment is indexed via semts: segmentIndex, pointing to an OWL-Time entity and it is indirectly controlled by the configuration (specification of the time index attribute column and the time mode).


```
{
  "@id": "https://example.org/kg/semts/sdr2025/segment/ROU-series",
  "@type": "semts:TimeSeriesSegment",
  "semts:title": "Time series for Romania (ROU)",
  "semts:segmentIndex": {
    "@id": "https://example.org/kg/semts/sdr2025/time/interval/ROU/2000-01-01T00-00-00Z__2025-01-01T00-00-00Z"
  },
  "semts:segmentDimension": [
    { "@id": "https://example.org/kg/semts/sdr2025/dimension/indexreg" },
    { "@id": "https://example.org/kg/semts/sdr2025/dimension/sdgi_s" },
    { "@id": "https://example.org/kg/semts/sdr2025/dimension/goal1" }
  ],
  "semts:segmentKnowledge": {
    "@id": "https://example.org/kg/semts/sdr2025/knowledge-group/series-metadata/ROU"
  }
}
```


Figure 3: Example output section representing the entity with some of the dimensions

The analytical indicators are converted into instances of *semts: DataDimension* class, i.e. each indicator is not only studied as a column name, but as a semantic dimension of the series. The link between the complete series and its dimensions is forged but the *semts: segmentDimension* property.

The annual observations encoded using row granularity strategy are exposed in Figure 4; this approach treat each temporal segment being assigned to a single knowledge node of type *semts: SegmentDataCharacteristic*, connected via *semts: segmentKnowledge* to its corresponding segment. This node holds the observation's values, expressed via *semts: hasValue* to a *semts: EmbeddedValue* and it stores them as a JSON object serialized in *semts: ValueString*.


```
{
  "@id": "ROU-t-2010-row10",
  "@type": "semts:TimeSeriesSegment",
  "semts:segmentKnowledge": {
    "@type": "semts:SegmentDataCharacteristic",
    "semts:hasValue": {
      "@type": "semts:EmbeddedValue",
      "semts:valueString": "{\"goal1\":\"77.279\",...}"
    }
  }
}
```

```
{
  "@id": "ROU-t-2000-row0-dim-goal1",
  "@type": "semts:TimeSeriesSegment",
  "semts:segmentDimension": { "@id": "goal1" },
  "semts:segmentKnowledge": {
    "@type": "semts:SegmentDataCharacteristic",
    "semts:hasValue": {
      "@type": "semts:EmbeddedValue",
      "semts:valueString": "77.279"
    }
  }
}
```


Figure 4: Compact section of an observation represented with row (left) / cell (right) granularity

In the cell granularity strategy (Figure 4), the temporal observation is no longer treated as a single compact package, but it is decomposed into individual values, each represented separately in the representation. Thus, each series dimension generates a distinct semantic unit associated with the time segment. A tabular record is represented by a semantic segment associated with a dimension via *semts: segmentDimension*, connected to the corresponding temporal segment and it receives a knowledge node of type *semts: SegmentDataCharacteristic*. The individual value is then attached via semts: hasValue to a *semts: EmbeddedValue* and the *semts: valueString* contains the explicit value.

Thus, one offers a descriptive analysis that is held in the same place with the original data, becoming a part of the same semantic structure, so the results mix both the time observations and derived features, facilitating unitarily reuse. The features sets characterize a univariate part of the series, creating a semantic segment that represents the projection of the complete series onto that dimension. A *semts: KnowledgeGroup* is attached and

the feature families are organized under, each representing a *semts: SegmentDataCharacteristic* and caring the determined value via *semts: EmbeddedValue* (Figure 5).



```
{
  "@id": "ROU-dim-goal1",
  "@type": "semts:TimeSeriesSegment",
  "semts:isPartOf": { "@id": "ROU-series" },
  "semts:segmentDimension": { "@id": "goal1" },
  "semts:segmentKnowledge": {
    "@id": "ROU-goal1-features",
    "@type": "semts:KnowledgeGroup",
    "semts:title": "Time series features",
    "semts:groupKnowledge": [
      { "@id": "ROU-goal1-stats" },
      { "@id": "ROU-goal1-acf" },
      { "@id": "ROU-goal1-entropy" },
      { "@id": "ROU-goal1-stl" },
      { "@id": "ROU-goal1-tests" }
    ]
  }
}
```

```
{
  "@id": "ROU-goal1-mean",
  "@type": "semts:SegmentDataCharacteristic",
  "semts:title": "mean",
  "semts:description": "Basic distributional statistic.",
  "semts:knowledgeGenerationEntity": {
    "@id": "feature-extraction-method",
    "@type": "semts:KnowledgeGenerationMethod",
    "semts:title": "Feature extraction tsfeatures"
  },
  "semts:hasValue": {
    "@id": "ROU-goal1-mean-value",
    "@type": "semts:EmbeddedValue",
    "semts:valueString": "94.008"
  }
}
```


Figure 5: Analytical features integration: feature organizing structure (left) and individual feature with value and provenance method (right)

In the expanded form of the representation, the features provide a wider set of feature families, capturing different properties of the time series. These derived properties are grouped into thematic groups, as follows: stats (statistics), acf (autocorrelation), entropy, frequency, heterogeneity, memory, pacf (partial autocorrelation), data shape, stl (seasonal and trend decomposition) and statistical tests, each bringing an analysis perspective. At the individual level, each family expands; there are basic groups, for example the statics family that carries descriptors such as: mean, median, distribution, missing or null values (Figure 6), but also time series analysis specifics, such as: entropy, seasonality or trend.

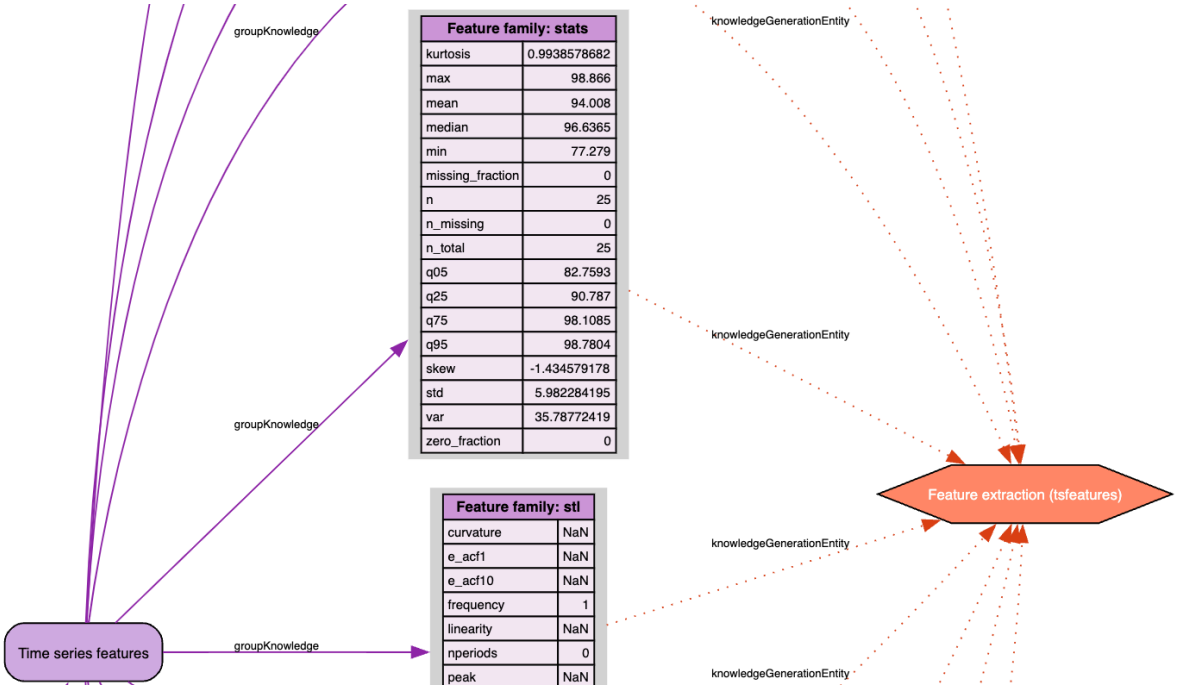


Figure 6: Visual representation of a part of a knowledge graph resulted from the time series analysis

Representing the time series in JSON-LD format allows the generation of a semantical knowledge graph, in which relationships between the entity, time segments, dimensions, observations and features are visually highlighted. This approach enables a visual manner to explore the structure of the encoded knowledge (Figure 6).

This logic is not specific to the example of time series chosen for the scope of this paper, and the tool is only instantiated with a custom configuration, according to the data columns. The same procedure could be applied

to any temporal dataset. In the resulting form, the time series is no longer just a collection of organized values, but it develops into a group of semantic artefacts in which data and derived knowledge reside together.

5. Conclusion

The proposed solution was designed to transform open time series provided as tabular representation into an enhanced form of semantic knowledge. The approach originates from the idea that simple public access to data is not enough to support knowledge distribution, but one needs an organized structure that preserves the relationships between observed entities, time indexes, measured dimensions and descriptive features derived from observations analysis. This linked structure approach allows attaching knowledge to data, meaning the analytical metadata to specify time intervals or dimensions.

The paper contribution includes a mapping process that iterates multiple steps: read and detect the structure of the input data, identify semantic meaning of the columns (entity, time, dimensions), standardize values, construct identifiers, model the series contents and its time segments according to the ontology specifications in a hierarchical structure. The ontology does not act as a vocabulary labelling unit, and it is conceived as a reproductible scheme for organizing the knowledge. SemTS was used as a conceptual scheme for representing the time series data, instantiating elements that give them meaning. By encoding observation, features and provenance into this schema, additional knowledge is then obtained by querying, comparing and visualizing the resulted semantic graph.

The paper included a case study based on open data for sustainability development and showed a fragment of the knowledge graph extracted from this analysis. This approach allows a universal form of representation, ready for integration. From a KM perspective, the specificity of the solution lays in the fact that it turns data into knowledge assets: knowledge objects (observations, derived characteristics and provenance) with defined relationships, which can be interrogated to gain knowledge insights. The solution urges to support KM concerns like knowledge organization and explanation, context preservation, addressing the availability open data insight.

Ethical Declaration: Ethical clearance was not required for the development of this research. The data analysis was conducted exclusively on publicly available online resources.

AI Declaration: AI assistance tools were used in the research process to enhance the search for suitable literature, to check grammar and spelling, and to review parts of the code.

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Belonging and Knowledge Articulation in Epistemically Fragile Communities of Practice

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Abstract: Organisations operate under conditions of social and technological acceleration, contested knowledge, and epistemic instability. Knowledge articulation is made difficult not only because knowledge is tacit but because the legitimacy of the knower is uncertain. This paper draws upon qualitative research conducted with two women-centered Communities of Practice (CoPs) showing how such spaces , were experienced by the women who participated in them less as formal, professional, knowledge-sharing communities and more as relational spaces for recognition, belonging and epistemic legitimacy. In particular, it reflects on how the spiritually-inflected relational practices of these CoPs enabled women community members to articulate knowledge and experience in ways that they generally found more difficult to do in other more formal settings in their organisations which were characterised by hierarchy, alienation and risk of testimonial injustice. This paper adds to KM scholarship through showing how relational recognition and spiritually-inflected belonging in these two CoPs created conditions in which knowledge became articulate.

Keywords: Communities of Practice, Epistemic fragility, Knowledge articulation, Relational field, Belonging, Post-truth organisations

1. Introduction

Alienation as a historical category has been understood as only arising with industrial capitalism and Marx's critique of labour (Marx, 2009). Yet, some contemporary theorists argue that late or technological capitalism has not overcome alienation but transformed it into other forms, such as acceleration, digitalization, performative labour , and fragmentation of social ties. (Illouz, 2007; Turkle, 2011).In these conditions alienation may be intensified by performance and visibility, rather than by mutual recognition.Digital culture, greater performance pressure, and longer periods of engagement with social media increase hyperconnectivity that is associated with emotional depletion, loneliness, and attenuated social connection (Turkle, 2011; Lawrence et al, 2024). As Turkle (2011) writes, while forms of connection may be increased, relational depth is not automatically increased. At the same time, organisational life is increasingly characterised by uncertainty, living costs have risen, economic conditions have become more volatile and institutional trust has diminished, contributing to a sense of anxiety and meaninglessness (Vervaeke, 2019; Yin and Mahrous, 2022; Mahand and Caldwell, 2023). Consequently, organisations are increasingly arenas in which meaning, recognition and legitimacy have to be negotiated amid uncertainty and mistrust (Neuburger et al., 2023; Winkler & Schoeneborn, 2025). Within this context Rosa (2019) shows that alienation in the workplace, has not gone way in the age of technological capitalism, but rather is an under-recognised reality of contemporary life. This paper explores whether Communities of Practice (CoPs) and, specifically, spiritually-inflected forms of relational engagement within CoPs are able to engender a sense of belonging and a discursive positioning of knowledge within the pervasive alienation and uncertainty that characterise many lives today (Block, 2008; Wenger, 1998; Frahm-Arp, 2014) .

Drawing on Fricker's (2007) account of epistemic injustice and Collins's (2000) account of Black feminist epistemology, this paper conceptualises epistemic fragility as a state of affairs where epistemic legitimacy for knowledge as well as for the knower is unstable, contingent, and contestable within a given organisational field. Drawing on these two CoPs, the paper argues that some women experienced spiritually-inflected relational practices as creating conditions of recognition, trust and legitimacy through which forms of knowledge, uncertainty and professional vulnerability which are otherwise inarticulable in organisational life became available. In this sense, the paper suggests that epistemic fragility may shape not only whether knowledge is shared but whether participants experience themselves as legitimate knowers capable of articulation in organisational contexts.The study found that some women experienced these CoPs as relational counterspaces in which organisational pressures, uncertainty, and vulnerability could be interpreted collectively.

2. Literature Review

Knowledge Management literature has long established that relational learning and social conditions affect the sharing of tacit or explicit knowledge (Polanyi, 1966; Nonaka & Takeuchi, 1995; Wenger, 1998; Bartol & Srivastava, 2002). In consideration of constructivist theories, KM scholars agree that knowledge is socially constructed, negotiated, and situated in concrete interaction and shared practice (Newell et al,2009). CoPs were interpreted as relational sites of learning, participation, and knowledge creation and sharing through shared practice rather than through hierarchical relations (Wenger, 1998). The KM literatures also recognized that tacit knowledge has a certain degree of "stickiness", making it difficult to be articulated and transferred (Szulanski, 2000), and that knowledge sharing depends on trust, reciprocity, and the organisational context (Newell et al., 2009, Wang and Noe, 2010). In contrast to Wenger's (1998) definition of CoPs as groups that share practice and identify themselves through their participation in this practice, the data of the present study suggest that the contribution CoPs can make in epistemically fragile organisational environments may lie less in knowledge sharing per se, but rather in their capacity to provide relational space for individuals to articulate their acquired knowledge through recognition.

Turning to the specific context of African women professionals, there is very little research into how these individuals navigate alienation in their organisations. Rudo Gaidzanwa's study of tearooms as counterspaces at the University of Zimbabwe demonstrates how women overcome racial and gendered alienation. She notes that "in the absence of significant material rewards and remuneration for their intellectual labour, they create meaning and support each other through their voluntary association" (Gaidzanwa, 2007 p.78). In this sense, CoPs may operate as voluntary or semi-voluntary bounded groups through which knowledge, meaning, and identity are collectively explored outside of the organisational structures of control.

In organisational literature, workplace spirituality has been framed as a remedy for alienation, fragmentation, and meaninglessness (Ashmos and Duchon, 2000; Fry, 2003; Giacalone and Jurkiewicz, 2003). In North American and European settings, workplaces perceived as spiritually meaningful have also been linked to trust, connectedness, ethical engagement in organisations, employee wellbeing, and knowledge-sharing (Milliman, Czaplewski and Ferguson, 2003; Padgett, 2008; Khasawneh, 2011). Ashmos and Duchon defined workplace spirituality as "an inner life that nourishes and is nourished by meaningful work in the context of community" (Ashmos and Duchon, 2000, p. 134).Some researchers have critiqued workplace spirituality as also being vulnerable to instrumentalisation, when spirituality, mindfulness and contemplative practices are detached from their ethical and transcendent foundations, and applied to aims of organisational resilience, productivity, or self-management (Purser, 2018, Ihl et al., 2022). This literature remains conceptually contested, with spirituality understood variably as an inner life, ethical conduct, expression of religion, or manifestation of secular well-being intervention (Krishnakumar & Neck, 2002, Eginli, 2017).

Internationally, studies on workplace spirituality have focused on meaning, inner life, community, values, wellbeing, ethics, leadership, organisational commitment, and knowledge-related behaviours. (Ashmos and Duchon, 2000, Krishnakumar & Neck, 2002, Fry, 2003, Giacalone and Jurkiewicz, 2003, Milliman, Czaplewski and Ferguson, 2003, Kinjerski and Skrypnek, 2004, Karakas, 2010, Eginli, 2017). Little is known, however, about the role of spirituality in South African workplace settings, especially concerning women's experiences of professional CoPs.South African scholars have examined religion, particularly Pentecostalism, and its impact on professional women, but there is no research on spirituality in South African corporate CoPs for women professionals specifically (Frahm-Arp, 2010, Frahm-Arp, 2014).

3. Methodology

The data presented in this paper is part of the qualitative research project which investigated two Communities of Practice (CoPs) as potential relational sites of resonance, belonging, and spirituality in professional contexts: the Women in Technology Community of Practice (WITCP) and an Enneagram Community of Practice (ECP).The WITCP is for women who are employed in technology occupations at a large company. The ECP members are employed or self-employed people, mostly women, working in a range of fields and professions. Both CoPs are predominantly online groups. For this study two rounds of semi-structured open-ended online interviews with 15 WITCP members and 8 ECP members (interview total of 30 for WITCP and 14 for ECP) were conducted. Additionally, 12 WITCPs and 8 ECPs sessions were observed. This paper only draws upon WITCP and ECP members who describe CoPs as a valuable or useful way of engaging in organisational life. Pseudonyms have been used throughout.Not every participant found the experience to be safe or affirming, with some describing discomfort with spiritual openness and vulnerability, and some noting the persistence of organisational

hierarchy. Thus, epistemic repair can be seen as not necessarily a function of CoPs as such, but rather contingent on participants being able to navigate vulnerability, trust, hierarchy, and relational acknowledgement within CoPs.

Social constructivism and hermeneutic phenomenology were used as philosophical perspectives for the research Hermeneutic phenomenology was considered appropriate for the study to explore how participants made sense of their lived experiences of belongingness, alienation, spirituality, and articulation of knowledge in organisational contexts. (Churchill and Bly, 1999). The study was interested in the meaning-making involved by CoP participants regarding their participation and the way this informed perceived recognition, legitimacy and relationality. Feminist epistemology was the underlying epistemological basis for the selection of both the sampling and the interpretive and analytical frames for the research, as well as for consideration of voice, legitimacy and power in organisational knowledge practices.

As with any hermeneutic phenomenology, the goal was not about objectivity or universalisable claims, but about interpreting what participants said in terms of their understanding and accounts of their lived experiences in particular organisational and relational contexts. The interviews were interpreted as interpretive encounters through which meaning was articulated, and sometimes newly recognised. Themes of belonging, legitimacy, spirituality, alienation, and articulating knowledge emerged through an iterative process of analysis and considering how participants narrated and made sense of their lived experiences in relation to their organisational and relational contexts.

4. Findings

The initial assumption was that WITC would be performative and inauthentic because it is mono-organisational with leaders from the organisation included in the group. The founders of both CoPs indicated that the groups' value lay primarily in teaching and learning, with the WITCP offering additional strategic retention benefits for the corporation. Against this backdrop of formal intent, the actual data were surprising.

As members joined the online fora, both CoPs used centring language, encouraging presence and embodiment, such as: "Let's become aware of our bodies in the room" (Thandi, 28 Jan 2026). This emerged as a normative opening ritual for both groups and a means of delineating the space for the gathering. Collins (2000) characterises alternative sites of knowledge as sites of resistance and collective sanctuaries for knowledge production. However, a shift in focus occurred as the prevalence and depth of discussions regarding spirituality became noticeable. Specifically, members' consistent engagement in spiritual discourse, including prayers, songs of worship, meditation, centring silence, and the spiritual reading of texts and poetry, extended beyond the groups' initial framing as knowledge-sharing communities.

During gatherings, members of both CoPs engaged with one another outside their designated identities and hierarchies. One member said: "In that space I am not my job title, I can actually show up as who I am" (Naledi, 22 September 2025). Within the WITCP group, the absence of explicit hierarchy allowed a diverse membership, from executive leaders to staff members who have newly joined the organisation, to engage in mutual recognition and personal disclosure. Participants discussed their identities, spiritual encounters and insights, and the erosion of women's sense of competence in the workplace. Ayanda observed: "We talk about being women in tech, women at home, women in the wider community, and it feels like we bring our home communities in with us at some level. They are listening too because we are all women being women" (12 September 2025). In the ECP community, women's experiences and challenges also foregrounded many conversations: "We need to dig so deep to survive as women, with debt, work and global financial instability. This space brings us grace" (Yumna, 20 February 2026).

These results suggest that spirituality in the case of these CoPs worked as a site for the negotiation of recognition, vulnerability, legitimacy, and belonging. The spiritual discourse created spaces within the CoP that allowed participants to make available to each other experiential forms of knowledge sometimes rendered inexpressible in performance-based, testimonial risk environments. On the other hand, some people spoke of the discomfort produced by the vulnerability of these spiritually-inflected forms of openness. Several participants reported that they remained quiet, and/or that the spaces in which they found themselves were emotionally unsafe or too exposing, and described these factors as contributing to their dropping out of the CoPs. This reinforces the argument that epistemic repair in CoPs is contingent, uneven, and relationally negotiated.

WITCP members reported that structured opportunities for discussing technical knowledge often took place outside WITCP meetings, and requests for knowledge assistance were shifted to one-to-one meetings. As

Kgomotso (12 September 2025) explained, "There is freedom to ask for help because it's based on a connection that won't judge. Asking a non-CoP colleague for help might be humiliating because not knowing is frowned upon in specialist circles". Within the ECP members said that they stayed quiet when they did not know about the topic “It often goes over my head, so I just listen ” (Lindiwe 15 September 2025). Coaching and knowledge articulation occur outside of community meeting times, however, in the weekly CoP, teaching in a more formalised manner also occurs.

These findings suggest that the formal CoP gatherings establish trust, recognition and legitimacy that enable participants to take the risk of reaching out for help, expressing uncertainty and negotiating forms of tacit or vulnerable knowledge in more private relational spaces. Thus, in this sense, it appears that knowledge articulation depended less on formalised knowledge-sharing mechanisms and more on participants' confidence that they would not be exposed, diminished, shamed or otherwise professionally degraded for being not knowing.

The members of both CoPs sought validation that they were not alone in experiencing exclusion, inadequacy or diminished professional standing within organisational life. Participants repeatedly used the phrase "is it just me or.." (Quinette, 22 October 2025; Zanele, 3 November 2025; Carol, 27 November 2025; Stephanie, 7 February 2026) to preface their descriptions of being ignored, weakened, excluded or made to feel professionally deficient. Participants also reflected on identity beyond their formal roles and titles, sharing fatigue with performance expectations and challenges with workplace hierarchies. The findings therefore suggest that these CoPs enable participants to narrate, and legitimate their own experiences collectively.

For WITCP members, a key concern was how to succeed in a male-dominated technology environment, with Iris (6 March 2026) noting: “I have noticed if I don’t get a man’s sponsorship for an idea it won’t go anywhere”. The challenges introduced by members during gatherings were rarely technical in nature. Instead, they focused on identity, shared reflection, and meaning-making. Examples included navigating social exclusion from informal organisational decision-making sites, such as “Padel” matches (Wilma, 4 December 2025), and the difficulty of gaining professional recognition from supervisors who might categorise working mothers into a “mom-box” (Nolwazi, 9 January 2026).

More than half the respondents in both CoPs used spiritual framing to describe their participation, viewing it as a personal journey alongside peers they trusted and respected both personally and professionally. For these women, the CoP was a refuge against workplace alienation. Zanele asserted that the space provided “deep nourishment” for her spiritual path (3 November 2025). Stephanie further highlighted this reorientation of identity, noting: “I get my priorities reordered, and remember I am a child of God, not an employee” (7 February 2026). Sally described the community as a space of “transformation”, where members feel “unashamed to speak” and thus are able to share their lives with one another at a “deeper, more personal” level (12 September 2025).

Participants referred to the CoPs as spaces in which they felt able to speak more openly about exhaustion, inadequacy, work pressures, structural inequity, and organisational alienation. Sally described the community as a space of "transformation" in which members felt "unashamed to speak" and were therefore able to engage one another at a "deeper, more personal" level (12 September 2025). These consisted of confession, sensemaking, and emotional repair, as well as addressing overwork, worthlessness, organisational mismatch and exclusion based on gender. Data from this analysis shows how the collective forms of practice could not only be therapeutic disclosure but also a form of collective recognition and legitimation of experiences related to the organisational conditions.

Kgomotso framed the gatherings as experiences of "holding holy knowledge together" (12 September 2025), suggesting a movement away from highly individualised understandings of knowledge toward relational and spiritually-inflected forms of knowing. She explained: "We pray together, we cry together and we remember who we really are unbelittled by the voice of the organisation." Others said they felt a sense of "being seen and heard" (Ray, 12 September 2025). They felt this was a space in which they were less interrupted and/or shown more respect than in the organisation (Quinette, 22 October 2025). Nothanda explained that she could feel like shea real person not just an entity that gets paid: "I can feel like I am me, in all that I am, not just the me on the payroll" (2 February 2026).

These findings suggest that the CoPs eased epistemic recognition through which participants experienced themselves as legitimate knowers who were able to articulate experiences of difficult topics often disguised, or suppressed in organisational life. Spirituality appeared less as doctrine than as a shared interpretive framework

by which participants understood their experiences of stress, exclusion, precarity and uncertainty. In contrast, participants reported openness within the CoP context. As Kgomotso put it, "I can't say to my boss, I have too much work, I have to say how excited I am to take on new work, otherwise I will get branded" (12 September 2025).Yet in the CoP she felt she could actually express how overwhelming her work load was.

Some participants expressed discomfort with the level of vulnerability and religiosity of the WITCP group. Julia said, "It's difficult when you've shared something personal, and then you have to sit in a performance meeting with that same person. She decides my increase, and she is my boss, and I can't turn that off" (3 February 2026) Palesa said, "I like to watch and listen, but when they start to criticise the organisation, I become anxious" (5 December 2025). There were also concerns to do with authority, legitimacy, and spirituality in the ECP. Some participants expressed discomfort with performative modes of spiritual knowledge-sharing and with members' attempts to position themselves as having greater spiritual knowledge or access to "truth" (Joan 20 March 2026). These dynamics produced new hierarchies of authority within the group that counteracted the CoP's potential to produce an unqualified space of epistemic openness.

These findings suggest that the value of these CoPs may lie in the relational/spiritual conditions in which participants are epistemically recognised, and able to articulate forms of knowledge and experience otherwise silenced in organisational life. They also indicate that tacit knowledge may be resistant to articulation not only because it resists codification, but also because articulating that knowledge in organisational contexts is a risky professional act. However, due to social hierarchies and varying abilities to embrace the CoP conditions, not all participants were able to integrate the relational dimensions of the CoPs.

5. Discussion

Knowledge Management researchers have suggested that sharing tacit and explicit knowledge usually requires contextually appropriate social conditions (Nonaka & Takeuchi, 1995, Polanyi, 1967). In a similar sense, knowledge articulation could result from participation in a shared practice (Wenger, 1998), although it does not automatically result in knowledge sharing or transfer (Bolisani & Scarso, 2014). While Polanyi's (1967) writing on tacit knowledge goes towards an explanation of why some forms of knowing are intractable to formal and explicit articulation, the current study's findings regarding epistemic and relational conditions indicate that participants in this study did not feel themselves to be legitimate knowers who can speak freely about their knowing and experience in the context of organisational life as employees or as consultants in organisations. In this sense, the findings complicate KM approaches that treat knowledge articulation mainly as a matter of codification, transfer, or practice-sharing.

The findings suggest that in certain contexts, spirituality may be a catalyst for creating these relational conditions. Within the WITCP and ECP, a willingness to share "messiness" and uncertainty emerged as a possible indicator of psychological safety that bypasses some formal hierarchies. This suggests that the relational field may be more than a backdrop for shared practice; it may be a mechanism for "epistemic repair". By "holding holy knowledge together", some members co-created a counterspace where the legitimacy of the knower could be restored, moving beyond the professional reciprocity described by Bartol & Srivastava (2002) toward a more spiritualised alignment.

Consequently, the role of the CoP in these contexts may shift from a functional tool for efficiency toward a site of ontological security. By providing a spiritualised form of trust, these communities may allow participants to navigate aspects of organisational life with less fear of being "branded" or diminished. In this context, spirituality appears to be a constitutive element that potentially allows the knower to re-emerge and contribute to the collective knowledge repository.

The re-emergence of the knower may be particularly relevant in contemporary organisational contexts characterised by competing knowledge claims and the accelerating technology and compressed temporality described by Rosa (2019). These conditions, often associated with the instability of beliefs in a "post-truth" era (Keyes, 2004), can create a context in which the legitimacy of both the knower and the knowledge is contested. In such environments, automated systems, metrics, and performance dashboards may be prioritised over individual interiority and meaning-making. Spiritually sustaining CoPs can foster belonging and recognition, enabling individuals to articulate experiences and engage in active epistemic participation. However, these communities are not without their own challenges. They may also contain mechanisms that exclude or block accessibility, thereby potentially manifesting internal forms of alienation.

The findings may be further interpreted through Biesta's (2010) distinction between qualification, socialisation, and subjectification. While CoPs are typically associated with qualification, the development of specific

knowledge and skills, the interactions observed in this study appear to align more closely with processes of subjectification. Within these spiritualised exchanges, some participants may experience themselves as recognised agentic subjects, capable of speaking and acting within and beyond their organisational roles (Biesta, 2010). Fisher (2009) similarly argues that contemporary organisational systems can create conditions that narrow expression, potentially limiting their capacity to engage with alternative ways of being and knowing. These CoPs, therefore, appear to offer a space where alternate epistemic approaches can be experienced. However, this perspective does not fully account for the complexities of epistemic injustice, which may persist despite these relational shifts.

Fricker (2007) characterises epistemic injustice as a form of injustice which weakens a person's capacity as a knower in the world. This research has found that women in this study have said they work in organisations where their knowledge was ignored, interrupted, or weakened relative to male colleagues. In addition, one outcome of the presence of epistemic injustice may be that it becomes difficult for members to give testimony, knowledge claims are silenced or are made difficult to articulate. For this reason, testimony in the CoPs may have been an important mechanism through which re-interpretation of subdued experiences helped in undoing the loss of trust in the group as an epistemic agent. The findings contribute to extending Fricker's theory of epistemic injustice by suggesting that epistemic repair may be achieved interpersonally through recognition and collective testimony rather than through formal corrections of under-representations of credibility.Fricker’s distinction between testimonial and hermeneutical injustice provides a clear conceptual analysis of the organisational credibility deficits articulated by the participants.

The difficulties participants had in re-legitimising themselves as knowers may be understood as an application of Collins' (2000) thesis regarding women as marginalised actors in epistemic practices, pointing to the tendency for women to be subject to heightened scrutiny, distrust, and rejection, leading to a reluctance to share even explicitly shareable knowledge due to social and professional costs. Collins' (2000) assertion that marginalised women constantly negotiate whether their knowership is legitimate is echoed in participants' expectations of being interrupted, belittled, excluded, or sullied due to providing alternative meanings within their organisations.

The data suggests epistemic fragility, where power and hierarchy undermine women’s knowledge in contested spaces. For many participants, and particularly Black women in South Africa, this reflects a broader historical continuity. As Ndlovu-Gatsheni (2013) and de Sousa Santos (2015) suggest, a post-apartheid context still rooted in coloniality often continues to assign status to certain forms of knowing while marginalising others. This study illustrates how these dynamics are often reproduced within the organisation, as members frequently had to negotiate the specific conditions under which they felt able to speak. Epistemic fragility within organisations is likely to be layered across the historical context rather than simply being an effect of being within the organisation.

The role of spirituality in these CoPs might also be understood in light of what Frahm-Arp (2014) observed in the South African context, namely, that the sacred often "finds its way into many corners of everyday life" (p.7), even in normally secular spaces. The findings suggest that spirituality in CoPs also acted as a relational and interpretive resource through which participants made sense of exclusion, precarity, exhaustion and organisational precarity. In this respect the findings support Fricker's (2007) argument regarding the centrality of the invalidation of knowers' credibility to epistemic injustice, and this study suggests that collective testimony and mutual recognition in CoPs are ways in which partial forms of epistemic repair are practiced. These results suggest that the repair was contingent, incomplete and distributed unevenly across the sample.

According to Taylor (2007, pp.31), the modern world is an "immanent frame": a world in which organisational and social life has to be effective and meaningful in its own right, without any reference to transcendence. This poses a challenge in the South African context. The participants did not bracket religion or spirituality in relation to work, the practice, or their peers. Spirituality was not peripheral to organisational participation in these CoPs. It was constitutive of how the workplace generates meaning as well as legitimacy and articulation. The workplace, in the South Africa context at least, is for many a context where spirituality informs the way they self-conceive and how they engage with their work, consistent with spirituality as a lived and enacted dimension of professional practice (Frahm-Arp, 2014) .

These findings suggest that when the relational field is interpreted as a spiritualised space, it may provide the necessary conditions for individuals to navigate the constraints of contemporary organisations and potentially engage in a process of epistemic repair. This study, therefore, contributes to KM literature on factors that

influence the effectiveness of CoPs by indicating the importance of relational and epistemic dimensions through which members consider themselves as legitimate knowers who can articulate their knowledge.

6. Conclusion

These CoPs were formally established as spaces of professional learning, and participants' storytelling, spirituality, and sense-making were part of how they made sense of their experience of organisational life. It was through these practices that some women were able to articulate and share their experiences of alienation, exclusion, and uncertainty.

This paper argues that while the CoPs in this study are sites of knowledge sharing, they are also sites where epistemic legitimacy is negotiated and sometimes even partially remade. It conceptualises these conditions as epistemic fragility, the condition where the legitimacy of both the knower and the knowledge they hold is contingent upon relations of power, recognition and context. In this sense, the findings suggest that relational, affective and epistemic conditions may shape the way tacit knowledge is articulable within organisational contexts. The study contributes to KM literature by articulating that knowledge-sharing can be (re)produced not only as a technical or procedural phenomenon but as a relational capacity premised on legitimacy, belonging and interpretive trust. Across both CoPs, spirituality is a relational resource some participants draw upon to negotiate these relations of legitimacy, belonging and interpretive trust.For some CoP participants, spirituality functions as a relational resource that enables them to repair some of the epistemic damage they have experienced at work and to some extent enhance their ability in knowledge production, consumption and creation.

Ethics Declaration: This study received ethical clearance from the Faculty of Humanities Research Ethics Committee (FREC) at the University of Johannesburg on the 6th of September 2025. All research activities were conducted in accordance with the ethical guidelines and requirements stipulated by the committee.

AI Declaration: AI tools were used for language refinement, structural organisation, and clarity of expression. All substantive components of the work, including the research design, empirical data, analytical processes, theoretical framing, and conclusions, are the original intellectual work of the authors. The authors retain full responsibility for the accuracy, integrity, and originality of the content.

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A Taxonomy and Reference Architecture for AI-enabled Industrial Knowledge Management

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Abstract: Much of the knowledge that keeps an industrial operation running is never written down: it sits with individual employees, scattered across incompatible systems, and cannot be found in time—a risk that becomes acute whenever people change roles or retire. Artificial intelligence (AI) is widely proposed as a remedy, but existing approaches concentrate on documentary, white-collar work; embodied, blue-collar work is comparatively underserved, particularly by large language models with no native grounding in physical activity. Existing work also treats AI as a single undifferentiated capability, leaving practitioners without a principled basis for choosing among technologies or integrating their outputs. This paper proposes a taxonomy of five AI paradigms (perceptive, dialogic, interpretive, structural and contextual), each defined by its contribution to one of three knowledge processes (capture, structuring, transfer) and by the type of work it serves, with a boundary marked where collective tacit knowledge resists codification. A separate orchestration layer, realised by autonomous agents and enabling technologies (knowledge graphs, retrieval-augmented generation, augmented reality), connects the paradigms into a pipeline. Applied diagnostically to three tools in one manufacturer's training programme, an assembly-guidance system, a structured interview system, and a RAG-based conversational assistant, the taxonomy shows all three occupy the capture or transfer columns while structuring goes unserved, leaving each tool's knowledge inaccessible to the others. A pump-assembly scenario shows how an agent-orchestrated pipeline over a shared knowledge graph, with human validation, could unify their outputs. The tools' reported gains, a 29 per cent onboarding-time reduction and an over 90 per cent retrieval-time reduction for 3,000+ daily users, are taken at face value; whether integration compounds them, and for whom, is a working hypothesis, not a demonstrated result. The paper concludes with a staged evaluation strategy measuring cross-tool retrieval coverage and validation throughput to isolate the structural layer's impact.

Keywords: Knowledge management, Knowledge transfer, Human-centred AI, Industrial AI, Reference architecture

1. Introduction

Industrial organisations depend on knowledge that is unevenly distributed and difficult to retain. A large share is never documented: it resides with individual employees and cannot be found quickly enough when needed. The risk spikes whenever a role changes hands or an employee retires, acute enough that ISO 9001:2015 obliges organisations to identify and retain the knowledge needed to operate their processes (Sumbal et al., 2017), while in German manufacturing the demographic transition has moved the problem from forecast to present concern (Ottersböck, Dander and Stowasser, 2026). Production-worker and manager departures damage performance through different mechanisms (Eckardt, Skaggs and Youndt, 2014); retention must therefore attend to both the type of work and the specific role.

A further share is nominally documented (work instructions, procedures, ticket systems) but scattered across incompatible systems, so locating the right version in time is itself the problem, and outdated content propagates into errors, the administrative counterpart of the searching-and-waiting waste that lean production systems target (Verein Deutscher Ingenieure, 2012). Capturing knowledge before it is lost, structuring it so it remains usable, and delivering it to those who need it are central industrial challenges; retention practice nonetheless remains inconsistent (Sumbal et al., 2017).

AI is widely proposed to address these tasks (Jarrahi et al., 2023; He and Burger-Helmchen, 2025; Olan et al., 2022; Dommermuth, 2026). Two difficulties follow. First, a coverage bias: approaches concentrate on indirect, white-collar work—not because manual work lacks judgement (assembly and maintenance require diagnosis and improvisation) but because the dominant paradigm of the last decade, the LLM, has no native grounding in physical activity. Purpose-built worker-guidance and AR systems do exist, but even where deployed their outputs are rarely organised into a form other tools can reuse. Second, an absence of shared classification: each technology is described in its own terms, with no basis for deciding which fits which task or worker. Recent skill-management work confirms that integrating individually successful AI pilots into a unified, agent-orchestrated platform with worker-differentiated delivery remains an open research problem (Dommermuth, 2026).

This paper contributes: a taxonomy of five AI paradigms with a separate orchestration layer distinguishing AI from the enabling technologies it employs (Section 3); a diagnostic application to three deployed tools that

identifies a systematic gap in structuring (Section 4); and an agent-orchestrated reference architecture resolving the gap by design (Section 5), while stating plainly that its integration benefit is a hypothesis to be tested, not an established finding (Section 6).

2. Background and Related Work

2.1 The Knowledge-loss Problem, and its Limits

Knowledge loss through staff departures is among the best-documented risks in the literature: the knowledge most at risk is experiential and tacit, accumulated over years and rarely written down, and organisations typically begin retention too late (Sumbal et al., 2017). Eckardt, Skaggs and Youndt (2014) show production-worker and manager turnover damage performance through distinct mechanisms; exposure is smallest where standardised work is strongest, since well-maintained work plans already absorb part of the loss.

A further complication is currency: workarounds become obsolete as processes or equipment change, so treating all captured knowledge as equally durable risks preserving advice that is no longer correct—a boundary condition on the capture mechanism of Section 5. Two anchors follow: support must span capture, structuring and transfer before holders depart, and the relevant unit is not just work type but the specific role within it.

2.2 Knowledge Types and the Limits of Codification

This paper collapses Nonaka and Takeuchi's (1995) SECI processes into three practitioners recognise: capture, structuring, transfer. Collins (2010) distinguishes somatic tacit knowledge (embodied, not reachable through text or motion-time notation), relational tacit knowledge (articulable but usually left unarticulated), and collective tacit knowledge (CTK, acquired only through participation in a social milieu). Sanzogni, Guzman and Busch (2017) argue CTK cannot be codified by any machine; treating it as capturable is a category mistake that undermined knowledge-management systems since the expert-systems era. AI therefore addresses explicit, externalisable knowledge; the collective residue remains the preserve of human, social transfer—a hard constraint in the taxonomy of Section 3, not a caveat added afterward.

2.3 AI in Knowledge Management: The Literature and the gap

Jarrahi et al. (2023) frame AI-in-KM as human–AI symbiosis and identify "know-who" as a contribution beyond direct codification; He and Burger-Helmchen (2025) stress that socialisation stays a human, community-situated process; Olan et al. (2022) show performance gains only when AI is combined with human knowledge sharing; Haefner et al. (2021) show the value of structured classification in innovation management. Dommermuth (2026) surveys multiple production units and reports capture and provision as by far the most frequently cited gaps, not structuring—the direct empirical anchor for the tool selection in Section 4. None of this literature supplies the bridge, at the level of Skill Management, between where a knowledge holder sits and where capture should be targeted.

3. Taxonomy: AI Paradigms, Enabling Technologies and the Orchestration Layer

Industrial knowledge management often groups machine learning, LLMs, knowledge graphs, RAG and AR under the broad label of "AI". This paper distinguishes AI paradigms, which learn from data, recognise patterns or generate outputs (computer vision, deep learning, LLMs, vision-language models), from enabling technologies, which operationalise them without themselves learning or generating: knowledge graphs provide structured knowledge, RAG grounds generative models in external sources, and AR delivers outputs to users. The distinction underpins the taxonomy, while acknowledging these technologies may be considered AI in a broader historical sense; all three are integral to the architecture in Section 5.

3.1 How the Taxonomy was Built

The taxonomy follows the iterative development method of Nickerson, Varshney and Muntermann (2013). The meta-characteristic was fixed first: the functional contribution a paradigm makes to the industrial knowledge flow. The object set comprised the three deployed tools of Section 4, decomposed into their constituent AI functions (detection, step-state tracking, interviewing, transcription, annotation, triple extraction, grounded retrieval and generation), plus the technologies named in the gap survey of Dommermuth (2026). An empirical-to-conceptual iteration grouped these functions by shared characteristics into candidate paradigms; a conceptual-to-empirical iteration checked the candidates against the two dimensions of Section 3.2, which are exhaustive by construction: any industrial knowledge activity captures, structures or transfers knowledge, for either embodied or documentary work. Development ended when every object was classified, a further pass

added no new characteristic, and no paradigm was redundant—Nickerson et al.'s objective ending conditions. Theofanos, Choong and Jensen (2024) apply the same classification-by-function principle. The five are not claimed as exhaustive, only as the smallest set covering every populated cell in this case material.

Because the paradigms were partly abstracted from the same three tools that Section 4 diagnoses, an empty cell recovered from that diagnosis is not, by itself, an independent discovery (Section 4.1). No independent study has tested these boundaries beyond the case material; validating the taxonomy against independently sampled deployments is future work (Section 6.3).

3.2 The two Classification Dimensions

The taxonomy classifies AI paradigms along two dimensions. The first is the knowledge process served: capture (acquiring knowledge from holders or physical activity), structuring (organising captured material into reusable form), or transfer (delivering knowledge when and where needed). The second is the type of industrial work: predominantly manual, embodied (blue-collar) work, as distinct from predominantly cognitive, documentary (white-collar) work.

Worker type is a coarse proxy for knowledge type (Collins, 2010): blue-collar work is dominated by somatic knowledge best surfaced by observing activity; white-collar work by relational and documentary knowledge best surfaced through dialogue and documents. It says nothing about role-level differences within a type (a line operator and a shift lead are both “blue-collar” but hold different knowledge) and should not imply manual work involves no judgement. Both types contain collective tacit knowledge no paradigm can codify.

3.3 Five AI Paradigms

Each paradigm is defined by its functional contribution to the knowledge flow, not by a specific product, vendor or model family.

Perceptive AI captures embodied knowledge by observing physical activity: computer vision and deep learning detect objects, recognise actions and track step states, yielding raw artefacts such as video segments and event logs.

Dialogic AI captures verbalisable but undocumented knowledge through structured conversation and, redeployed as a conversational assistant, transfers knowledge back through natural language.

Interpretive AI bridges raw multimodal captures and usable structure, aligning video, transcripts, audio and sensor logs into semantically annotated form, occupying the boundary between capture and structuring.

Structural AI organises annotated knowledge into a relational, navigable representation: knowledge-graph construction and ontology alignment turn heterogeneous sources into one queryable body.

Contextual AI transfers knowledge by grounding generated answers in that structured base; trustworthiness at the point of transfer is consequently a function of Structural AI upstream, not of the language model alone.

3.4 The Orchestration Layer

A sixth role, orchestration, functions distinctly from the five. AI agents act as orchestrators: chaining paradigms, routing requests, monitoring confidence and triggering human review when uncertain. Because an agent coordinates rather than itself perceiving, conversing, interpreting, structuring or delivering knowledge, it is not a knowledge paradigm and is therefore depicted separately in Table 1, spanning every process column.

3.5 The Capability map

Table 1 positions the five paradigms and the orchestration layer against the two dimensions of Section 3.2.

Table 1: Five AI paradigms plus the orchestration layer mapped to three knowledge processes and two worker types. Em-dashes mark inactive pairs; enabling technologies appear in italics. [B] = blue-collar; [W] = white-collar

Role	Capture	Structure	Transfer
Perceptive AI	Object detection, step-state tracking → raw event log [B]	—	—
Dialogic AI	Expert interview, audio capture [B,W]	—	Conversational Q&A, LLM guidance [B,W]

Role	Capture	Structure	Transfer
Interpretive AI	Multimodal annotation, transcription [B,W]	Cross-modal indexing → annotated records [W]	—
Structural AI	—	KG construction, ontology alignment → *knowledge graph* [W]	—
Contextual AI	—	—	*RAG*-grounded answers, *AR*-delivered guidance [B,W]
Orchestration	Monitors capture sources	Triggers structuring; routes low-confidence items to review	Selects delivery channel (text, audio, AR)

Boundary: collective tacit knowledge is AI-resistant in both worker types; the collective residue requires human-to-human transfer (Collins, 2010; Sanzogni, Guzman and Busch, 2017).

3.6 Reading the map

The taxonomy situates widely discussed technologies within one structure: RAG is a mechanism through which Contextual AI operates, conditional on Structural AI upstream; AR is a delivery channel; knowledge graphs are the output of Structural AI and the input to Contextual AI; agents are connective tissue, not a sixth kind of knower.

Table 1 also exposes a dependency chain: Perceptive and Dialogic AI produce raw captures → Interpretive AI annotates → Structural AI builds the knowledge graph → Contextual AI retrieves → orchestration sustains confidence and routes exceptions to human review. Breaking any link, particularly Structural AI, disconnects capture from transfer—which Section 4 shows is what happens today across three tools built by the same organisation.

4. Diagnosis: Applying the Taxonomy to three Deployed Tools

4.1 Why These Three Tools, and a Caveat on Independence

The three tools are not presented as the best instances of their category; they are an existing empirical case flagged by a prior, independent gap analysis as addressing the two most frequently reported problems. Dommermuth (2026) found that, across production units of a large manufacturer, capture and provision were named as deficient far more often than structuring. The three tools below are that organisation's deployed answers to those gaps, each built for one problem and one user group rather than for interoperability—precisely the pattern this paper diagnoses.

A methodological caveat belongs here. Since the five paradigms were abstracted from these same three tools (Section 3.1), finding the Structure column empty when the taxonomy is applied back onto them is not an independent discovery. What licenses the diagnosis is the prior, independent gap analysis (Dommermuth, 2026), which identified capture and provision as the dominant gaps before the taxonomy existed, from practitioner interviews. The taxonomy's role is to show why, structurally, that gap recurs across independently commissioned tools, not to establish that it exists (Section 6.3).

The diagnosis is a single-organisation, embedded case design: each tool is a unit of analysis, classified against Table 1 using system documentation, deployment reports and the prior gap survey as data sources. Because the three are a diagnostic instance rather than a recommendation, the argument does not depend on their being optimal; a different organisation might select different tools, and the taxonomy is meant to remain applicable there. What generalises is the diagnostic pattern, not the tool names. Table 2 positions each on the capability map.

The AR-guided assembly-guidance system is a computer-vision and augmented-reality system at the assembly workstation. Its Perceptive AI component detects parts and tools as oriented bounding boxes in a workstation-fixed frame and drives a per-step state machine; the detector is fine-tuned on assembly-specific imagery, since generic detectors do not reliably distinguish similar fasteners under shop-floor lighting. This yields a structured event log and drives in-situ AR guidance directly, since no shared structured base exists. A single-area pilot reported a 29 per cent reduction in onboarding time (Dommermuth, 2026)—an indicative one-workstation result whose sample size and comparison group are unavailable (Section 6.3). Records are produced every cycle,

but without a Structural AI step recurring error modes remain in the raw log. (Figure 1's "AR overlay" channel refers to the proposed architecture of Section 5, not this tool's current operation.)

The structured interview system is a dialogic capture tool eliciting expert knowledge through conversations with a human interviewer or a protocol-following AI avatar, over 900 questions designed to surface reasoning and exceptions (Dommermuth, 2026). Each interview yields a transcript and person–concept–step triples, but the system stops at capture, so the record waits to be found. No throughput or completion figures are available; it is reported as deployed but not yet evaluated.

The RAG-based conversational assistant is a multi-agent system returning grounded, source-referenced answers with a trustworthiness indicator to both worker types, reporting over 90 per cent reduction in typical retrieval time across more than 3,000 daily users (Dommermuth, Riesch and Guedria, 2025; Dommermuth, 2026). This organisation-wide aggregate, with no variance by role or query type, is a ceiling on what already-indexed content delivers, not a role-disaggregated effect size. It transfers only what it can reach: no shared structured base connects the three tools.

Table 2: Three deployed tools positioned on the capability map.

Tool	Capture	Structure	Transfer	Result	Evaluation basis
AR-guided assembly system (blue-collar)	Vision, step-state tracking	—	In-situ AR guidance (state machine, not graph retrieval)	29% onboarding time reduction	Single-area pilot; N and comparison group unreported
Structured interview system (white-collar)	AI-avatar interviews, 900+ items	—	—	Deployed; not yet evaluated	No quantitative data available
RAG-based assistant (blue- and white-collar)	—	—	RAG retrieval, trust indicator	>90% retrieval time reduction	Org-wide, 3,000+ users; period and variance unreported

Diagnosis: all three tools occupy the Capture or Transfer columns; the Structure column is empty in every case—corroborated by, not independently re-derived from, the survey of Dommermuth (2026); see Section 4.1.

4.2 A Systematic gap, and What it Costs Concretely

The pattern is systematic: three independently commissioned tools all stopped short of structuring, which the prior gap analysis suggests is not unique to them (Dommermuth, 2026). Structuring has no payoff visible to a point-solution project—it neither captures from a holder nor delivers at the moment of need—so it is the first thing cut from scope.

The cost is concrete. An operator's error, once resolved through the AR overlay, exists only in that system's log; a similar error elsewhere cannot benefit, because the conversational assistant has no route to it. Symmetrically, a senior planner's interview may contain the exact nuance a worker is asking about, and the assistant will not find it, since it was never indexed anywhere it looks. The missing structuring step and the inter-tool silo problem are the same fact.

4.3 A Concrete Scenario: Pump-assembly Error Capture, Validation and Reuse

The scenario below is a composite of workflows already in place; the integration layer of Section 5 does not yet exist. It builds on Deviation Management, already present in most assembly operations: the missing piece is a systematic route from the record to knowledge that prevents recurrence.

A less-experienced operator assembles a hydraulic pump at a workstation equipped with the assembly-guidance system. At step 7 (torquing the end-cap bolts) it detects a deviation and raises an AR alert; the operator corrects the sequence and the alert clears. This event—exactly what Deviation Management would already log—is step one.

The proposed pipeline additionally captures step two—how and why it was resolved—via a short hands-free audio comment through the AR headset: "What made this step difficult, and what helped you fix it?" Interpretive AI transcribes the note and appends it to the record with the AR frames; a process expert then assesses whether the fix is correct and generalisable. If accepted, Structural AI ingests it into the shared knowledge graph as a node linked to the assembly step, pump model, remediation sequence and commentary.

When the same deviation recurs elsewhere, or a new operator trains on this assembly, the conversational assistant can retrieve the validated fix and the AR overlay can display it in situ—knowledge previously held only by those who had seen the error before.

5. An Agent-orchestrated Reference Architecture

5.1 From Diagnosis to Design

The diagnosis motivates the architecture directly: fill the Structure column, connect the tools through what fills it, and govern the quality of what enters it. Three failure modes traceable to the empty Structure column are resolved by design: inter-tool silos (knowledge captured by one tool is unreachable by another), ungrounded transfer (Contextual AI without Structural AI upstream must rely on curated content or risk unsupported output), and absent expertise metadata (no tool can answer who knows what organisation-wide).

None of this is new: knowledge graphs, ontologies and expert systems targeted the same problem two decades ago and largely failed, chiefly because manual ontology curation scaled linearly with domain size and no natural-language interface let non-specialists query the result. What has changed is the cost: LLM-based agents now propose graph updates from unstructured material at a fraction of manual-curation cost (Zhu et al., 2024), and RAG lets the graph be queried in natural language.

RAMI 4.0 (Deutsches Institut für Normung, 2016) organises Industry 4.0 assets along hierarchy, life-cycle and layer axes, but treats its information and functional layers generically, without distinguishing knowledge processes, worker types or a codification boundary; the present architecture is best read as a knowledge-specific refinement of those layers, not a competing model. Equally, the design is deliberately socio-technical (Baxter and Sommerville, 2011): the validation gate, the CTK boundary and the retention of accountability with human experts treat the social subsystem as a design object, not an afterthought.

5.2 Architecture

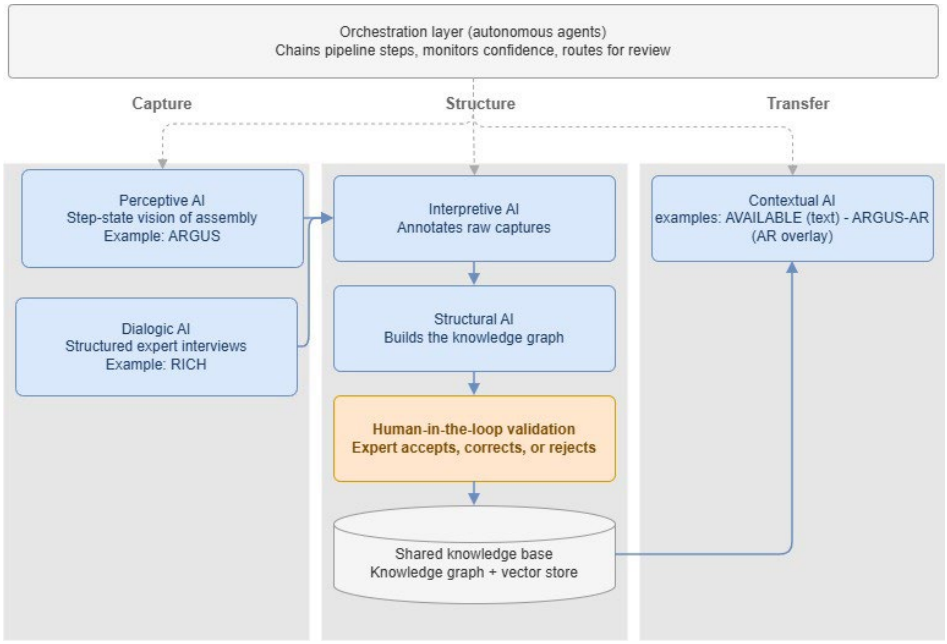


Figure 1: Reference architecture. Capture: the assembly-guidance system (Perceptive AI) and the interview system / operator voice note (Dialogic AI) generate raw records. Structure: Interpretive AI annotates; Structural AI builds the knowledge graph; a human-in-the-loop gate routes low-confidence proposals to expert review. Transfer: the conversational assistant (text) and the AR overlay (in-situ) retrieve from the shared base. Connection to systems of record (e.g. SAP PM) is a required integration outside the pipeline shown (Section 6.3). The figure retains internal project codenames (ARGUS, RICH, AVAILABLE), which map to the assembly-guidance system, the structured interview system and the RAG-based conversational assistant respectively

A knowledge graph with a vector store is the single source of truth: Interpretive and Structural AI write to it, Contextual AI reads from it (Figure 1). A pump-assembly error record and a senior engineer's interview record land in the same graph with provenance intact and both become retrievable by the conversational assistant,

whose trustworthiness indicator (Dommermuth, Riesch and Guedria, 2025) is thereby grounded in structured evidence rather than model weights alone. In production it must also reconcile its entities with enterprise systems of record such as SAP Plant Maintenance work orders and formal work plans—a requirement, not a solved problem (Section 6.3).

LLM-based agents extract entities and relations from heterogeneous material (event logs, video frames, transcripts, voice notes), propose graph updates with confidence scores, and align new material with the existing schema—the pattern whose feasibility Zhu et al. (2024) demonstrate. Because multimodal extraction adds latency and per-event agents multiply compute cost, the design treats structuring as an asynchronous step queued after the event closes rather than blocking the AR guidance loop; sizing that queue, like prompts and routing rules, is left to implementation.

A primary deployment challenge is the prevalence of unverified, outdated or conflicting information—"knowledge junk"—whose direct ingestion into a RAG system leads to hallucinations and incorrect instructions reaching shop-floor employees (Dommermuth, 2026). The human-in-the-loop gate of Figure 1 counters this: agent-proposed extractions below a confidence threshold go to a domain expert, who sees the proposal alongside source evidence and can accept, correct or reject it; accepted items enter the shared base, and corrections improve agent calibration. Operationally, the gate prevents a wrongly documented step from being retrieved as guidance by every subsequent operator; organisationally, it keeps accountability with humans, so AI augments judgement rather than replacing it (Jarrahi et al., 2023; Olan et al., 2022). This three-stage pattern—capture, expert validation, single curated base—is already implicit in the tools' workflows; the architecture makes it explicit.

The shared base dissolves the silos, grounds transfer in curated content, and functions as cross-tool expertise metadata supporting "know-who" queries (Jarrahi et al., 2023). Two boundaries remain: it cannot codify CTK (Section 2.2), though the graph can identify which human holds it; and nothing substitutes for keeping work plans current—where a documentation problem is really a maintenance problem, the fix is to update the work plan.

6. Discussion, Limitations and Next Steps

6.1 Contributions and their Value

The taxonomy offers three kinds of value. Descriptively, it separates AI paradigms from enabling technologies, preventing category errors that inflate claims. Diagnostically, applied to three independently built tools, it located a systematic blind spot—the unserved structuring step—grounded in a prior, independent gap analysis rather than the three tools alone. Prescriptively, it turns technology selection into a structured decision: identify the work type and knowledge process, locate the paradigm in Table 1, and check the enabling technologies it requires.

6.2 Scope of the Hypothesis

Both headline figures in Table 2 are aggregate averages—from a single-area pilot and an organisation-wide rollout (Dommermuth, Riesch and Guedria, 2025; Dommermuth, 2026); neither reports how the effect varies by knowledge type, tool-use pattern or user segment, so it is unknown whether the benefit accrues mainly to the worker or to those managing onboarding and quality around them. They are the baseline from which the hypothesis is stated, not evidence for the architecture. Its components are grounded in deployment results, the integration mechanism has demonstrated feasibility elsewhere (Zhu et al., 2024), and the failure of the prior generation of knowledge-graph systems (Section 5.1) is a caution built into the design.

6.3 Limitations

The taxonomy is conceptual, derived from the same three tools and one gap survey in a single organisation that Section 4 diagnoses; whether it holds elsewhere is open (Sections 3.1 and 4.1). Worker-type tags are coarse: a role-level analysis distinguishing a line operator from a shift lead could shift which paradigm is most relevant, and is left to future work.

On the architecture side, the validation gate checks correctness at review time only, not durability. The confidence threshold routing items to it needs calibration by assembly type and criticality; access control—who may read or validate what—is not yet addressed; and reconciliation with systems of record such as SAP PM and formal work plans remains a required integration not yet designed.

Tool selection, while grounded in a prior gap analysis, is one defensible choice among several, and the claim that the architecture is agnostic to it is untested against a second tool set. Neither headline figure includes sample size, comparison-group composition or variance by role; both are reported at face value from their sources.

6.4 Proposed Evaluation Strategy and Next Steps

Evaluation must isolate the structuring layer's contribution from the tools' baselines. The proposed design: (1) a staged rollout—a baseline period on the standalone tools, then a treatment period after the shared structuring layer is added, holding the capture tools unchanged, so any measured change is attributable to structuring; (2) cross-tool retrieval coverage as primary KPI—the share of validated fixes captured at one tool that the assistant can retrieve from a different workstation; (3) validation throughput—expert accept/correct/reject rates and time-to-validate at the gate; and (4) disaggregation of every KPI by knowledge type, tool and user role, directly answering who benefits from integration.

A second, upstream direction is the coupling this diagnosis points to but does not test—between Skill Management, which locates knowledge holders and roles needing support, and the capture tools then applied to them. Investigating it across a broader set of tools and organisations would address whether point solutions should keep being built in isolation, consistent with the call for a unified, agent-orchestrated AI platform (Dommermuth, 2026).

Ethics Declaration: Ethical clearance was not required as this research focuses on conceptual development and uses anonymised, aggregated operational data. This independent doctoral research at the Karlsruhe Institute of Technology involves no conflicts of interest and received no employer funding.

AI Declaration: AI was used solely for editorial assistance with proofreading and formatting. All core concepts, architecture, and intellectual property are the work of the human authors, who bear full responsibility for the content.

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Tax Incentives and Knowledge Heterogeneity: Short-term Stimulus or Long-term Stock?

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Abstract: This paper unpacks the black box of knowledge accumulation by examining how tax incentives affect three distinct types of knowledge: high-quality (highly cited) patents, AI patents, and green patents. We find that the long-term accumulation effect is not uniform across knowledge types. High-quality and AI patents respond significantly only in the short term (lag 1), with no long-term accumulation; green patent quantity expansion generates bubbles without quality improvement. These findings suggest that durable knowledge accumulation is primarily driven by ordinary, low-depreciation patents. From a knowledge management perspective, this implies that policies should distinguish between "short-shelf-life" and "long-shelf-life" knowledge, and avoid over-incentivizing short-lived innovation at the expense of durable knowledge infrastructure.

Keywords: Tax incentives, Knowledge heterogeneity, Knowledge depreciation, AI patents, Green innovation bubbles

1. Introduction

Tax incentives have become a widely used policy tool to stimulate corporate innovation. Governments around the world employ R&D tax credits, accelerated depreciation, and reduced tax rates to encourage firms to invest in knowledge creation (Hall & Van Reenen, 2000; Bloom et al., 2002). A substantial body of empirical evidence suggests that these incentives effectively increase R&D expenditure and patent output (Czarnitzki et al., 2011; Howell, 2017; Dechezleprêtre et al., 2023). However, much of this literature focuses on the quantity of innovation inputs and outputs, with considerably less attention paid to the quality and durability of the knowledge that firms accumulate.

From a knowledge management perspective, these questions are critical because not all knowledge is equally valuable over time. Some knowledge depreciates rapidly due to technological obsolescence, while other knowledge retains its value for decades (Argote & Miron-Spektor, 2011; Hall et al., 2010). Understanding how tax incentives affect different types of knowledge is therefore essential for both organizational knowledge strategies and public policy design. If tax incentives primarily stimulate short-lived knowledge, their long-term impact on innovation efficiency may be limited. Conversely, if they encourage the accumulation of durable knowledge, the efficiency gains may be sustained over time (Nonaka & Takeuchi, 1995; Grant, 1996).

This paper unpacks the black box of knowledge accumulation by distinguishing three types of knowledge: high-quality (highly cited) patents, AI patents, and green patents. Using a panel of Chinese listed firms from 2012 to 2023, we find that:

- High-quality patent stock responds significantly to tax incentives only in the short term (lag 1), with no long-term effects.
- AI patent applications similarly show a short-term response (lag 1) that does not persist.
- Green patents: tax incentives do not directly affect green innovation bubbles, but green patent quantity itself is positively associated with bubble formation, indicating a quantity-quality decoupling.

These patterns reveal that durable knowledge accumulation is driven not by frontier or high-visibility knowledge, but rather by ordinary, stable, and low-depreciation knowledge that accumulates slowly over time. This finding has important implications for knowledge management: it suggests that organizations and policymakers should distinguish between "short-shelf-life" and "long-shelf-life" knowledge, and design incentives that support durable knowledge infrastructure rather than short-lived innovation spikes.

This paper contributes to the knowledge management literature in three ways. First, it extends the concept of knowledge accumulation by introducing knowledge heterogeneity—the idea that different types of knowledge have different accumulation patterns and policy responses. Second, it provides empirical evidence on the life-cycle of policy-induced knowledge, showing that short-term responses do not necessarily translate into long-term stocks. Third, it offers practical implications for both firms and policymakers, suggesting that

knowledge management strategies should align with the depreciation characteristics of different knowledge types.

2. Literature Review and Theoretical Background

2.1 Tax Incentives and Knowledge Accumulation

A large body of literature has examined how tax incentives affect firm innovation. Early studies establish that R&D tax credits lower the marginal cost of R&D and stimulate investment in innovation (Hall, 2002; Hall & Van Reenen, 2000; Bloom et al., 2002). Subsequent research confirms that tax incentives increase R&D expenditure and patent output, though the magnitude of effects varies across institutional contexts and firm characteristics (Czarnitzki et al., 2011; Dechezleprêtre et al., 2023; Gaessler et al., 2021).

Chinese studies similarly find that tax incentives have a strong influence on R&D investment and innovation output, particularly by alleviating financial constraints and improving access to internal resources (Chen et al., 2018; Liu & Mao, 2019; Cao et al., 2021; Sun et al., 2022). However, most of these studies focus on innovation inputs and outputs, with relatively limited attention given to innovation efficiency or the quality of knowledge accumulation (Hall & Lerner, 2010). Assessing tax incentives merely by input or output indicators may not fully capture their actual effects on firms' long term innovation capabilities (Griliches, 1990).

2.2 Knowledge Depreciation and Heterogeneity

An important but often overlooked dimension of knowledge accumulation is knowledge depreciation. Unlike physical capital, knowledge decays over time due to technological obsolescence, competitor imitation, and shifts in market demand (Argote & Miron Spektor, 2011; Argote, 2013). However, the depreciation rate varies considerably across knowledge types. Patents in fast moving fields such as AI and digital technologies lose their value quickly, while patents in mature technological fields may retain their value for decades (Hall et al., 2010).

This heterogeneity has direct implications for policy evaluation. If tax incentives primarily stimulate short lived knowledge that depreciates rapidly, their long term impact on innovation efficiency may be limited. Conversely, if they encourage the accumulation of durable knowledge, the efficiency gains may be sustained over time. Thus, distinguishing between knowledge types is essential for understanding the true impact of tax policies (Trajtenberg, 1990; Hall et al., 2005).

2.2 Knowledge Management Perspective

From a knowledge management perspective, the distinction between short lived and long lived knowledge is critical. Nonaka and Takeuchi's (1995) SECI model provides a useful lens: tax incentives that lower patenting costs primarily facilitate the Combination phase—recombining existing knowledge into new patentable forms—but do little to support Internalization, where knowledge becomes embedded in organizational routines and durable capabilities. This distinction directly explains our empirical expectations: if tax incentives primarily stimulate Combination-based outputs (patent filings), we should observe short term patent surges (high quality and AI patents) without lasting accumulation; long term efficiency gains, by contrast, require the slower process of Internalization, which we expect only in ordinary, low depreciation knowledge. Thus, our heterogeneity predictions (H2–H4) are not merely descriptive but theoretically grounded in the SECI framework's distinction between combinative and internalized knowledge.

2.3 Hypotheses

Based on the above discussion, this paper proposes the following hypotheses:

H1: Tax incentives significantly increase high-quality patent stock, but this effect is short-lived (lag 1 only).

H2: Tax incentives significantly increase AI patent applications, but this effect is also short-lived (lag 1 only).

H3: Tax incentives do not directly drive green innovation bubbles; however, green patent quantity expansion is positively associated with bubble formation.

3. Methodology

3.1 Sample and Data Sources

This study uses panel data of Chinese A-share listed firms over the period 2012–2023. Financial variables and tax indicators are sourced from the CSMAR database. Patent-related variables are obtained from the Chinese patent database, and patent citation data are derived from the Google Patent database. The final sample is an unbalanced panel of firm-year observations, with financial firms excluded and observations with missing key variables removed.

3.2 Variable Definitions

3.2.1 Tax incentives

Following the existing literature (Chen et al., 2018; Liu & Mao, 2019), we measure tax incentives using the effective tax rate (ETR), calculated as income tax expense divided by pre-tax profit. To capture the intensity of tax incentives, we use the negative of ETR (tax_incentive = -ETR), so that a higher value indicates stronger tax incentives.

3.2.2 Knowledge types

We construct three measures of knowledge accumulation:

1. High-quality patent stock. Based on patent citation data, we identify patents in the top 10% of citations within each year (highly cited patents) and apply the perpetual inventory method (depreciation rate 15%) to calculate the high-quality stock (Trajtenberg, 1990; Hall et al., 2005).
2. AI patent applications. We identify AI-related patents using IPC codes (G06F, G06N, G06K, G10L, B25J, etc.) and take the natural logarithm of annual AI patent applications (Cockburn et al., 2018; Agrawal et al., 2018).
3. Green innovation bubble. Following Geng et al. (2024), we construct a bubble index (CGI_bub) to capture the mismatch between green patent quantity and quality. The index is calculated as:

$$CGI_bub_{it} = \frac{GreenPatentApplications_{it} - GreenPatentsGranted_{it}}{GreenPatentApplications_{it} + 1}$$

A higher value indicates a greater divergence between applications (firms' innovation claims) and granted patents (a minimal external quality certification). This gap serves as a conservative proxy for quantity–quality decoupling, as patents that fail to be granted cannot contribute to genuine technological progress. The measure has been validated in prior research (Geng et al., 2024).

3.2.3 Control variables

Following the existing literature, we include firm size (natural logarithm of total assets), leverage (total liabilities divided by total assets), and profitability (ROA, net profit divided by total assets). Firm fixed effects and year fixed effects are included in all regressions.

3.3 Empirical Model

To examine the impact of tax incentives on knowledge accumulation, we estimate the following fixed-effects model (Hsieh & Klenow, 2009):

$$Knowledge_{it} = \alpha + \beta_1 Tax_{i,t-k} + \gamma Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \quad (k = 1, 2, 3)$$

Where Knowledge_it represents one of the four knowledge measures for firm I in year t , Tax_(i,t-k) is the tax incentive variable lagged by k years (k = 1, 2, 3), Controls_it is a vector of firm-level control variables, μ_i captures firm fixed effects, and λ_t captures year fixed effects. Standard errors are clustered at the firm level to account for serial correlation.

4. Empirical Results

4.1 Tax Incentives and High Quality Patent Stock

Table 1 presents the results for high quality patent stock. The coefficient of L1_tax (lag 1) is positive and significant at the 1% level, while lags 2 and 3 are insignificant. This suggests that tax incentives quickly stimulate high value knowledge, but such knowledge depreciates rapidly and does not accumulate into long term stock (Trajtenberg, 1990; Hall et al., 2005).

Table 1: Tax Incentives and High Quality Patent Stock

Variable	Coefficient	Std. Error	p-value
L1_tax	0.0989	0.0316	0.002
L2_tax	0.0395	0.0302	0.191
L3_tax	0.0431	0.0317	0.173
Size	0.1529	0.0163	0.000
Leverage	-0.0220	0.0126	0.081
ROA	-0.0402	0.0140	0.004

Observations: 32,299 (L1), 28,666 (L2), 24,863 (L3). Firm and year fixed effects included.

4.2 Tax Incentives and AI Patent Applications

Table 2 reports the results for AI patent applications. Similar to high-quality patents, the coefficient of L1_tax is positive and significant (p = 0.015), while lags 2 and 3 are insignificant. This confirms that frontier technologies, despite their initial responsiveness, face high obsolescence and fail to form persistent knowledge bases (Cockburn et al., 2018; Agrawal et al., 2018).

Table 2: Tax Incentives and AI Patent Applications

Variable	Coefficient	Std. Error	p-value
L1_tax	0.1097	0.0451	0.015
L2_tax	0.0795	0.0501	0.113
L3_tax	0.0358	0.0509	0.482
Size	0.1170	0.0119	0.000
Leverage	-0.0270	0.0190	0.155
ROA	0.2197	0.1172	0.061

Observations: 27,288 (L1), 24,360 (L2), 21,223 (L3). Firm and year fixed effects included.

4.3 Tax Incentives and Green Innovation Bubbles

Table 3 presents the results for green innovation bubbles. Tax incentives do not have a significant direct effect on CGI_bub. However, green patent quantity itself is positively and significantly associated with bubble formation ($\beta = 0.014$, $p < 0.01$). This indicates that pure quantity expansion—regardless of its policy source—can drive a wedge between innovation quantity and quality in the green technology domain (Geng et al., 2024; Lyon & Maxwell, 2011; Delmas & Montes-Sancho, 2010).

Table 3: Tax Incentives, Green Patent Quantity, and Green Innovation Bubbles

Variable	(1) CGI_bub	(2) CGI_bub	(3) CGI_bub
Tax incentive (ETR)	-0.0082		-0.0084
Green patent quantity		0.0140***	0.0140***
Size	-0.0005	-0.0026	-0.0026
Leverage	0.0164	0.0147	0.0150
ROA	0.1081**	0.1154***	0.1083**
Observations	32,746	32,746	32,746
R^2	0.533	0. 534	0.534

***p < 0.01, *p < 0.05. Firm and year fixed effects included.

4.4 Summary of Findings

The contrasting patterns across knowledge types can be explained by knowledge depreciation (Argote & Miron-Spektor, 2011; Argote, 2013). High-quality and AI patents represent fast-moving technological frontiers where knowledge becomes obsolete quickly; their short-term responsiveness to tax incentives does not

translate into long-term stock. Green patents, often driven by regulatory or signaling motives, may suffer from quantity-quality decoupling (Geng et al., 2024). In contrast, ordinary patents—those not distinguished by high citations or specific technology classes—tend to cover more mature, stable technologies with longer useful lives. It is precisely this "slow-and-steady" knowledge that accumulates over time and ultimately improves innovation efficiency (Fleming, 2001).

5. Discussion

5.1 Implications for Knowledge Management

Our findings offer a granular, theory grounded insight for knowledge management: policy incentives shape not just the quantity, but the "term structure" of a firm's knowledge portfolio. Just as financial managers distinguish between short term and long term assets, knowledge managers must distinguish between short shelf life (exploratory) knowledge and long shelf life (exploitative) knowledge, because they serve different strategic purposes and respond differently to external stimuli.

For firms, the results suggest three actionable strategies:

First, diagnose the "knowledge depreciation profile" of your portfolio. Using patent citation data or technology life cycle analysis, firms can assess whether their knowledge stock is skewed toward fast depreciating frontier patents (like AI) or slower depreciating core technologies. Our evidence shows that tax incentives disproportionately boost the former in the short run, which may create an illusion of innovation vitality. Managers should therefore adjust their internal resource allocation—if external incentives are fueling exploratory patents, they should proactively redirect internal R&D funds toward internalization activities (e.g., process improvement, employee training, cross functional integration) to convert transient knowledge into durable organizational routines (Argote & Miron Spektor, 2011).

Second, avoid the "policy capture trap". Firms that aggressively file patents solely to capture tax benefits may accumulate a hollow knowledge stock—numerous but ephemeral. This is particularly evident in our green patent finding, where quantity expansion drives bubbles without quality improvement. Knowledge managers should treat tax incentives as a supplement, not a substitute, for organic capability building. Sustainable advantage comes from the sticky, tacit knowledge that competitors cannot easily imitate or arbitrage (Nonaka & Takeuchi, 1995).

Third, adopt differentiated performance metrics. Rather than evaluating R&D success by total patent counts alone, firms should develop balanced dashboards that track both "knowledge velocity" (speed of generating new exploratory patents) and "knowledge persistence" (citation weighted stock, technology renewal rates, and internal utilization of patented knowledge). This dual metric system aligns with the exploration exploitation balance that high reliability organizations maintain (March, 1991).

For policymakers, our knowledge management lens offers a critical corrective. The common practice of rewarding aggregate patent output implicitly treats all knowledge as homogeneous and infinitely durable. We demonstrate that this assumption is empirically false. Therefore, policy design should:

- Introduce "durability weighted" incentives—for example, higher tax credits for patents that survive beyond a certain citation threshold or that are classified in mature technology classes with low depreciation rates.
- Reform green innovation policies by shifting from application based subsidies to grant based and citation based rewards, directly addressing the quantity quality decoupling we observe.
- Consider temporal differentiation: exploratory, frontier technologies (AI) may benefit from short term, high intensity project grants that match their fast depreciation cycle, whereas foundational, exploitative technologies benefit from long term, stable tax reduction schemes that encourage patient accumulation.

In essence, our findings reposition the debate from "how much innovation" to "what kind of innovation and for how long". This aligns knowledge management theory with public policy, arguing that the ultimate goal is not to maximize annual patent counts, but to build a resilient, multi temporal knowledge infrastructure that supports sustained efficiency gains over decades.

5.2 The Role of Knowledge Depreciation

A key theoretical contribution of this paper is the introduction of knowledge depreciation as a boundary condition for policy induced knowledge accumulation (Argote & Miron Spektor, 2011; Argote, 2013). Our findings suggest that tax incentives are most effective at building knowledge stocks when the knowledge in question has a low depreciation rate. High depreciation knowledge—whether in AI, high quality patents, or green technology—responds quickly but does not accumulate. This insight aligns with the knowledge management literature on knowledge life cycles and extends it to the policy domain (Nonaka & Takeuchi, 1995).

5.3 Policy Implications

From a policy perspective, our findings suggest three main recommendations:

First, tax incentives should be complemented with quality oriented evaluation mechanisms. Rather than rewarding patent quantity alone, policies should track indicators of knowledge durability, such as patent citations, technological impact, or commercialization outcomes (Trajtenberg, 1990; Hall et al., 2005).

Second, green innovation policies should be redesigned to avoid quantity quality decoupling. The positive association between green patent quantity and bubbles suggests that current policies may inadvertently encourage symbolic innovation (Geng et al., 2024; Lyon & Maxwell, 2011). Combining quantity incentives with quality requirements—such as mandatory post grant evaluation or citation targets—could help mitigate this problem (Delmas & Montes Sancho, 2010).

Third, policymakers should consider differentiated incentives for different types of knowledge. Short lived frontier knowledge may benefit from more frequent but smaller incentives, while long lived foundational knowledge may require sustained, patient support (Cockburn et al., 2018; Agrawal et al., 2018).

5.4 Limitations and Future Research

This study has several limitations. First, our classification of knowledge types is based on patent characteristics; future research could incorporate additional dimensions such as knowledge novelty, technological impact, or economic value. Second, our analysis focuses on listed firms; findings may not generalize to non listed or small firms. Third, the green bubble measure captures only one aspect of quality; more refined quality indicators would enhance future research. Fourth, we focus on Chinese firms; cross country comparisons would help establish the generalizability of our findings (Hsieh & Klenow, 2009; Liu & Mao, 2019). Fifth, this paper does not re examine the long term accumulation effect of total patent stock; rather, we focus exclusively on the heterogeneity across knowledge types. Future research could explore whether the observed patterns hold for broader measures of knowledge stock.

6. Conclusion

This paper unpacks the black box of knowledge accumulation by examining how tax incentives affect three distinct types of knowledge: high-quality patents, AI patents, and green patents. High-quality and AI knowledge respond only in the short term, while green knowledge quantity may generate bubbles. The common denominator of these three is high depreciation or low persistence—they are "fast knowledge" that does not build lasting capabilities (Argote & Miron-Spektor, 2011; Argote, 2013).

Theoretically, this paper demonstrates that knowledge depreciation is not merely a technical parameter but a strategic boundary condition that determines the effectiveness of external incentives. By bridging the exploration-exploitation framework (March, 1991) with the SECI model (Nonaka & Takeuchi, 1995), we show that policy-induced knowledge accumulation is path-dependent: incentives that favour combinative outputs (patent filings) may inadvertently crowd out internalization, leading to a fragile knowledge base. This insight extends the knowledge-based view of the firm by specifying how external institutional forces can distort internal knowledge portfolios—a mechanism largely overlooked in prior KM literature.

From a knowledge management perspective, these findings suggest that knowledge life cycle should be integrated into both organizational strategies and policy design (Nonaka & Takeuchi, 1995; Grant, 1996). Tax incentives should not be evaluated solely by immediate patent counts; rather, they should consider the durability and eventual contribution of accumulated knowledge to organizational efficiency (Hall et al., 2010; Griliches, 1990). By shifting from a one-size-fits-all approach to a differentiated knowledge perspective, both firms and policymakers can better align incentives with the long-term goal of sustainable innovation.

Ethics Declaration: No ethical approval was required for this study because the research used publicly available secondary data from Chinese A-share listed firms.

AI Declaration: AI tools were used only for language polishing, grammar checking, and improving readability. All academic content, analysis, and conclusions were developed and verified by the author.

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Working with AI: A Practice-based Study of Knowledge Sharing in a Multinational Enterprise (MNE)

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Abstract: Knowledge sharing is central to intraorganisational collaboration in multinational enterprises (MNEs), where employees work across functions, locations and linguistic contexts. Existing research has highlighted the potential of AI to enhance knowledge management and organisational performance, but there is still limited understanding of how employees use AI in their everyday knowledge sharing practices in MNEs. This study therefore examines how AI influences these practices within an anonymised MNE, referred to as GlobalMFG. The study adopts a qualitative single-case study design and draws on six semi-structured interviews with managers and knowledge workers from different organisational functions. The findings demonstrate that AI supports knowledge sharing by improving access to information, assisting communication across geographically dispersed teams and supporting meeting follow-up. Its effectiveness remained dependent on employees' ability to formulate appropriate prompts and assess how AI-generated outputs could be applied within specific organisational contexts. AI was primarily used before and after interpersonal interactions. Experienced colleagues continued to be the preferred source of specialist and contextual knowledge. Although organisational documents reflected a strong strategic commitment to AI adoption, interview data revealed inconsistencies in access to AI tools, system integration, and governance, resulting in uneven implementation across the organisation. These findings highlight the need to connect AI investment with clear governance, consistent access to approved tools and task-specific employee support. Establishing ongoing employee feedback mechanisms can further support the responsible, effective, and contextually appropriate adoption of AI-enabled knowledge sharing practices within such MNEs.

Keywords: Knowledge sharing, Artificial intelligence (AI), Multinational enterprises (MNEs), Knowledge management, Practice-based perspective

1. Introduction

Knowledge sharing is a central process through which MNEs integrate dispersed expertise, coordinate work across subsidiaries and convert individually held knowledge into broader organisational capabilities (Grant, 1996; Gupta and Govindarajan, 2000; Gaur, Ma and Ge, 2019). In MNEs, geographically distributed units operate across different institutional, cultural and linguistic contexts, making knowledge sharing strategically important but difficult (Gupta and Govindarajan, 2000; Noorderhaven and Harzing, 2009; Gaur, Ma and Ge, 2019). Existing knowledge sharing practices have long relied on governance structures, social interaction and technology-enabled repositories. However, barriers remain. Studies have repeatedly identified cultural and cognitive distance, weak trust, limited incentives and tacit knowledge as persistent challenges in knowledge sharing (Riege, 2005; Wang and Noe, 2010).

Recent advances in AI, particularly GenAI systems built on advances in NLP, introduce new possibilities for organisational knowledge sharing. Earlier knowledge management systems (KMS) placed substantial emphasis on the codification, storage and retrieval of organisational knowledge (Alavi and Leidner, 2001). More recent AI-enabled systems extend these functions through conversational search, recommendation tools, translation support and content generation (Jarrahi et al., 2023; Alavi, Leidner and Mousavi, 2024; Benbya, Strich and Tamm, 2024). In this sense, GenAI and NLP-based tools may help employees access dispersed knowledge, reduce certain language-related barriers and prepare for cross-boundary interaction (Malik et al., 2021; Benbya, Strich and Tamm, 2024). These technologies also raise questions about whether employees can trust AI outputs, how they should verify them, how organisations govern data quality, and how far AI can support tacit, situated and relational knowledge sharing (Jarrahi et al., 2023; Alavi, Leidner and Mousavi, 2024; Ritala et al., 2024).

Existing research links AI with knowledge sharing and organisational performance, although the empirical base remains uneven and concentrated in particular sectors or applications (Malik et al., 2021; Olan et al., 2022). For instance, Lee et al. (2023) observe that "*there remains a lack of complete and comprehensive understanding of the use of AI, specifically its impact, influence, and critical success factors in organizations*" (pg.2). Their review identifies a broad implementation gap. This paper focuses on employees' knowledge sharing practices within an MNE. A practice-based perspective directs attention to the routines and interactions through which employees seek, interpret and use knowledge in their work (Orlikowski, 2002). The study therefore examines how AI is

integrated within these practices through a shared organisational setting. The paper addresses the following research question: How does AI influence knowledge sharing practices within an MNE?

2. Knowledge Sharing

This paper positions knowledge sharing as the core social process that connects individual insight with organisational capability. Wang and Noe (2010) define knowledge sharing as the process by which individuals or organisations provide one another with task information, expertise and advice to help others solve problems, develop new ideas or implement procedures. Van den Hooff and de Ridder (2004) consider knowledge sharing to be a bidirectional process that includes bringing or 'donating' knowledge and getting or 'collecting' knowledge. This paper therefore defines knowledge sharing as a bidirectional process through which individuals and teams provide, receive and use task-related knowledge.

Knowledge sharing is central to the realisation of value from knowledge management. In this paper, knowledge management refers to the broader organisational processes through which knowledge is created, stored, shared and applied (Alavi and Leidner, 2001). Grant (1996) argues that the fundamental purpose of enterprise knowledge management is to transform the scattered knowledge held by individuals into the collective capabilities and strategic assets of the organisation. Al-Busaidi and Olfman (2017) describe knowledge sharing as one of the major processes of knowledge management. Its frequent appearance across knowledge management frameworks indicates its central place in organisational knowledge processes.

More recent research, such as Castaneda and Cuellar (2020) and Nguyen, Siri and Malik (2021), examines knowledge sharing in relation to organisational innovation and employee participation. For instance, Castaneda and Cuellar (2020) review the development of research on knowledge sharing and innovation, identifying collaboration as a central theme and connecting knowledge sharing with absorptive capacity, understood as the organisational ability to recognise, assimilate and apply relevant knowledge.

Wang and Noe (2010) review studies showing how knowledge sharing helps employees solve work-related problems and develop new ideas. Ahmad and Karim (2019) identify workplace learning as an important outcome, suggesting that knowledge sharing helps employees assimilate and apply knowledge in their work. These studies locate the effects of knowledge sharing in employees' everyday learning and problem-solving. With the increasing digitisation in the current era, this provides a basis for examining how digital technologies influence the practices of current organisations through which knowledge is shared.

3. AI-enabled Knowledge Sharing in MNE

The development of knowledge sharing technologies has moved from repository-based KMS to Web 2.0 platforms[1], and then to AI-enabled systems. Jarrahi et al. (2023) explain that AI is relevant to knowledge management because it supports how organisations organise, access, share and apply knowledge. For knowledge sharing, the shift is that technology does more than store codified knowledge after employees have entered it into a system. AI-driven tools may help locate knowledge sources, identify bottlenecks in knowledge flows and connect employees working on related projects or technical problems (Jarrahi et al., 2023). Alavi, Leidner and Mousavi (2024) further argue that GenAI changes employees' interaction with KMS by making large knowledge bases easier to access and by supporting the analysis and use of organisational knowledge. In MNEs, projects are coordinated across geographically dispersed units operating in different institutional settings. Subsidiaries develop knowledge shaped by their local operating contexts and organisational roles. Knowledge moves from headquarters to subsidiaries and from subsidiaries back to headquarters. It also circulates among subsidiaries (Yang, Mudambi and Meyer, 2008; Gaur, Ma and Ge, 2019). This distributed pattern gives knowledge flows strategic importance and creates coordination difficulties. Gaur, Ma and Ge (2019) show that these flows depend on relationships between organisational units and the employees who enact them.

Haas and Cummings (2015) find that geographic and structural differences create stronger barriers to knowledge seeking than differences associated with nationality or demographic characteristics. Employees working in different business units or functions may use specialised terminology and assess the relevance of knowledge differently. Ford and Chan (2003) identify language differences as a source of knowledge blocks in a multicultural subsidiary. Their case also shows that culturally shaped advice-seeking affects the direction of knowledge flows.

[1]Web 2.0 platforms are understood here as participatory digital platforms that allow employees to contribute, interact and share knowledge through collaborative functions (Paroutis and Al Saleh, 2009).

Cross-boundary knowledge sharing therefore depends on employees' ability to recognise the relevance of colleagues' expertise and on familiarity developed through prior interaction.

Jarrahi et al. (2023) explain that AI-enabled KMS can make dispersed expertise more visible and connect employees facing related technical problems. Mikalef and Gupta (2021) move the discussion from technical functionality to organisational capability. Their empirical study of senior technology managers links AI capability to organisational creativity and firm performance. Their capability construct gives technical resources a central place and considers the skills and coordination needed for deployment. Ritala et al. (2024) examine how such capability develops in industrial enterprises. Their analysis shows that AI-enabled exploration and exploitation can reinforce one another as enterprises adapt established operations and investigate emerging business opportunities. Learning accumulated during implementation shapes subsequent AI initiatives.

Barriers emerge when employees interpret and act on AI outputs. Jarrahi et al. (2023) identify continuously generated and unstructured data as an obstacle to timely AI-supported analysis. The study also warns that excessive reliance on AI may produce cognitive complacency, reducing employees' scrutiny of system outputs. Benbya, Davenport and Pachidi (2020) discuss limited explainability as a source of weak trust in AI-assisted decisions. Algorithmic bias can make problematic outputs appear authoritative. Responsibility for harmful or incorrect outcomes also becomes harder to assign as AI assumes a larger role in organisational processes. The MNE context adds a further layer because AI outputs are interpreted across units whose vocabularies and local working arrangements differ. Existing research identifies potential organisational value and recurring barriers. However, there is still limited understanding of how individual employees and project teams use, question, and adapt AI-enabled tools in their everyday knowledge sharing practices.

4. Research gap

Based on the literature review, there are several gaps related to AI-enabled knowledge sharing in practice. Yeboah (2023) shows that knowledge sharing studies give greater attention to enabling conditions than to barriers. The review also points to limited examination of the alignment between knowledge sharing processes and organisational strategy, alongside a strong emphasis on financial outcomes.

Empirical research on AI-enabled knowledge sharing remains concentrated in specific organisational applications and outcome measures. Malik et al. (2021) situate AI-enabled knowledge sharing within global talent management in an IT-based MNE, whereas Olan et al. (2022) examine the integration of AI and knowledge sharing in relation to organisational performance. This emphasis leaves employees' routine use of AI-enabled tools less fully explained. Lee et al. (2023, pg. 2) similarly identify "*a lack of contextual understanding of why and how AI is being implemented by organizations"*. This concern is especially relevant to MNEs, where employees encounter AI through different organisational systems and local working arrangements.

In MNEs, knowledge sharing crosses organisational units and remains shaped by local working contexts (Gaur, Ma and Ge, 2019; Haas and Cummings, 2015). Existing research offers limited empirical explanation of how employees and project teams use AI-enabled tools under these conditions. As part of an ongoing research project for a PhD, the paper addresses the following research question:

How does AI influence knowledge sharing practices within an MNE?

5. Methodology

This study adopts a qualitative single case study design based on semi-structured interviews. The focal case is an anonymised MNE, referred to as *GlobalMFG*, which was selected as an information-rich case (Yin, 2018) because of its extensive multinational operations and active adoption of AI-enabled technologies. Established over 100 years ago, the organisation provides a mature organisational setting in which to examine the influence of AI on knowledge sharing practices over time. Employees routinely collaborate across functions and national locations, making knowledge sharing a central organisational activity. The case also provided access to participants from different organisational functions.

Primary data were collected through semi-structured interviews with managers and knowledge workers in GlobalMFG during Jan- June 2026. For this paper, the participants will be referred as P1–P6 as shown in Table 1. Names and operational details that could identify the enterprise were generalised. Participants were recruited from different roles and functions within GlobalMFG, and their familiarity with AI-enabled tools is varied. Semi-structured interviews provided a common focus across participants and allowed the interviewer to pursue relevant issues raised during each discussion (Brinkmann and Kvale, 2015).

Table 1: List of Interview Participants

	Role	Experience in the current role (Years)
P1	Motor Engineer	9
P2	Research and Development (R&D) Engineer	11
P3	Principal Testing Engineer	22
P4	Application Engineer	8
P5	Engineer Leader/Test Engineer	10
P6	Procurement Specialist	8

The interview guide included questions such as how participants shared and accessed knowledge in day-to-day work, and how AI-enabled tools affected these practices.

Secondary data were collected to establish the organisational context for the case including company press releases. Interview recordings were transcribed in Chinese and translated into English for analysis and the translations were independently reviewed by a professional translation service to provide a further quality check and enhance the reliability of the translated data. Thematic analysis was used for coding meaningful extracts; Codes were compared across participants and developed into final themes for interpretation NVivo 15 – a popular tool for qualitative data analysis was used to store the transcripts and code extracts and identify the core themes.

6. Case Study - GlobalMFG

GlobalMFG is an information-rich MNE, with international networks connecting multiple subsidiaries and operating units across many countries, making cross-border collaboration a routine feature of organisational work. Knowledge sharing therefore occurs repeatedly across locations and functions.

This organisation combines engineering-intensive manufacturing with advanced digital technologies. Documentary sources indicate that AI is embedded in operational technologies and enterprise-wide digital services across GlobalMFG. Its organisational reach extends across different functions and creates routine opportunities for employees to encounter AI-enabled tools in their work. These features create a strong setting for examining how AI influences knowledge sharing practices.

7. Analysis

The analysis of the interviews with the six participants produced five themes concerning how AI influences knowledge sharing practices in GlobalMFG:

- AI Supports Initial Access to Work-Related Knowledge
- AI Supports Cross-Border Communication
- Human Judgement Mediates AI-Supported Knowledge Sharing
- AI-Enabled Efficiency and Reconfiguration of Work
- Organisational Conditions Shape AI-Enabled Knowledge Sharing

Participants described AI use as localised within particular tools and work situations rather than through an enterprise wide AI-enabled knowledge sharing system. These practices occurred at the individual and team levels, and their use depended on employees' expertise, access to approved tools and the degree of integration between organisational systems.

7.1 AI Supports Initial Access to Work-Related Knowledge

Participants associated AI with faster initial access to work-related knowledge. This initial access represented individual knowledge acquisition rather than knowledge sharing. P1 used AI to develop a preliminary understanding of unfamiliar technical topics. When moving from motor-related work to sensors, he asked AI to

explain the relevant product principles because this was "*faster than searching online for documents myself and saves time".* P4 identified a related possibility in application work: existing databases provided product information but offered limited support for questions tied to a specific application context. P4 therefore viewed an AI-supported knowledge base as a potentially useful future development rather than a tool currently used in knowledge sharing.

This use of AI changed the preparation that took place before interpersonal knowledge sharing. P1 still approached colleagues when he needed detailed explanations, but he first used AI to build enough background knowledge to ask a more focused question. As P1 explained, *"I do not need to ask them very basic questions. I can approach them with at least an introductory or preliminary understanding of the product".* AI therefore supported the preparatory stage of knowledge sharing rather than replacing colleagues as sources of contextual or specialist knowledge.

7.2 AI Supports Cross-border Communication

Engineers used AI-enabled functions when communicating with colleagues in other locations. The design engineer P1 used real-time subtitles when unfamiliar accents made spoken English difficult to follow. He explained, "*I can read the subtitles directly, which improves communication".* P3 who is a testing engineer, used Teams captions and translation in meetings with colleagues from other countries. P6 also used English captions when he could not clearly understand parts of a discussion.

Meeting-summary tools supported the work that followed these discussions. P4 used an AI-enabled function that organised the meeting content and recorded agreed actions and responsibilities. The resulting record helped employees return to the discussion after the meeting.

These uses were relevant to the MNE context because participants regularly communicated across national locations. Differences in accents and language proficiency sometimes made technical discussions difficult to follow. Captions and translation helped employees understand parts of these discussions as they occurred. Meeting summaries made some of the exchanged knowledge available afterwards. The findings therefore show that AI supported specific moments in cross-border knowledge sharing. Employees still needed contextual knowledge to interpret and use what had been communicated.

7.3 Human Judgement Mediates AI-supported Knowledge Sharing

Participants described human judgement as the mechanism through which AI-generated information became usable in knowledge sharing. Employees needed prior knowledge to formulate relevant questions, evaluate AI outputs and translate them into advice, discussion or work decisions that colleagues could use. P2 argued that useful AI use required an existing knowledge base: "*The precondition is that you already have half a bottle of knowledge, and AI helps fill it up*". Without basic understanding, employees might struggle to frame questions or respond to specialist terminology.

P6 connected output quality to the detail of the input, explaining that users needed to articulate their requirements clearly. P4 raised a related concern about specialised and local market contexts. AI could generate an initial view, but employees still needed to assess its relevance before making a decision. P5 placed the same boundary around interpersonal knowledge sharing, observing that tools could shorten communication time and that important issues still came down to direct discussion between colleagues.

The value of AI depended on the employee's ability to define the problem and interpret the response in relation to the work context. P5 made this boundary explicit: "*the most important factor in all information sharing and knowledge sharing is still the human factor*". Human expertise remained part of the process through which AI-generated material became usable organisational knowledge.

7.4 AI-Enabled Efficiency and Reconfiguration of Work

Efficiency was the most consistent benefit associated with AI. Participants described shorter search times and faster preparation of work materials. P5 stated that, in information sharing and knowledge acquisition, "*something that might previously have taken two hours may now be solved in twenty minutes*". He also questioned the completeness and reliability of AI answers, explaining that employees still needed to screen information and examine responses from different angles. P5's wider account connected the use of AI to the organisational setting. He described separate enterprise platforms whose integration was constrained by access controls and legal requirements. These conditions limited the extent to which faster retrieval could be extended across organisational units.

The time saved during retrieval or drafting changed how effort was distributed across the task. P6 stressed that "*the better and more detailed the input, the more accurate the AI output will be*". P4 described AI as capable of producing an initial version of a document, which the employee could then review and revise. AI reduced the time required for some activities and increased the significance of input preparation and output verification. Within the MNE context, these changes were relevant to work involving knowledge drawn from different functions and locations. AI could shorten the preparation required before employees exchanged information across organisational boundaries, although the resulting material still needed to be assessed against technical requirements and local working conditions. Efficiency therefore depended on employees' ability to connect AI-generated material with the distributed knowledge available across the organisation.

7.5 Organisational Conditions Shape AI-enabled Knowledge Sharing

Access permissions, awareness and fragmented organisational systems shaped whether AI-enabled functions could become part of employees' knowledge sharing practices. These conditions affected who could use AI-supported meeting, retrieval and documentation functions and whether such practices could extend across teams and locations. P1 described the formal use of AI in knowledge sharing as very limited. P3 observed that employees could already be using automated live captions or real-time translation during meetings without recognising these functions as AI-enabled. P2 was aware of AI-enabled meeting functions but lacked permission to use some of them: *"We do not have the permission. I know about it, but we do not have access".* AI-related functions could therefore be embedded in commonly used platforms without being recognised as AI or available under the same conditions to all employees.

Governance and system architecture further shaped use. P3 reported that the organisation *"has not yet issued an AI-related policy",* although existing IT controls placed strict limits on external access and data movement. P1 linked restricted use to confidentiality and intellectual-property concerns. P5 described barriers between AI functions embedded in different enterprise platforms and explained that broader integration would encounter security and legal boundaries. P3 also described a global platform that was being introduced gradually through separate functional modules. AI-enabled retrieval was discussed as a possible later development rather than a function currently used in the knowledge sharing practices reported by participants. This account provides evidence of the organisational conditions surrounding future AI integration rather than evidence of current AI-enabled knowledge sharing. Across the six interviews, AI use appeared to remain localised within particular tools and work situations. The interview evidence indicates that the organisational availability of AI-related functions had not yet translated into consistent knowledge sharing practices across the parts of GlobalMFG represented in the sample. P2 described his experience of fragmented systems by saying that "*all the functions you just mentioned are on separate websites"* and that *"there is no integration at all".* This account reflects one participant's experience of system fragmentation; it does not by itself show that the whole organisation lacked integration.

The findings show that AI influenced knowledge sharing in GlobalMFG through local changes in how employees accessed work-related knowledge, used meeting-support functions and recorded shared information. Employees continued to evaluate AI outputs and decide how they could be used in specific work contexts. Secondary data present a broader strategic picture of AI development. The interview accounts show that this corporate commitment had reached roles and units unevenly. AI use therefore remained distributed across separate platforms and work settings, with broader integration still developing at the level of employees' reported practice.

8. Discussion

Knowledge sharing in this study included routine exchanges between colleagues across teams and organisational locations. AI-supported search can help employees develop an initial understanding before they approach colleagues. Meeting functions can assist comprehension and preserve parts of a discussion for later use. AI can alter the timing and preparation of knowledge sharing even when an enterprise-wide AI knowledge system remains under development.

Faster access leaves interpretation as a central part of the task. Employees need prior knowledge to formulate useful questions and assess the relevance of a response. This finding supports Ackerman, Pipek and Wulf's (2003) account of the continuing need for expertise when information is removed from its original context. In GlobalMFG, AI expanded access to codified and semi-codified material. Its use remained dependent on situated judgement and knowledge of the work setting. This pattern is consistent with Orlikowski's (2002) view of knowing as something enacted through practice.

Participants described language-related difficulty during meetings involving colleagues from other countries. Live captions and real-time translation improved comprehension in these situations. Automated summaries supported the later retrieval of discussion content in the work settings as highlighted by participants P4 and P5. These functions addressed specific moments of cross-border interaction. Employees still relied on shared terminology and contextual interpretation when using the knowledge exchanged. AI therefore supported communication at identifiable points without resolving the wider organisational conditions surrounding cross-border knowledge sharing.

The case highlights a gap between organisation-level AI ambition and employees' everyday use. Organisation-level materials suggest that AI forms part of GlobalMFG's wider digital and innovation agenda. The interviews show a slower movement into local practice.

The findings also indicate performance-oriented accounts of AI-mediated knowledge sharing. AI reduced the time required for search, preparation and documentation. The surrounding work remained significant. Employees had to formulate requests carefully and carry out responsibility for deciding how each response could be applied to the task. Efficiency therefore involved a redistribution of effort across the activity. Some participants connected future AI development with job insecurity or reduced demand for expertise. These views add employee-level uncertainty to studies that emphasise employee experience and organisational performance (Malik et al., 2021; Olan et al., 2022).

Access to approved tools provides one part of the required infrastructure. Employees also need clear guidance on data use and support when interpreting AI outputs. This indicates the need for proper training and guidance for employees in the effective use of AI tools. Training can strengthen question formulation and critical evaluation. Governance needs to improve coordination between separate platforms and preserve confidentiality controls.

9. Conclusion

This paper examined how AI influences knowledge sharing practices within an MNE through the case of GlobalMFG. The findings provide a clearer account of how AI-enabled knowledge sharing develops in everyday organisational practice. AI was most prominently used before and after interpersonal interactions, with employees relying on it to prepare for discussions and to capture, organise, and retain information from meetings. However, experienced colleagues remained the primary source of knowledge when tasks required specialist expertise, prior experience, or an understanding of local contexts. While AI facilitated access to information and supported certain stages of the communication process, direct interaction with knowledgeable colleagues continued to play a central role in effective knowledge sharing.

Organisational documents demonstrated a strong corporate commitment to AI adoption, while interview accounts provided insight into how this commitment was experienced in employees' day-to-day work. Although AI technologies were being introduced across the organisation, access to AI-enabled tools varied between participants, and some applications remained disconnected from the systems used for routine work. Also, governance and data security requirements restricted the types of organisational information that could be entered into certain AI tools. These findings suggest a gap between corporate investment in AI and the organisational conditions required to support its consistent and effective use across the organisation.

For MNEs, investment in AI needs to be accompanied by practical arrangements at team level. Employees require clear guidance on approved tools, data use and responsibility for validating AI-generated outputs. Organisations should also improve integration between AI-enabled functions and existing knowledge management systems to support more consistent knowledge sharing.

Organisational support should also be aligned with employees' day-to-day work activities. Training should begin by developing employees' ability to formulate effective prompts and then progress to evaluating and validating AI-generated outputs using relevant workplace knowledge and professional judgement. Guidance on the appropriate use of organisational information should be embedded within training activities rather than presented as a separate compliance exercise. Using examples drawn from real workplace scenarios can help employees recognise when AI provides valuable support and when consultation with experienced colleagues remains essential. In addition, managers or designated AI experts can serve as local points of contact to assist employees when organisation-wide guidance does not adequately address specific issues. Finally, Organisations should also establish employee feedback mechanisms to refine AI access, governance and training over time.

The study is limited to one case organisation and six participants. Future research could examine whether the patterns identified are evident across different organisational contexts, providing a more comprehensive understanding of AI-enabled knowledge-sharing practices.

Acknowledgements

The authors would like to thank Dr Maher Alzyadat for his valuable feedback during the preparation of this paper.

Ethics Declaration: Ethical approval for this PhD research project was granted by the Research Ethics Committee of the School of Physics, Engineering and Technology, University of York. All participants provided informed consent before taking part in the interviews.

AI Declaration: Generative AI tools were used to assist with language editing, grammar checking and improving the clarity of the manuscript. The authors retained full responsibility for the interpretation of the data, the analysis, the conclusions and the final content of the paper.

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Rethinking Knowledge Creation in the age of Digital Innovation: Insights from IT Sector

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Abstract: Recent literature highlights that generative artificial intelligence (GenAI) is expected to play a central role in knowledge-intensive work, particularly in sectors strongly exposed to technological innovation. Beyond facilitating existing knowledge management (KM) practices, GenAI appears to introduce a fundamentally new epistemic dimension that challenges traditional models of organizational knowledge creation, most notably Nonaka's SECI model. While the SECI framework has long explained knowledge creation through the dynamic interaction between tacit and explicit human knowledge, it does not explicitly account for knowledge processes emerging from human-AI interaction. Drawing on these premises, the aim of this research is to investigate how GenAI alters knowledge creation dynamics and to identify new knowledge conversion mechanisms emerging from human-machine interaction. To achieve this, the study adopts an exploratory single case study within the IT sector, an environment characterized by high innovation intensity and rapid technological change. The selected case organization was chosen based on its positioning along three key dimensions known to influence technology adoption: orientation to innovation, technological culture and organizational complexity. Data were collected over a period of one year and five months through thirty semi-structured interviews with employees across R&D, operations and senior management. Data were triangulated by direct observation and analysis of project documentation. The qualitative data were analysed using content analysis supported by inductive coding techniques inspired by grounded theory. This process led to the construction of an inductive coding tree capturing core themes and their relationships. Findings reveal that GenAI generates knowledge dynamics that cannot be fully mapped onto the traditional model. In particular, new knowledge conversion modes emerge between human knowledge, machine-generated data and artificial knowledge. These include transformations from human tacit and explicit knowledge into data, from data into artificial knowledge and from artificial knowledge back into human explicit knowledge. Alongside these conversion modes, several conceptual domains were identified. Based on these results, the study proposes a novel conceptual framework that integrates the SECI model with a machine dimension, offering a more comprehensive representation of contemporary knowledge creation in organizations which integrate GenAI into their processes. The framework highlights the importance of strategic integration of GenAI into KM processes and the value of human-in-the-loop validation. This research contributes to KM theory by extending classical models to account for artificial knowledge generation and provides a foundation for future empirical studies on human-machine knowledge ecosystems.

Keywords: Artificial intelligence (AI), Artificial knowledge management (AKM), Artificial knowledge generation, SECI, Generative artificial Intelligence (GenAI), DIKW hierarchy

1. Introduction

Generative Artificial Intelligence (GenAI) has demonstrated significant potential to enhance human productivity and support complex cognitive tasks, as it is capable of autonomously generating new forms of content by identifying patterns within large volumes of previously available data. Owing to these capabilities, increasing attention has been directed toward this technology by both public and private organizations (Zhang et al., 2025). Consequently, substantial investments are currently being made by many firms to develop and integrate GenAI solutions into their operational processes. According to recent studies, the widespread diffusion of GenAI is expected to produce considerable transformations for both individuals and organizations in the coming years, even in situations where its formal adoption remains limited (Albashrawi, 2025). Within this evolving landscape, a major challenge for managers will consist in understanding how GenAI affects organizational activities, particularly those related to decision-making processes and knowledge-intensive work. In such a context, knowledge management (KM) assumes a particularly relevant role. KM refers to the set of processes through which knowledge is collected, shared and created within organizations in order to effectively leverage available informational resources. When properly structured, KM practices enable organizations to enhance operational efficiency while simultaneously strengthening their capacity for innovation. To explain how knowledge is generated and circulated within organizations, several established theoretical frameworks have been developed. Among the most influential are the Absorptive Capacity Model, the Organizational Learning Model (Crossan et al., 1999), and Nonaka's SECI model (Nonaka, 1994). These frameworks have provided organizations with valuable conceptual foundations for structuring knowledge processes and maximizing the strategic value of their knowledge assets. Among them, the SECI model, by explicitly describing the dynamic interaction between tacit and explicit knowledge in knowledge creation, appears to provide a particularly suitable lens through which to analyse the integration of GenAI from an organizational knowledge creation perspective.

Specifically, previous studies have begun to examine the relationship between GenAI and knowledge creation from two complementary perspectives. First, research has explored how GenAI influences the different phases of the SECI model, highlighting its potential impact on traditional knowledge conversion processes (Liccardo and Cerchione, 2025). Second, recent studies have acknowledged the existence of a machine dimension in organizational knowledge creation (Cerchione et al., 2026). However, the specific mechanisms through which human tacit and explicit knowledge interact with data and artificial knowledge remain underexplored. This study addresses this gap by empirically identifying and systematizing knowledge conversion modes emerging from human-GenAI interaction within organizational workflows. To reach this objective, the present study develops an integrated conceptual framework that captures these interactions and contributes to a deeper understanding of GenAI-enabled knowledge creation. In doing so, the research seeks to stimulate further discussion on the role of GenAI in knowledge management and to provide a systematic foundation for future studies in this field.

2. Theoretical Background

The growing body of literature addressing the use of GenAI in organizational contexts highlights its transformative implications from a knowledge management perspective. In particular, previous studies suggest that GenAI has significant potential to influence the acquisition, dissemination and creation of knowledge within organizations (A Mooradian, 2024). However, interpreting GenAI solely as an auxiliary tool supporting existing knowledge management practices may represent an overly limited perspective. Rather than simply enhancing traditional processes, GenAI appears to introduce a new dimension within knowledge generation (Figure 1).

Scholarly work increasingly suggests that organizational knowledge creation may involve the interaction of two distinct yet interconnected dimensions. The first is the human dimension, which encompasses conventional knowledge creation processes and has been extensively conceptualized within the literature, most notably in the work of Nonaka (Nonaka, 1994). Alongside this, a machine dimension can be identified, enabling new forms of human-machine and machine-machine interactions that contribute to the emergence of novel knowledge.

While the human-centered processes described by Nonaka (1994) have been widely studied, a structured framework for understanding knowledge generation within the machine domain remains largely underdeveloped. For this reason, the present study adopts an exploratory case study approach to investigate the fundamental relationships between the human and machine dimensions. In doing so, it seeks to further examine a concept that Nonaka and Toyama (2003) had already suggested, but which has remained conceptually ambiguous in light of the recent emergence of GenAI technologies.

Within the machine dimension, data represents the fundamental component enabling knowledge-related processes. The ability of GenAI systems to autonomously generate new content is largely dependent on the extensive datasets from which they learn and upon which they perform analysis. In general terms, data can be described as symbols representing the properties of objects, as well as factual recordings or measurements used as the basis for reasoning and computation (Rowley, 2007). Consequently, both the quantity and the quality of available data significantly influence the performance of GenAI models. For this reason, effective data management and governance become essential for unlocking the full potential of GenAI technologies, in a way that is comparable to how the richness of human experience contributes to the development of human knowledge. From a cognitive perspective, human reasoning is often supported by the construction and manipulation of analogies based on mental models, structured representations of reality that guide interpretation, reasoning and decision-making (Johnson-Laird, 1995). A similar logic can be extended to machines, which process large volumes of data through algorithmic systems in order to generate new outputs. In this sense, the “mental models” of machines may be understood as structured combinations of data and computational processes, such as those implemented in foundation models and deep learning architectures. Over time, the machine dimension has evolved beyond its traditional role as a simple data repository, increasingly performing functions related to data processing, pattern recognition and automated decision support. This evolution raises an important question regarding whether the outputs produced by such systems can be considered a distinct form of knowledge, often referred to as artificial knowledge. Conceptualizing artificial knowledge, however, remains challenging, as even traditional human knowledge is widely recognized as a complex and multifaceted construct. Some contributions in the literature suggest that machines may already possess a form of knowledge, particularly what has been described as actionable knowledge, referring to the practical use of information for solving specific problems (Jashapara, 2004). Nevertheless, further research is required to determine whether machines are capable of developing deeper conceptual forms of knowledge comparable to those produced through human cognition. Based on these considerations, it may be argued that machines are currently able to process and utilize information in ways that resemble the human use

of actionable knowledge. However, the extent to which machines can engage in genuine conceptual reasoning remains an open question that lies beyond the scope of the present study.

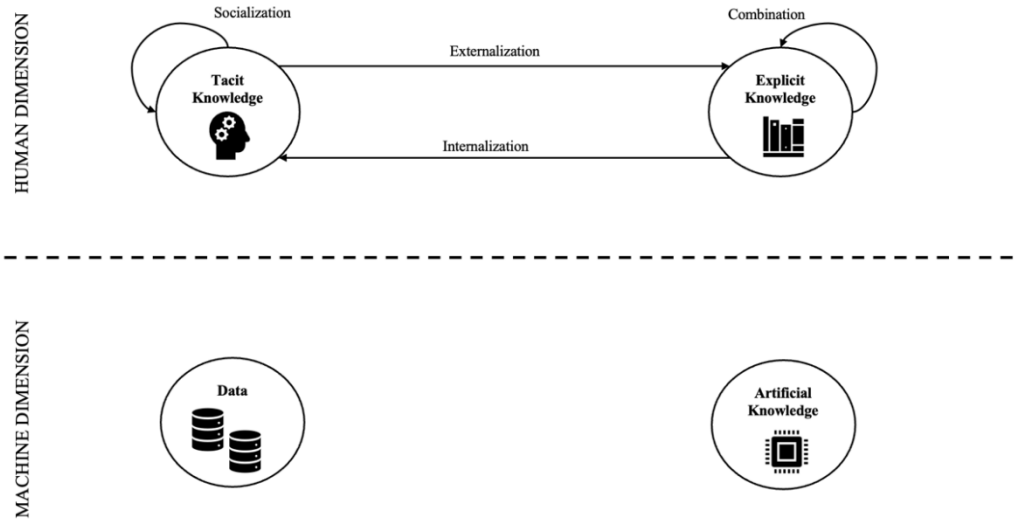


Figure 1: Human and Machine dimension

3. Methodology

The empirical investigation focuses on a single organization, in line with the logic of exploratory case study research (Ridder, 2017). The selected company is a small enterprise operating in the cybersecurity sector, providing services ranging from cybersecurity solutions to customized software development. The case was purposefully chosen based on its positioning across three key factors widely recognized as influencing the adoption of new technologies within firms (Teece, 2007): a) orientation toward innovation, b) prior technological culture and c) organizational complexity. These dimensions have been extensively discussed in the literature as critical determinants of a firm's openness to technological change, making the selected organization particularly suitable for investigating the integration of GenAI into operational processes. Building on this premise, the study was designed as an exploratory single case study. Following Ridder (2017), a case study was adopted to investigate GenAI integration into organizational workflows, analysing their implications beyond the knowledge creation processes described by Nonaka's SECI model. Data collection relied primarily on qualitative methods. The main sources included in-depth interviews with company employees and field notes gathered during a direct observation period lasting one year and five months. In addition, secondary materials, such as the company website and internal project documentation, were used to triangulate the empirical evidence (Yin, 2014). In total, thirty semi-structured interviews were conducted at different stages of the observation period. Participants occupied key roles within the R&D and operations departments, as well as within the senior management team, thus covering a broad spectrum of professional experience, from junior developers to senior managers. All interviews were audio-recorded and subsequently transcribed to ensure accuracy and completeness of the dataset. For data analysis, content analysis was adopted as the primary methodological approach (Bryman and Burgess, 1994), as it enables the systematic examination of complex phenomena through structured coding procedures (Saldaña, 2013). To support the development of inductive categories, coding techniques inspired by grounded theory were employed. The analysis began with a detailed examination of interview transcripts, which were subsequently organized using specialized qualitative analysis software. Data collection continued until theoretical saturation was reached, namely when additional interviews no longer generated substantially new codes or conceptual categories. An inductive coding tree was then developed, combining in vivo codes, which captured participants' original expressions, with researcher-generated descriptive codes derived from analytical interpretation. Through an iterative process, codes were progressively refined and validated through triangulation across interviews, field observations and internal documentation. Finally, codes were systematically compared and grouped into higher-order themes and overarching conceptual domains (CDs).

4. Results

Through an inductive coding process, several higher-level conceptual domains (CDs) were identified. These domains aggregate related themes emerging from the empirical data and represent broader analytical dimensions that characterize how GenAI reshapes knowledge creation processes within organizations. In particular, they highlight mechanisms and dynamics that cannot be fully explained by the traditional SECI phases alone, thus providing additional insights into the evolving relationship between human and machine dimensions in knowledge generation.

CD1: Data synthesis

The findings (Figure 2) indicate that the generation of synthetic data represents a significant advantage for organizations, provided that data validity is ensured and potential biases are effectively controlled. In the context of cybersecurity, the use of GenAI offers particularly valuable opportunities, especially through its capacity to create synthetic datasets for testing and experimentation purposes. As highlighted by a senior developer, "Generating synthetic data allows us to conduct in-depth analyses on the algorithms that form the core of new services".

Within the case study organization, this potential is supported by the implementation of rigorous validation protocols, which involve multiple stages of human oversight. As one participant emphasized, "Careful human supervision is essential to effectively mitigate bias and discrimination". In addition, specific privacy filters are applied to ensure compliance with regulatory requirements, as "data is shared only after all necessary measures have been implemented to guarantee privacy protection". Overall, the adoption of structured strategies for synthetic data generation appears to be crucial for fully leveraging its benefits. Such approaches enable organizations to access large volumes of specialized data that would otherwise be difficult to obtain, while maintaining control over data quality, ethical considerations and regulatory constraints.

1st order codes ("in vivo and descriptive coding)	*2nd order themes*	*Conceptual domains (CD)*
Providing alternative approaches and solutions in development *new data synthesis to produce new services* *test software functioning via synthetic data*	*Application of synthetic data*	*Data synthesis*
Synthetic data production and elaboration *Software development production* *Data analysis* *R&D tool* *Assisting in the generation and validation of synthetic data*	*Synthetic data generation*	
Human validation on a subset of data *"Using privacy filters"* *"Random sample validation"* *"Protocol to autonomously check the data produced"*	*Validation and filtering of synthetic data*	

Figure 2: Coding tree for "Data synthesis" conceptual domain

CD2: GenAI as innovation catalyst

The findings from the case study (Figure 3) confirm the strong potential of GenAI to act as both a driver of innovation and a source of productivity enhancement. By enabling the generation of original content and the aggregation of fragmented information, GenAI contributes to accelerating innovation cycles and fostering a more creativity-oriented organizational environment. In this sense, it supports not only idea generation but also the development of a broader innovation culture. In addition to its impact on creativity, GenAI plays a significant role in workflow automation and process optimization, leading to tangible productivity improvements, particularly in software development contexts. Its contribution also extends to managerial activities, where it supports tasks such as project planning and resource allocation. As one manager noted, "GenAI helps me in GNATT scheduling activities". However, the evidence suggests that these benefits are not automatically realized. Their full potential depends on the organization's ability to actively and strategically integrate GenAI into existing workflows. As emphasized by a senior team member, "effectively integrating GenAI in workflow processes is the key, the risk is to be passively affected by this revolution." This perspective was consistently reinforced by multiple managers and senior professionals, highlighting the importance of a deliberate and structured approach to GenAI adoption.

1st order codes ("in vivo and descriptive coding)	2nd order themes	Conceptual domains (CD)
"GenAI is a colleague in code production"	collaboration with GenAI	GenAI as innovation catalyst
Human-machine new insight generation		
Learning path discovery		
Service optimization via simulation		
Increase learning speed	driving organizational innovation	
Innovation catalyst		
"Promoting an innovation-oriented ambience"		
"Communicating operational results"	increase in productivity and workflow optimization	
Accelerating software development through AI-generated code suggestions		
Organizational process optimization		
Improving communication		
Improving productivity		
Proactive integration		
Internal process optimization		

Figure 3: Coding tree for "GenAI as innovation catalyst" conceptual domain

CD3: GenAI new insights

GenAI has demonstrated a strong capability to identify hidden patterns and connections within large and complex datasets, making it particularly valuable in domains that rely on advanced data analysis. By enabling the detection of relationships that might otherwise remain unnoticed, it supports more informed and insightful decision-making. As one participant observed, "GenAI allows you to notice some elements that you may overlook". Within the case study organization, this potential is applied to tasks such as detecting anomalous patterns, mapping network traffic, and uncovering previously unrecognized links between security threats (Figure 4). When integrated responsibly into operational processes, these capabilities contribute to enhancing the overall value of the services delivered, particularly by strengthening proactive defence mechanisms against cyber threats.

1st order codes ("in vivo" and descriptive coding)	2nd order themes	Conceptual domains (CD)
	identify hidden connections	GenAI new insights
Highlighting connection that were not evident		
Putting in evidence new elements		
"Finding the link between phenomena"		
New feature extraction	Pattern recognition	
"Mapping traffic and anomaly detection"		

Figure 4: Coding tree for "GenAI new insights" conceptual domain

CD4: Human role in GenAI-assisted workflows

The case study confirms that ethical considerations and human oversight remain central in GenAI-assisted workflows (Figure 5). Despite being an early adopter of these technologies, the organization has implemented a range of practices to ensure their responsible use. These include both simple measures, such as anticipating outputs and ensuring proper understanding of results, and more structured approaches, such as periodic compliance audits, described by one participant as "strict protocols that include periodic audits for data monitoring and control." Additional practices involve validation procedures, prompt engineering, "good answers mainly depend on good prompts", and the use of explainable AI (XAI) techniques. Across the organization, a strong emphasis is placed on critically reviewing GenAI outputs. As highlighted by the technical director, users are expected to actively interpret and validate results rather than passively accept them, recognizing that outputs are not error-free and must be carefully analysed. This need for oversight is particularly relevant in the cybersecurity domain, where strict data protection and privacy requirements make human validation indispensable. Moreover, current GenAI systems still present limitations, including overly simplified responses and the risk of hallucinations, which further reinforce the importance of human intervention. To address these challenges, the organization adopts a set of mitigation strategies aimed at balancing automation with human control. These include testing GenAI in synthetic scenarios, promoting prompt-sharing practices to enhance user capabilities, and providing structured training on both model functioning and validation procedures. As one employee noted, "I participate in training sessions organized by the company, where both the functioning of the models used and the procedures for validating the obtained results are explained". Overall, the findings suggest that the effective use of GenAI depends on fostering a critical mindset among employees, where outputs are not treated as definitive truths but as inputs to be actively evaluated and refined.

1st order codes ("in vivo and descriptive coding)	2nd order themes	Conceptual domains (CD)
low-biased algorithm use	Ethical use	Human role in GenAI-assisted workflows
Balancing AI-generated insights with human judgment		
"Explaining results in formation sessions"		
Respecting privacy policy		
Responsibility in using GenAI outputs		
Human revision for critical data	Human supervision	
Periodical conformity audit		
Having an expected output in advance		
Bias management		
"Correct use of the prompt engineering"		
"human supervision is still necessary due to the hallucinations and complex task resolution"		
"Integration mediated by actors' comprehension"	Managing risk of using GenAI	
Testing GenAI on synthetic scenario first		
Informal and formal best practice in using GenAI		
Explaining the functioning of the models		
Dealing with policy regulations		
XAI		
Critical thinking preservation		
GenAI hallucinations in answering		
Impossibility to completely substitute human interactions		

Figure 5: Coding tree for "Human role in GenAI-assisted workflows" conceptual domain

CD5: Risks associated with GenAI misuse

Despite its advantages, the use of GenAI also introduces significant risks, particularly those related to excessive dependence and the potential erosion of human capabilities (Figure 6). The findings suggest that employees may increasingly rely on AI-generated content, leading to a "loss of capacity to elaborate data from their own". This risk appears to be especially pronounced among less experienced professionals, who may attempt to compensate for knowledge gaps by relying heavily on GenAI, potentially bypassing essential learning processes. As a result, there is concern that the habitual use of AI for immediate solutions may reduce opportunities to "emulate the best ones", ultimately hindering the development of professional expertise over time. However, these risks are not limited to junior employees. More experienced professionals and managers may also be affected, as the automation of complex cognitive tasks can diminish their competitive advantage, or what one participant described as "working power". Over time, an overreliance on GenAI in decision-making processes may weaken critical thinking and creative problem-solving abilities. More broadly, the evidence points to a transformation in traditional experiential learning dynamics. In particular, younger professionals may face increasing difficulties in developing independent analytical skills. Additionally, uncritical reliance on GenAI outputs can lead users to "lose focus and explore wrong alternatives", resulting in inefficient use of time and resources. To mitigate these risks, organizations need to actively integrate GenAI into both operational workflows and employee training programs, ensuring that it functions as an augmentation tool rather than a substitute for human expertise. Equally important is the establishment of clear guidelines for responsible AI use, fostering a balanced approach that combines technological support with human judgment.

1st order codes ("in vivo" and descriptive coding)	2nd order themes	Conceptual domains (CD)
Decrease in the process of emulating the best	dependence	Risks associated with GenAI misuse
Excessive dependence from this tech		
the most skilled are the most in danger to lose their competitive advantages.	loss of skill	
Preventing knowledge stagnation by fostering independent thinking		
Avoiding excessive AI dependence in problem-solving		
Poor control on the use of GenAI		
Lack of deep context	issue on output	
Strongly dependant from prompt		
Difficulties in using it to share knowledge		
Frequent hallucinations		

Figure 6: Coding tree for "risk associated with GenAI misuse" conceptual domain

5. Discussion

Within these conceptual domains, several potential knowledge conversion modes (CMs) emerged from the empirical analysis. These conversion modes represent specific mechanisms through which knowledge is transformed across the human and machine dimensions. While the conceptual domains capture broader thematic areas describing how GenAI reshapes organizational knowledge practices, the conversion modes provide a more granular perspective on how knowledge flows and transformations occur between humans, data and AI systems. In this sense, the identified CMs extend the traditional SECI knowledge conversion logic by

incorporating new forms of interaction involving human and machine dimensions. To provide a comprehensive overview, a conceptual framework was produced (Figure 7).

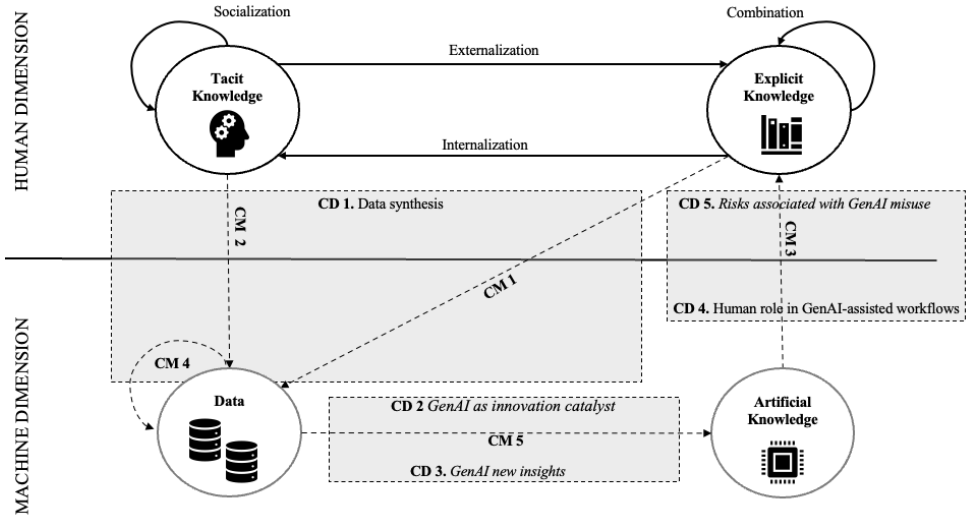


Figure 7: GenAI integrated framework

The empirical findings reveal several knowledge conversion dynamics that describe how human and machine dimensions interact within AI-mediated knowledge processes. These dynamics can be interpreted as a set of conversion modes that connect the elements of the human dimension (tacit and explicit knowledge) with those of the machine dimension (data and artificial knowledge). Each conversion mode emerges from specific conceptual domains identified in the coding process and highlights different mechanisms through which knowledge is transformed across human and machine actors. More specifically, the conversion modes emerged as analytical abstractions linking recurring empirical patterns observed across interviews, field observations and project documentation.

A first conversion dynamic emerged from the conceptual domain related to data synthesis and concerns the transformation of explicit human knowledge into machine-processable data (CM1). In this process, human actors play a crucial role in translating structured knowledge, such as documentation, guidelines or technical procedures, into datasets that can be used to train AI systems. For this transformation to be effective, data must accurately represent the complexity of real-world contexts and must be carefully filtered and validated before being used for training purposes. Within the case study organization, this process was particularly evident in the development of internal security policies and algorithmic specifications for GenAI applications. Through this approach, explicit organizational knowledge contained in technical documentation was intentionally converted into machine-readable data, providing a reliable foundation for AI training and strengthening trust in AI-assisted workflows. The same conceptual domain of data synthesis also revealed a second conversion dynamic involving the transformation of tacit human knowledge into data (CM2). Existing research suggests that tacit knowledge can be partially externalized through digital traces such as audio recordings, video material or textual artefacts. The findings of this study extend this perspective by highlighting how AI systems can learn from human-generated outputs even when these artefacts were not originally produced for the purpose of AI training. In practice, AI models analyse large volumes of human-produced material to detect recurring patterns embedded in everyday activities. These patterns may include linguistic structures extracted from written communication, visual cues derived from images or videos, and decision-making behaviours inferred from historical records of professional activity. The learning process therefore becomes continuous and dynamic, integrating heterogeneous data sources such as digital documentation, social media content and interactions captured through Internet of Things (IoT) devices. A major challenge associated with this conversion dynamic lies in the design of algorithms capable of identifying meaningful patterns while filtering out noise, errors and biases embedded in the source data. If not properly addressed, these biases may be reproduced or amplified by AI systems. For this reason, organizations must complement algorithmic design with clear internal guidelines regulating how employees interact with AI technologies. As one R&D manager explained, “internally validated best practices on how to interact with AI systems are the key for an ethical and responsible use of this powerful tool.” A concrete example of this mechanism emerged from the analysis of developers’ historical coding practices and interaction logs. Although these behaviours were not originally produced for AI training purposes,

GenAI systems were able to identify recurring problem-solving strategies from source code repositories and development histories, effectively transforming tacit human expertise into structured data. These observations were grouped under themes related to behavioural trace extraction and pattern formalization, which informed the conceptualization of CM2. Another relevant conversion dynamic emerged from the conceptual domain related to ethics and the human role in GenAI-assisted workflows and concerns the transformation of artificial knowledge into explicit human knowledge (CM3). This finding is consistent with recent work emphasizing the importance of human oversight in AI-assisted decision processes, while extending these contributions by framing interpretability as a knowledge conversion mechanism enabler. GenAI systems rely heavily on deep learning architectures that often operate as complex "black boxes". Unlike traditional machine learning techniques, whose decision rules can sometimes be partially interpreted, deep learning models provide limited transparency regarding how outputs are generated. For this reason, translating AI-generated outputs into forms that can be understood and interpreted by human actors becomes essential. In other words, artificial knowledge must be converted into explicit human knowledge that can inform responsible decision-making. This issue has become increasingly relevant across multiple domains, including education, healthcare and finance. In this context, Explainable Artificial Intelligence (XAI) techniques play a key role in increasing the transparency of AI systems by clarifying the rationale behind predictions, recommendations and classifications. By making AI outputs more interpretable, these approaches contribute to building trust, strengthening accountability and enabling responsible adoption of AI technologies in knowledge-intensive environments.

A further conversion dynamic, again linked to the conceptual domain of data synthesis, describes the transformation of explicit artificial knowledge into new data. In this stage, AI systems begin to assume a more proactive role in the knowledge creation process (CM4). Generative models such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) are capable of producing synthetic datasets that can subsequently be used for additional training and experimentation. As one senior R&D member explained, "we use variational models to generate and validate synthetic data. These datasets are part of a dynamic and cyclical process. The intentional disturbance allows the data to be reintroduced into the system for further learning." Through this mechanism, the knowledge embedded in trained models is transformed into new data that feeds further learning cycles. This process represents an important step in the evolution of AI systems, shifting their role from purely human-operated tools to increasingly autonomous contributors to knowledge generation. Nevertheless, greater autonomy also raises important challenges. The creation and reuse of synthetic datasets require rigorous validation procedures to ensure data reliability, prevent the propagation of errors and avoid ethical issues such as bias amplification. Consequently, human oversight remains a crucial element of this stage, particularly in validating both AI-generated inputs and outputs.

Finally, a conversion dynamic emerging from the conceptual domain of GenAI-driven insights concerns the transformation of data into artificial knowledge (CM5). This mechanism represents one of the central motivations of the present study, as it illustrates the capacity of AI systems to generate new knowledge from large datasets. By leveraging foundation models and deep learning algorithms, AI systems can process vast quantities of structured and unstructured data to identify patterns, correlations and anomalies that may not be immediately observable by human analysts. These capabilities have already led to significant advancements in several fields, including drug discovery, materials engineering, manufacturing optimization and personalized education. Within the case study organization, this process was particularly visible in the analysis of large-scale datasets aimed at identifying emerging cybersecurity threats. As one participant observed, "GenAI helps re-elaborate explicit knowledge and transform it into a potential source of innovation and improvement, even starting from previously produced synthetic data." Despite these capabilities, human actors remain essential in evaluating and validating AI-generated insights. The interpretation and critical assessment of newly generated knowledge are necessary to ensure its reliability and practical relevance. In this sense, humans play a key role in integrating AI-generated outputs into organizational knowledge processes. Ultimately, this conversion dynamic represents the culmination of the AI-mediated knowledge creation cycle, generating new forms of artificial knowledge that may trigger further iterations of learning, refinement and innovation.

5.1 Managerial Implications

From a managerial perspective, the framework suggests that GenAI should be embedded into knowledge management processes through clearly defined use cases, such as data synthesis, documentation support and exploratory analysis, rather than being adopted in unsanctioned manner. Managers are encouraged to formalize human-in-the-loop validation practices, assigning explicit responsibility for reviewing, interpreting and approving GenAI outputs in critical decision processes. Furthermore, continuous training initiatives and shared

guidelines on responsible GenAI use are essential to prevent over-reliance on automation while sustaining employees' critical thinking and learning capabilities.

5.2 Limitations and Future Research

Like any research, this study presents several limitations that should be acknowledged. First, the findings are derived from a single case study. Although the selected company represents a particularly suitable context for investigating the integration of GenAI into knowledge-intensive workflows, the results cannot be generalized without caution. Future research could address this limitation by adopting a multiple-case study design, allowing the proposed framework to be tested and refined across organizations with different levels of technological maturity, innovation orientation and organizational complexity. A second limitation concerns the sectoral scope of the study. The empirical investigation focuses on a single industry context, namely the IT sector, which is characterized by high technological intensity and strong familiarity with digital tools. As a result, the dynamics observed in this environment may differ from those found in other industries where the adoption of GenAI is less mature. Extending the analysis to organizations operating in different sectors could provide valuable insights into the broader applicability of the proposed framework. As with most qualitative research, the findings may also be subject to potential observer and participant biases. To mitigate these risks, the study relied on established qualitative research methods and rigorous procedures for data collection and analysis, including systematic coding, iterative validation of categories and triangulation through multiple data sources. Finally, while the study proposes an integrated conceptual framework for understanding the interaction between human and machine dimensions in knowledge creation, further research is required to clarify its boundary conditions and applicability. In particular, future studies could examine how the framework performs across different organizational contexts, levels of GenAI adoption and knowledge management practices.

Acknowledgement

The author sincerely thanks Prof. Roberto Cerchione for his insightful guidance and valuable support throughout the course of this research.

Ethical Declaration: All participants were informed about the nature of the study and participated voluntarily. Clearance was not required for the research.

AI Declaration: Generative AI tools were not used in the production or analysis of the empirical data. All interpretations and findings are the result of the authors' critical analysis and are not generated by AI.

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Tracing Knowledge Flows in Financial Markets with Hybrid Sentiment AI

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Abstract: Financial markets are commonly described as information-efficient, yet the phrase conceals more complexity than it clarifies. Between the arrival of information and the adjustment of prices lies a process that is neither fully observable nor mechanically uniform. Interpretation mediates how signals are received, credibility shapes their perceived relevance, and responses unfold unevenly across participants. From a knowledge management perspective, this raises a central question: how does dispersed information consolidate into knowledge that meaningfully informs decisions? The framework we developed does not seek to model the entire market mechanism. We concentrate instead on a measurable segment of that transformation. Media sentiment is examined using a hybrid analytical approach that combines the lexicon-based VADER model with the domain-specific transformer model FinBERT. The two models do not always converge, and this divergence provides additional insight rather than methodological weakness. Their integration enables us to capture both surface polarity and contextual financial nuance within a single structure. Because informational inputs differ in reliability, sources are weighted by credibility and filtered through an entity-based relevance mechanism. Sentiment scores are aggregated across adjustable time windows, enabling us to detect whether informational pressure accumulates before a price adjustment. Using selected S&P 500 firms characterised by sustained media exposure and high liquidity as the empirical setting, we conduct structured backtesting to evaluate directional alignment and interval coherence across multiple horizons. The main objective of this paper is to assess whether consistent relational patterns can be identified. Our results indicate that such patterns are present, although their strength varies across horizons and informational density. In some instances, aggregated sentiment precedes adjustment, while in others it dissipates without measurable impact. This unevenness suggests that sentiment analysis may be more appropriately understood as a mechanism for tracing knowledge flows within financial ecosystems rather than as a deterministic forecasting device. From this perspective, our study contributes to knowledge management by offering a computational approach for examining how dispersed information becomes actionable knowledge in high-velocity environments.

Keywords: FinBERT, Strategic forecasting, Hybrid AI framework, Financial sentiment Analysis, Distributed knowledge systems

1. Introduction

Financial markets are traditionally viewed through the lens of the Efficient Market Hypothesis (EMH), which holds that prices reflect all available information immediately. However, from the perspective of Knowledge Management (KM), this view oversimplifies a much more complex cognitive and technical process. The path from the generation of raw, scattered information to the actual adjustment of asset prices is mediated by interpretation, the credibility of sources, and varying speeds of information dissemination. In a highly dynamic environment, the main challenge is no longer a lack of data but rather information overload and significant semantic noise.

The central question this study addresses is the mechanisms by which unstructured news data is consolidated into actionable market insights. Although sentiment analysis has become a standard tool for financial forecasting, traditional models often lack the sensitivity needed to process complex financial narratives or the varying reliability of news sources. A gap between signal and noise arises, where meaningful insights are often diluted by general market noise or fleeting media optimism. Therefore, the primary objective of this study is to assess whether aggregated media sentiment contains a measurable information signal regarding subsequent price movements in financial markets and, under what conditions, such signals are most reliable. By combining domain-specific NLP models with credibility-weighted aggregation and structured backtesting, this research advances the understanding of how dispersed financial information consolidates into actionable market knowledge.

To address these challenges, this work presents a hybrid sentiment modelling framework. Unlike homogeneous approaches, our framework employs a dual-engine logic that combines the emotional sensitivity of the VADER lexicon with the deep contextual understanding of the FinBERT transformer. At the same time, we acknowledge that the market processes information with varying time delays. Therefore, our system analyses news at configurable intervals. For purposes of this study, we tested three specific historical windows of 2, 5, and 7 days to examine the depth of historical data needed to generate a reliable sentiment signal. The model tracks how

accumulated news gradually transforms into actionable knowledge within the S&P 500 ecosystem by weighing sources according to their credibility (W_s).

Overall, this study contributes to the field of knowledge management by demonstrating that computational sentiment analysis can serve as a viable mechanism for tracking how dispersed financial information consolidates into actionable market knowledge, particularly within short forecasting horizons and under conditions of sustained media exposure.

The literature review is presented in the next section. Section 3 describes our proposed methodology and the analysed data. Our results are presented in section four. Finally, section 5 concludes our findings.

2. Literature Overview

2.1 Knowledge Management and Financial Intelligence

The traditional understanding of financial markets is increasingly shifting from the analysis of numbers to the knowledge management (KM) flows. In his work, Ajayi (2022) emphasises that KM is not merely an archive of information but a critical strategy for the survival of stockbrokers, enabling the transformation of scattered investment insights into a competitive advantage. However, this process faces challenges with big data. Chierici et al. (2018) argue that the mere existence of large volumes of data does not create value. What is crucial is the specific KM practice that can transform this unstructured data into actionable knowledge. In the current context of 2026, this process cannot proceed without advanced artificial intelligence (AI). Abboud (2025) notes that modern AI systems function as strategic assets, making financial expertise accessible to the broader public by continuously scanning vast data streams and identifying warning signs that would otherwise remain hidden from human analysts. This perspective situates sentiment analysis not as a predictive algorithm but as a knowledge-extraction mechanism. This framing is consistent with KM literature's emphasis on converting raw signals into structured, actionable intelligence (Chierici et al., 2018).

2.2 Market Efficiency and the Role of Information

The theoretical basis for examining the relationship between sentiment and prices stems from Fama's (1970) Efficient Market hypothesis (EMH), which assumes that asset prices fully and immediately reflect all available information. Although the weak and semi-strong forms of the EMH have received considerable empirical support, this hypothesis is based on an idealised assumption. In practice, interpretation influences how signals are received, and differences in cognitive abilities, access speed, and assessments of credibility mean that market participants do not react uniformly. Fama (1991) himself acknowledged that evidence of the predictability of returns based on variables complicates the original framework, suggesting that not all information is immediately and fully reflected in prices. This theoretical gap, between the arrival of information and the adjustment of prices, is precisely the space in which sentiment analysis operates. It is also the space this study seeks to empirically investigate.

2.3 From Lexicons to Transformers: The Evolution of Financial Sentiment Analysis

The use of sentiment analysis as a financial intelligence tool has evolved significantly over the past two decades. Earlier approaches relied on lexicon-based models that assigned polarity scores to words in financial texts. Although these methods were readily available, they were found to have limited ability to handle the contextual ambiguity characteristic of financial language. Mishev et al. (2020) conducted a systematic comparative study evaluating a wide range of NLP approaches for financial sentiment analysis, ranging from dictionary-based methods to word- and sentence-level encoders and modern transformer architectures. Their results confirm that contextualised transformer inputs significantly outperform approaches based on dictionaries and fixed-word encoders, with the BART model achieving the highest classification accuracy among all evaluated models. Araci (2019) directly addressed the limitations of general sentiment models by introducing FinBERT, a domain-specific transformer pre-trained on financial news corpora, which substantially outperformed both lexical methods and general deep-learning classifiers on financial sentiment benchmark datasets. Buckman et al. (2020) further found, based on a sentiment index of daily news reports over a period of four decades, that sentiment indicators derived from news reports lead survey-based measures of consumer confidence by several weeks, a finding with direct implications for the timeliness of any sentiment-based signal. Based on this, Fazlija and Harder (2022) demonstrated that incorporating sentiment from FinBERT, along with historical price data, into predictive models improves the accuracy of forecasts of the S&P 500 index's direction. Puh and Bagić Babac (2023) confirmed that combining sentiment analysis with the FinBERT model and recurrent neural network

architectures yields more accurate stock price forecasts than models that rely solely on historical prices, thereby strengthening the case for hybrid approaches.

2.4 Source Credibility, Aggregation Windows, and Knowledge Flow Dynamics

In addition to the choice of model, the structure of information aggregation also plays a decisive role in determining whether media signals translate into meaningful market insights. Financial news is not homogeneous, as institutional sources such as news agencies operate under different editorial standards and reach different audiences than aggregators for retail investors or social media platforms. Chierici et al. (2018) argue in the knowledge management literature that not all data gathered from social media have the same level of informativeness. Firms must therefore evaluate which inputs are worth processing through knowledge management practices to generate actionable knowledge. The time dimension is equally important, as sentiment does not immediately translate into price adjustments. Fazlija and Harder (2022) demonstrated that incorporating FinBERT-based sentiment scores from financial news improves the accuracy of S&P 500 price direction forecasts. Their results further showed that sentiment derived from content significantly outperforms that derived from headlines, suggesting that the depth of processed information plays a decisive role in the quality of the signal. Taken together, these findings support a framework in which credibility-weighted sentiment aggregation and time windows serve as a mechanism for tracking knowledge flows in financial ecosystems. This perspective is consistent with Abboud (2025), who argues that AI-driven financial systems are most valuable not as deterministic forecasting tools, but as instruments for mapping how informational pressure accumulates and dissipates over time.

While Fazlija and Harder (2022) demonstrated the predictive value of FinBERT-based sentiment, their framework does not incorporate source credibility weighting or examine how aggregation depth affects signal stability. Similarly, existing knowledge management frameworks, such as those of Chierici et al. (2018), address the transformation of big data into actionable knowledge but do not operationalise this process in a financial sentiment context. The present study addresses this gap by integrating credibility-weighted aggregation, hybrid sentiment modelling, and structured backtesting into a unified framework explicitly positioned within the knowledge management tradition.

3. Methodology

The methodology focuses on the technical design of data processing, sentiment analysis, and price trend integration. The system analyses news at configurable time intervals. Three aggregation windows were selected to capture distinct informational dynamics. The 2-day window reflects immediate, recency-weighted sentiment, capturing the most current informational signals before a price adjustment. The 5-day window corresponds to a standard trading week and reflects the accumulation of sentiment across a full cycle of market activity. The 7-day window extends coverage to a full calendar week, including weekend news and commentary that may influence market-opening conditions. Together, these windows enable a systematic comparison of how the depth of sentiment accumulation affects predictive reliability. The research implements a modular computational pipeline designed to transform unstructured financial news into quantified signals, prioritising transparency in the logic of data cleaning and sentiment weighting.

3.1 Data Acquisition and Credibility Weighting

The system utilises an automated data extraction module based on the feedparser library (McKee, 2023) to aggregate news from global financial RSS feeds. Unlike general data scrapers, this system applies a Source weight (W_s) based on perceived institutional credibility at the point of entry, following the principle that not all data inputs carry equal informative value (Chierici et al., 2018). This credibility-weighted filtering represents the first stage of knowledge refinement, in which raw informational inputs are evaluated and prioritised before entering the sentiment processing pipeline. Each news item *I* from source *i* is stored with its associated weight, ensuring that high-credibility institutional nodes have a greater influence on the resulting aggregation than broader retail aggregators.

The mathematical representation of the initial information base at time *t* is:

$$E_t = \sum_{i=1}^{n} \left(I_{i,t} \cdot W_{c,i} \right) \quad (1)$$

The weights are distributed across three tiers based on professional reputation and market relevance:

- **Tier 1 ($W_c = 1.0 - 0.9$):** Primary news agencies (e.g., Reuters, Bloomberg).
- **Tier 2 ($W_c = 0.8 - 0.7$):** Major financial news agencies (e.g., CNBC, BBC).
- **Tier 3 ($W_c = 0.6 - 0.4$):** General aggregators (e.g., Yahoo Finance, Google News).

Before the sentiment analysis, the source HTML content is processed with the newspaper3k library (Ou-Yang, 2013) for in-depth text cleaning. To maintain a high signal-to-noise ratio, the system performs three sequential layers of heuristic filtering:

1. **Structural Validation (Ticker Matching):** The algorithm scans the URL and the headline for the presence of a specific "Cashtag" (e.g., $AAPL) or an official company name. This ensures the article concerns a specific subject, not just a general overview of the sector.
2. **Frequency Analysis and Entity Significance:** The system performs a full-text analysis to calculate a composite relevance score (*R*) based on multiple signals, including the presence of the ticker or company name in the headline and URL, the frequency of entity mentions throughout the full text, and penalties for articles dominated by general market terminology without a specific company identifier. Articles where the entity appears only marginally are excluded entirely, preventing signal dilution and ensuring that sentiment reflects only knowledge flows directly relevant to the target firm.
3. **Automatic Content Filtering using regular expressions:** The system automatically extracts junk content by utilising regular expressions. This includes automated industry reports, general CAGR forecasts, and promotional summaries of research reports that lack new information based on current events.

3.2 Hybrid Sentiment Modelling (VADER + FinBERT)

A key component of the framework is a length-dependent hybrid sentiment engine. It recognises that different NLP architectures excel at different text densities and semantic complexities, a distinction confirmed by comparative evaluations of sentiment methods in financial contexts (Mishev et al., 2020). This length-dependent weighting reflects a sensemaking logic, in which the depth of textual analysis is adapted to the informational density of the input, enabling the framework to extract more nuanced knowledge signals from complex financial narratives.

A. Model convergence logic

The engine combines VADER (Valence Aware Dictionary and sEntiment Reasoner) (Hutto and Gilbert, 2014) with FinBERT, a transformer model pre-trained on financial text (Araci, 2019), which itself builds on the foundational BERT architecture (Devlin et al., 2019). Integration is governed by a length factor (*L*):

- **Headline Polarity (L < 40 words):** VADER is assigned a 70% weight, as short headlines rely primarily on surface-level polarity signals where lexicon-based scoring demonstrates greater sensitivity than contextual transformer models.
- **Contextual Analysis (L > 180 words):** FinBERT is assigned a weight of 70%, thereby leveraging its ability to decode complex financial semantics and specialised terminology.
- **Balanced weighting (40 $\leq L \leq$ 180 words):** Both models contribute equally to the final score.

B. Contrastive sentence splitting

To handle the concession-signal structure common in financial reporting (e.g., profits stagnated, but growth is accelerating), the system implements a contrast multiplier. The algorithm splits sentences at contrastive conjunctions to ensure accurate capture of each clause's sentiment. The clause following the conjunction is assigned a multiplier of 1.6x (β):

$$S_{sent} = \frac{s_{pre} + (s_{post} \cdot \beta)}{1 + \beta} \quad (2)$$

3.3 Aggregation and Signal Construction

Once individual article scores are calculated, they are aggregated within adjustable time windows. The system calculates a weighted average to prevent volume-based distortion, consistent with the principle that the quality of aggregated knowledge inputs matters more than their quantity (Chierici et al., 2018):

$$S_{avg} = \frac{\sum \left(S_{core_j} \cdot W_{c,j} \right)}{\sum W_{c,j}} \quad (3)$$

This aggregation process operationalises the concept of knowledge flows, transforming dispersed media signals into a consolidated informational input that reflects the cumulative sentiment pressure within a defined time window. The resulting S_{avg} is then mapped to directional recommendations:

- **Buy ($S \geq 0.2$):** Indicates a strong positive knowledge flow, suggesting upward price pressure.
- **Neutral ($-0.2 < S < 0.2$):** Reflects a state of informational equilibrium or high signal variance where no clear directional trend is identifiable.
- **Sell ($S \leq -0.2$):** Indicates a dominant negative sentiment, indicating potential downward movement.

This directional signal represents the conversion of aggregated sentiment into actionable knowledge, providing a structured basis for investment decision-making (Chierici et al., 2018). The threshold of $\pm 0{,}2$ was deliberately conservative relative to standard VADER classification thresholds (±0,05; Hutto and Gilbert, 2014) to reduce signal volatility and restrict directional recommendations to periods of stronger, more sustained sentiment pressure. These thresholds provide a consistent quantitative basis for the subsequent backtesting phase, enabling the predictive accuracy of the model to be thoroughly evaluated based on historical price movements.

3.4 Trend Adjustment and Forecasting Horizons

The final stage integrates real-time price data retrieved by the yfinance library (Aroussi, 2024) to calibrate the sentiment signal against market reality through two technical mechanisms:

- **The Trend Safety Mechanism:** Using the yfinance API, the system monitors price movements (*T*) over a 3-day lookback period. If a price decline below ($T < -1\%$) is detected, the system reduces the positive sentiment score. If the decline exceeds ($T < -2\%$), the safety mechanism is fully activated and automatically caps positive media sentiment to a neutral level. This reduces the impact of temporary optimism in news reports during periods of demonstrable asset price declines, addressing the known tendency of media sentiment to lag behind the actual market movements (Buckman et al., 2020).
- **Interpolated Predictive Horizons:** The model generates a 14-day Prediction Band that provides a detailed forecast for each upcoming trading day. Based on sentiment intensity, the model calculates daily price milestones (P_n) for the entire duration ($n = 1{,}2, \ldots, 14$) using a sentiment-scaled interpolation scheme. The base price movement is derived from the aggregated sentiment score, which is then scaled using predefined multiplier points and linearly interpolated for intermediate days. The projected price for a given day n is determined according to the following formula:

$$P_n = P_{current} \cdot \Big(1 + direction \cdot \left(M_{base} \cdot interp(n)\right)\Big) \quad (4)$$

This process generates a dynamic range between values: P_{min} and P_{max} for each day in the horizon. These values are also used during the backtesting phase to assess the model's interval coherence, measuring the extent to which the actual market price consistently remains within the predicted trajectory (Fazlija and Harder, 2022).

3.5 Sample and Empirical Design

The empirical analysis was conducted on a sample of firms selected from the S&P 500 index, chosen based on sustained media exposure and high market liquidity. Data collection was performed using an automated RSS aggregation pipeline drawing from seven sources: Reuters, Bloomberg, CNBC, BBC, Yahoo Finance, Investopedia, and Google News. The observation period spans from November 2025 to March 2026, covering approximately five months of systematic data collection. A multi-layer data cleaning pipeline was applied, including blacklist filtering of generic industry reports, ticker-based relevance scoring, entity frequency analysis, and duplicate removal. A total of 10,725 directional predictions were generated and evaluated across three aggregation windows of 2, 5, and 7 days. Backtesting was conducted under the assumption of no transaction costs, with predictions evaluated against actual closing prices retrieved via the yfinance library (Aroussi, 2024).

4. Results and Discussion

4.1 Directional Accuracy Analysis

The backtesting evaluation was performed on 10,725 predictions. These were divided into three news collection windows: 2-day (n = 3,118), 5-day (n = 3,242), and 7-day (n = 4,365).

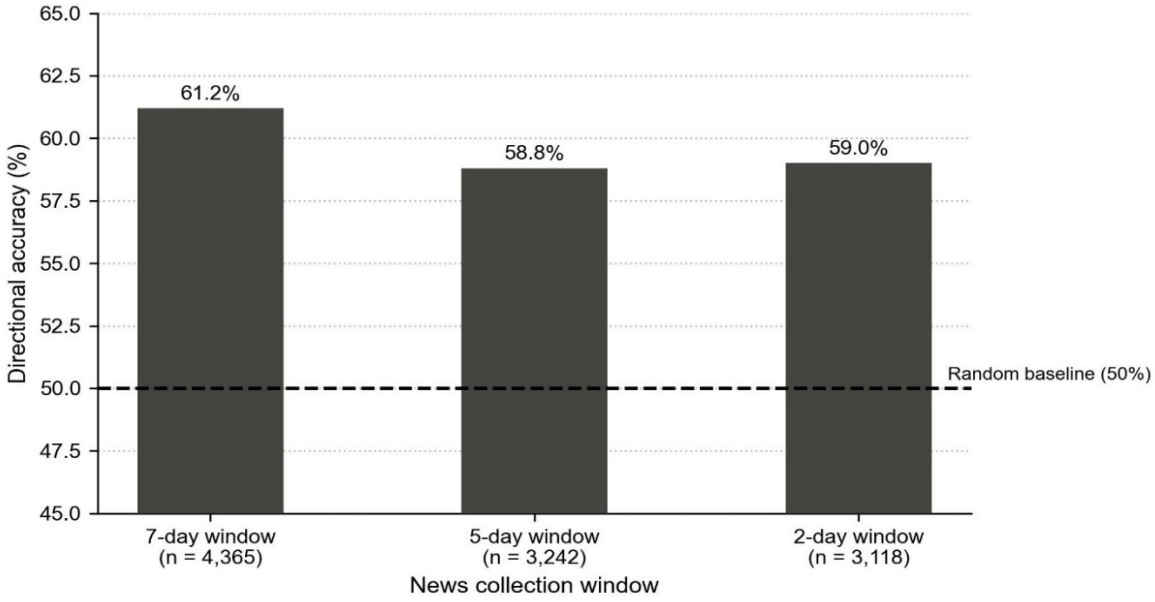


Figure 1: Overall Directional Accuracy (%) by News Collection Window. The chart compares prediction accuracy across three aggregation windows (2-day, n = 3,118; 5-day, n = 3,242; 7-day, n = 4,365) against a random baseline of 50%. All three windows exceed the baseline, with the 7-day window achieving the highest accuracy of 61,2%. Total predictions: n = 10,725. Source: Authors

As shown in Figure 1, all three windows achieved directional accuracy above the random baseline 50%. The 7-day window performed best with an accuracy of 61,2%. The 2-day and 5-day windows performed at 59,0% and 58,8%, respectively. This confirms that aggregated media sentiment carries a measurable informational signal regarding subsequent price movements. The dominance of the 7-day window suggests that broader news accumulation yields a more stable sentiment-based signal. This is consistent with Buckman et al. (2020), who found that information pressure requires time to consolidate before it generates a measurable market effect. Markets react only when sufficient informational pressure from credible sources accumulates, which a 7-day period captures more effectively than shorter windows (Ajayi, 2022; Chierici et al., 2018).

4.2 Signal Type Analysis

Figure 2 shows the accuracy distributed by signal type. The results indicate a significant asymmetry across the three recommendation categories.

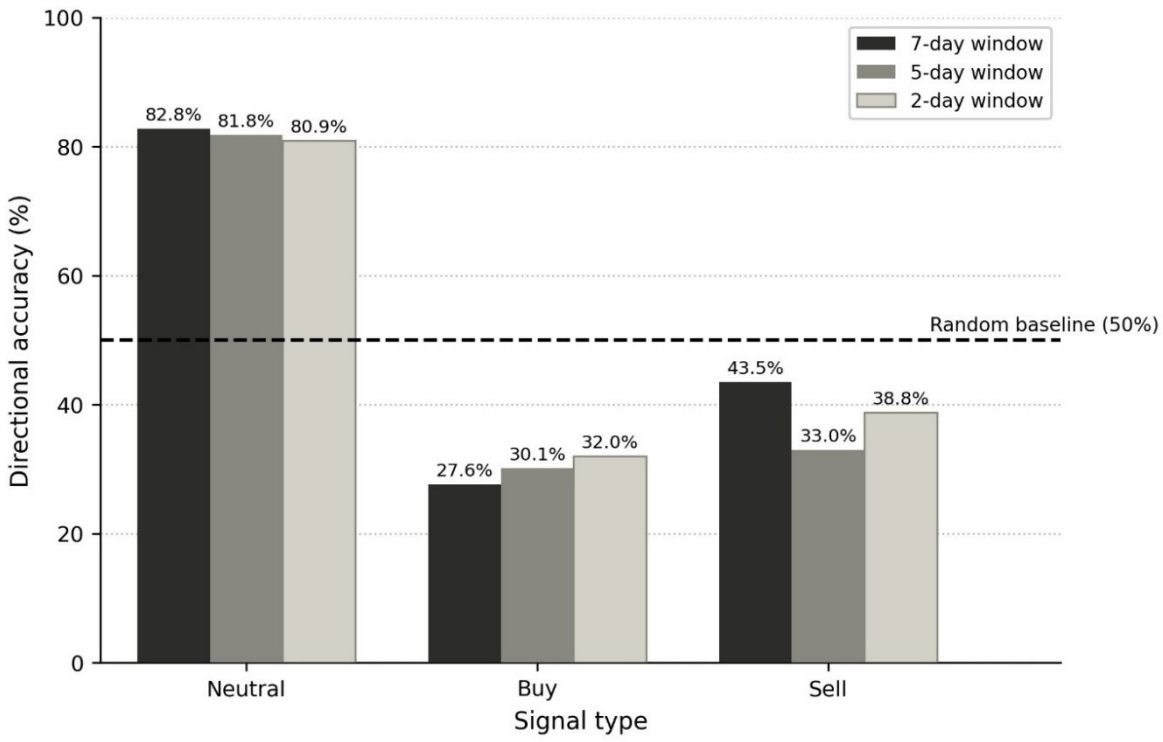


Figure 2: Directional accuracy (%) by signal type across news collection windows. The chart displays the accuracy of Buy, Neutral, and Sell signals separately for each aggregation window. The Neutral signal consistently exceeds 80% across all windows, while Buy and Sell signals fall below the random baseline of 50%. Source: Authors

The Neutral signal, which means hold, was the most accurate across windows. It reached 82,8% in the 7-day window, 81,8% in the 5-day window, and 80,9% in the 2-day window. The Buy signal fell below the random benchmark in all three windows. Accuracy ranged from 27,6% to 32,0%. The Sell signal showed average performance ranging from 33,0% to 43,5%. The consistently high accuracy of the Neutral signal warrants closer examination. From a theoretical perspective, this finding is consistent with the semi-strong form of the Efficient Market Hypothesis (Fama, 1970), which implies that asset prices already incorporate publicly available information during periods of informational equilibrium. Under such conditions, accumulated media sentiment does not generate sufficient directional pressure to produce a measurable price adjustment, a state that the framework captures more consistently than directional market reversals. It should be noted, however, that the dominance of the Neutral signal is also partially attributable to the conservative threshold of $\pm 0{,}2$ applied to the sentiment scale of -1 to +1. This boundary defines a relatively wide neutral zone, which structurally limits the frequency of Buy and Sell signals. The weak performance of directional signals should therefore be interpreted with this design choice in mind. Whether narrower or adaptive thresholds would improve the framework's discriminatory power without sacrificing stability remains an open question and represents a natural direction for future research.

4.3 Forecasting Horizon Analysis

Figure 3 illustrates how accuracy varies across different forecast horizons from day 1 to day 7. Several patterns can be observed.

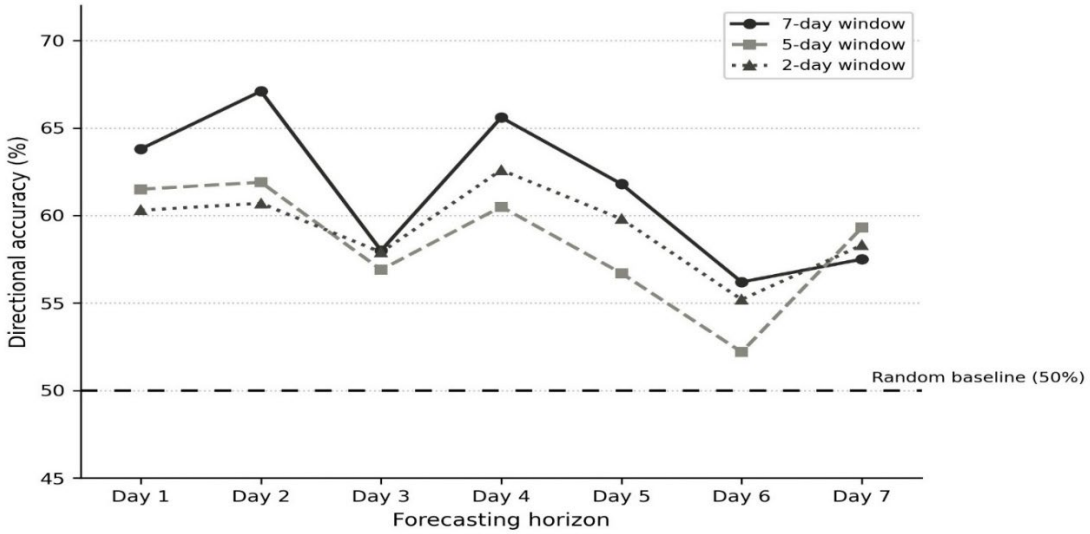


Figure 3: Directional accuracy (%) by forecasting horizon (Day 1-Day 7) across three news collection windows (2-day, 5-day, 7-day). The highest accuracy of 67,1% is achieved at the 2-day forecasting horizon with a 7-day window. All windows show a consistent decline in accuracy at the 3-day horizon. The random baseline of 50% is shown for reference. Source: Authors

First, the 7-day window has the highest accuracy at the 2-day horizon, at 67,1%. This is the highest value in the study. Second, all three windows show a consistent decline in accuracy at the 3-day horizon. This suggests that sentiment signals in this interval are experiencing a temporary dispersion effect. Third, accuracy partially recovers on the 4th day before declining more significantly on the 6th day. The 5-day window drops to 52,2% on the 6th day, approaching the random baseline. Our findings confirm that sentiment signals are most reliable within short forecasting horizons of one to two days. This is consistent with Buckman et al. (2020), who demonstrated that sentiment indicators derived from news articles capture changes in economic conditions earlier than traditional survey-based measurements, suggesting that their informational value is concentrated in the immediate period following publication. The nonlinear pattern further supports the view that sentiment functions more as an indicator of information flow than as a stable predictive variable. This pattern may reflect the multi-stage nature of information dissemination, where market participants process news at different speeds.

4.4 Interval Coherence Analysis

The interval coherence analysis evaluated what proportion of actual prices fell within the price ranges predicted by the system. Table 1 presents the results of all three time windows and forecast horizons.

Table 1: Interval coherence rates (%) by forecasting horizon (Day 1-Day 8) and news collection window. Interval coherence measures the proportion of actual closing prices that fell within the model's predicted price band for a given day. Values above 50% indicate that the prediction band captures actual price movements more often than chance would predict. The highest coherence is observed at the 2-day horizon across all windows (57,3%-61,4%). Coherence declines progressively from Day 5 onwards. Source: Authors

Horizon	7-day window	5-day window	2-day window
Day 1	35,8%	32,3%	35,2%
Day 2	60,3%	61,4%	57,3%
Day 3	48,2%	62,4%	50,7%
Day 4	61,5%	60,0%	58,3%
Day 5	54,8%	50,6%	52,7%
Day 6	48,8%	50,6%	50,0%
Day 7	47,5%	52,0%	48,1%
Day 8	41,4%	51,6%	42,9%

The best results are obtained with a 2-day horizon, with the coherence rate ranging from 57,3% to 61,4% across all windows. From the 4th day onward, a general downward trend is observed, particularly in the 7-day and 2-day windows. By the 8th day, coherence drops to 41,4% in the 7-day window and to 42,9% in the 2-day window.

This decline suggests that predicting price magnitude is inherently more challenging than predicting price direction. Media sentiment alone cannot capture how strongly markets will react, nor how fundamental factors such as earnings data or macroeconomic reports will amplify or suppress the signal. Consequently, sentiment-based interval forecasting requires additional inputs to improve accuracy over longer horizons (Abboud, 2025). Nevertheless, the results confirm that the prediction bands remain meaningful for horizons of up to four days.

5. Conclusion

This study aimed to examine whether aggregated media sentiment contains a measurable information signal regarding subsequent price movements in financial markets and under what conditions such signals are most reliable. The results, obtained through structured backtesting of 10,725 forecasts across three news-collection time windows, confirm the existence of consistent relational patterns, although their strength varies significantly by forecast horizon and signal type.

All three news collection time windows of 2, 5 and 7 days exceeded the random baseline of 50%, with the 7-day window achieving the highest overall directional accuracy of 61,2%. This finding supports the knowledge management perspective adopted in this study. Markets do not react to information immediately; rather, they respond when sufficient informational pressure from credible sources accumulates over time. The maximum accuracy of 67,1% was recorded for a 2-day forecasting horizon using a 7-day news window, further suggesting that the informational value of aggregated sentiment is most concentrated in the immediate period following its accumulation.

An analysis of signal type revealed significant asymmetry. The "Neutral" signal consistently demonstrated high accuracy across all time windows, ranging from 80,9% to 82,8%, suggesting that this framework is particularly effective at identifying states of information equilibrium. The weaker performance of the "Buy" and "Sell" signals, ranging from 27,6% to 43,5%, suggests that while the system reliably detects the absence of dominant directional pressure, distinguishing the directional pressure from informational noise remains a challenge. This finding is consistent with the broader sentiment analysis literature. It reinforces the view that sentiment-based systems are better understood as knowledge flow trackers rather than as deterministic forecasting tools.

Interval coherence analysis confirmed that prediction intervals are most reliable in the short term, up to four days, after which coherence gradually declines. This limitation reflects the inherent complexity of price forecasting, where fundamental factors such as earnings announcements and macroeconomic reports introduce variability that media sentiment alone cannot capture.

These findings suggest several avenues for future research. First, social media sentiment or earnings call transcripts could improve the accuracy of Buy and Sell signals. Second, applying this framework to markets outside the S&P 500 index, such as European or emerging markets, would test the generalizability of the findings. Third, combining sentiment signals with fundamental financial indicators may improve interval coherence over longer forecasting horizons.

Ethics declaration: This research did not require ethical clearance. The study relies exclusively on publicly available financial news data and stock price information. No human participants were involved in the research process.

AI declaration: Claude (Anthropic) was used in the development of this paper. The tool assisted with improving the language and clarity of the text and with structuring individual sections of the paper. All intellectual content, research design, data collection, analysis, and conclusions are the work of the authors.

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Reframing Substantive Privacy Compliance as Dynamic Capabilities: An Integrated Conceptual Model

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Abstract: Despite the widespread introduction of privacy protection laws globally, many organizations continue to treat privacy compliance as an administrative practice focusing on compulsory policies and documentations. However, many organizations have treated privacy protection compliance as a way to enhancing organizational dynamic capabilities from effectively using technology, people and processes required to implement privacy protection. Drawing on the Technology-Organization-Environment (TOE) model, Institutional Theory, and the Dynamic Capabilities View (DCV), the paper proposes that developing Substantive Privacy Compliance (SPC) through meeting regulatory, organizational, and technological requirements enables organizations enhance their dynamic capabilities. Theoretically, it fills the gap between the institutional legitimacy view and the dynamic capabilities lens, providing a comprehensive explanation of how external pressures can develop adaptive organizational capabilities. Practically, the model emphasizes the critical role of integrating privacy governance in both strategic and operational activities in enriching the firm's resilience and sustainable competitiveness.

Keywords: Privacy compliance, Dynamic capabilities, Technology-organization-environment model, Institutional theory

1. Introduction

In the modern digital economy, personal data has emerged as a strategic asset to facilitate innovation, personalisation and value creation in divergent sectors (Birch et al., 2021). Governments worldwide, in turn, have been passing stricter privacy laws, such as the General Data Protection Regulation (GDPR) in the European Union (*General Data Protection Regulation (GDPR)*), or California Consumer Privacy Act (CCPA) in the United States ("California Consumer Privacy Act (CCPA)", 2018), all of which have required organizations to strengthen privacy management systems. Such legal frameworks are not intended to be a simple procedures checklist, they require proven accountability, internal controls and ongoing operational correspondence. Consequently, privacy compliance has ceased to be a back-office or legal issue but it has become a fundamental organizational concern directly affecting customer confidence, digital transformation, and future competitiveness (Schäfer et al., 2023).

However, organizations still found it hard to fulfill these expectations and implementations vary across industries (Li et al., 2022). Although there are management systems and standards for examples ISO/IEC 27701 (Iso/Iec, 2019) and the NIST Privacy Framework (Standards & Technology, 2020) have developed for practical controls, analysis of these information systems and data governance documents inevitably show fracturing and lack of verified and predictive measures (Raji Abraham et al., 2019). In other words, current standards (ISO, NIST) mainly describe what is expected to be performed, however, do not quantify the actual results and ability of the system to improve over time. They fail to predict whether the company is actually prepared to adjust for changes, learn and enhance their compliance behaviours. The lack of predictive measures in existing privacy management standards highlights the need to reconceptualise privacy compliance as an organizational capabilities. In addition, evidence has indicated that the compliance effort into privacy protection is rather reactive and motivated by the fright of penalty or damaged reputation instead of being strategic (von Davier et al., 2023). This type of privacy compliance could meet expectations from the external auditors but fail to facilitate substantive compliance in which privacy protection becomes an internalised ability (Klymenko et al., 2023). Consequently, organizations that are not well-prepared for preemptive privacy compliance will exhibit a corrosion of customer and partner confidence (Martin et al., 2017). More than that, such organizations are susceptible during a constant rate of technological transformation and a revolution in the regulatory demands (Saeed et al., 2023).

Information security research has long stressed technical security to enforcing privacy controls, which is mainly concerned with encryption, access control, intrusion detection and secure architecture (Delso-Vicente et al., 2025). These approaches are necessary, but they can be criticized as simply being unaware of the social, managerial and organizational processes involved in long-lasting privacy management. Moreover, many theories and frameworks have been used to explain compliance at an individual behavioural level but fail to explain compliance as an organizational process (Herath & Rao, 2009).

On the other hand, organizational compliance and legal literature focuses on the interpretation of regulations, audit processes and procedures, and relatively little on how organizations operationalize compliance (Khan, 2025). As such, privacy compliance is often predicated as a fixed requirement as opposed to an adaptive organizational capability. Such difference in technical and managerial frames causes a critical theoretical ambiguity: why some companies can maintain privacy performance whereas others fail to do so, despite comparable regulatory pressure and technological drivers. That is, the existing behaviour and technical frames fail to explain how company adapts to the regulation of privacy. In other words, there is an interdisciplinary gap, with no unified model that connects the technological, legal and managerial dimensions of privacy compliance.

This paper suggests an alternative approach to theorizing privacy compliance that views it as a dynamic capabilities within an organization rather than a requirement or status quo (Bernardo et al., 2024). In this perspective, privacy compliance entails the intuiting and continually reshaping routines to provide effectiveness in the long run (Alrub & Sánchez-Cañizares, 2025; Waldman, 2021). This interpretation keeps the legal privacy compliance with the strategic management theory as a bridge between the information security, governance and organizational capabilities building. It also gives a reason why organizations that manage privacy in a strategic manner are likely to be more successful in terms of trust, resiliency, and data-driven innovation. In general, we posit that privacy compliance is to be theorised as an organizational dynamic capabilities.

2. Background

Over the past decades, early research on privacy focused on individuals, mainly investigating to understand users' feelings and responses to privacy protection including who they trust, and under what circumstances they distribute information online (Bélanger & Crossler, 2011). Diverse theories including the Theory of Planned Behavior (Ajzen, 1991), Protection Motivation Theory (Rogers, 1983), Neutralization Theory (Altamimi et al., 2018), Control/Restricted Theory, Cognitive Theory of Multimedia (Lee et al., 2013), Deterrence Theory (Kuo et al., 2017), and Theory of Reasoned Action (Sher et al., 2017), are leveraged to comprehend how privacy concerns are perceived by individuals. While useful in explaining attitudes and intentions, these models keep privacy at the individual level and focus on user behavior. Few research has examined privacy issues at the organization level (Martin et al., 2017) and organzsational level processes underlying sustained compliance remain underexplored.

This focus begins to shift as the concept of data protection has become a strategic asset and organizations increasingly recognize that implementing privacy controls cannot be a single project (Bennett, 2018). The firms' privacy compliance involves cross-functional structures, governance routines, resource allocation as well as strategic alignment which are beyond individuals' behavioral perspectives. The classical behavioral models do not provide a description of an organization's learning and adaptation process to changes in the market, technology, and legal environment (Raju Abraham et al., 2019).

Moreover, existing research shows that firms often approach privacy safeguards as reactive and protective mechanisms focused on risk avoidance and legal defence, rather than as strategic capabilities integrated into organizational learning and innovation (Parks et al., 2017). This reactive orientation is perpetuated by regulatory environments that emphasise penalty avoidance and bureaucratic formality, including extensive documentation and audit submission requirements (Grant & Crowther, 2016). As a result, privacy management currently is seen as an administrative burden.

In spite of this, there is another perspective, companies may view privacy compliance as Substantive Privacy Compliance (SPC), not limited to procedural privacy compliance and can internalize privacy values. In other words, they are able to integrate them into its regularly repeated processes, and make compliance an adaptive capabilities. Although it has been used to explain a proactive action in sustainability, it has not been expanded in privacy research (Hyatt & Berente, 2017). Our study redefines the concept of privacy compliance in terms of a capacity building where organizations can use resources and other capabilities to improve not only compliance performance but also long-term competitiveness.

3. Proposed Substantive Privacy Model

This paper puts forward an integrated conceptual model that explains how Technology – Organization – Environment (TOE) factors (Tornatzky et al., 1990) coupled with institutional pressures ((DiMaggio & Powell, 1983) constitute the development of the SPC and how SPC, in turn, generates the emergent dynamic capabilities in organizations. The model represents an evolutionary view where privacy compliance is regarded as not an end goal but a phase in the continual process of development of adaptive capabilities.

3.1 Substantive Privacy Compliance

The conceptualisation of privacy compliance has traditionally been seen as a legal or procedural construct (Ataei et al., 2018). The current research, however, show that organizations differ in compliance adherence and internalisation (Issaoui et al., 2023). This difference leads to the concept of SPC, which is the form of compliance that goes beyond the statutory compliance and is the actual expression of privacy ideals that are reflected in the strategy of an organization, its activities, and culture (Failla, 2020).

Formal or symbolic compliance means an organizational effort to present compliance by the means of documentation, audit, or certification and not necessarily incorporating privacy values into routine decision making (Berrone et al., 2009). These compliances are usually inspired by the coercive forces and their purpose is not to pursue efficiency but rather legitimacy (Hyatt & Berente, 2017). Conversely, substantive compliance could be understood as a real behaviour alteration, which represents the level of privacy principles' learning, adoption, and performance in the organization (Chen et al., 2025). It is evident that companies go beyond the mandatory requirements such as deploying privacy-by-design principles, conduct training of employees, encouraging open communication, and introducing accountable governance systems (Yang & Kim, 2025). These activities help enhance responsibility, create more trust and develope competitive advantages for companies (Schäfer et al., 2023). Viewed through the DCV lens, SPC allows organizations to sense the changing regulatory and technological cues, seizing opportunities through reorganization privacy governance and resources, and turn organizational routines into privacy centric culture.

3.2 TOE Framework and Institutional Theory

The initial design of the TOE framework by Tornatzky et al. (1990) is a classic framework in the process of innovation adoption. It proposes three contextual dimensions, namely technology, organization, and environment, on which the assimilation of new technologies or the management practices rely. The technological environment entails internal and external technologies pertinent to the firm including information infrastructure, data management processes and automation mechanisms that enable the privacy compliance (Oliveira & Martins, 2011). All privacy governance facilitates the process of data discovery, consent management, and auditing, all of which are needed to ensure a regulatory compliance (Ali et al., 2025). The costs of implementation, complexity and compatibility with existing systems as well as skill deficiencies make implementation however a difficult process (Chander et al., 2021).

Organizational contexts are associated with internal properties of innovation adoption, such as support by the leaders, competence of employees, formalization of the processes, and communication of privacy policies (Salleh & Janczewski, 2016). These are the aspects that dictate the capabilities of an organization to integrate compliance processes and strengthen them within the organization and culture (Iwaya et al., 2022; Raddatz et al., 2025).

Lastly, the environmental context or the external pressures exerted by the governmental regulations, industry standards, and competition that compel organizations to change (Layode et al., 2024). The privacy compliance is highly affected by privacy laws and regulations. The compliance efforts are also driven by the stakeholder expectations like the customer, partner, investor and public expectations concerning the protection of the personal data (Gupta, 2025). Despite its usefulness as a descriptive framework to study contextual influences, the TOE framework has been criticized as being inactive by nature. It is adoption intention phase and does not give an insight into how organizations change and remain compliant in the process (Nguyen et al., 2022).

The Institutional Theory describes the impact of the external societal and regulatory expectations on the organizational privacy behaviour via coercive, normative and mimetic pressure (DiMaggio & Powell, 1983; Scott, 2017). These pressures in the proposed model are the environmental and institutional pressures that lead to the development of SPC. Coercive forces are obtained through legal penalties, normative through professional norm, and mimetic through imitation by peers. The examples of the coercive pressures are the legal regulations, such as the GDPR and CCPA, where the organizations are under a compulsion to observe the privacy requirements in order to avoid fines, reputational costs, and the legal penalties (Kakooza et al., 2025). The professional associations, certification programs and industry wide standards provide normative pressures that outline what is acceptable (Hyatt & Berente, 2017). Mimetic pressures are the pressure that occurs as a result of imitating others who were viewed as successful or effective in relation to their privacy practices (Zhang et al., 2022). They encourage firms to go beyond the merely symbolic compliance and internalize privacy norms, using SPC, which turns the external forces of legitimate conduct into dynamic capabilities. The Institutional Theory is

not intense on the processes of internalizing and sustaining compliance practices, although it sheds more light on the effects of compliance (Hu et al., 2007).

3.3 Dynamic Capabilities View

This part explains how SPC is the working mechanism that develops these three aspects of dynamic capabilities (DC), sensing, seizing, and transforming, in privacy management. In this paper, we apply the Dynamic Capabilities View (DCV) developed by Teece (2007) to explain the internal mechanism through which organizations transform contextual and instutional pressures into adaptive privacy routines. The difference between DC and other operational capabilities is that DC allows organizations to perceive new opportunities and threats arising, exploit them with the help of mobilizing resources and alter internal structures to remain competitive (Eisenhardt & Martin, 2000). In the context of privacy management, the DC indicate the ability of the firm to transform procedural compliance to the learning and adaptive approach that responds to evolving regulatory requirements, technological changes, and stakeholder expectations (Klymenko et al., 2023). This ability establishes in three dimensions including sensing, seizing and transforming which are interdependent (Zahra et al., 2006). Sensing refers to searching the technological and regulatory environment to determine the risk of privacy, consumer expectations, and new legal requirements (Konopik et al., 2022). Seizing means organizing technical, human, and managerial resources to create and put into effect the right compliance schemes, either privacy-by-design methodologies or automated consent management systems (Quayson et al., 2023). It also means building privacy training programs, developing data management processes, and implementing data protection technologies (Labadie & Legner, 2023). Turning them into routines and refining them on a regular basis is called transforming the privacy awareness to organizational routine and culture (Schilke & Helfat, 2025). As the previous discussion of SPC mentions, this paper will highlight the dynamic capabilities functionality, and through it, organizations can become dynamic learners as opposed to passive rule followers in reacting to the changing privacy regulations (Pigola & Da Costa, 2023).

3.4 Synthesis

A synthesis of TOE, Institutional Theory and the DCV as an integrated theoretical approach to SPC provides more insight into the matter (Abdurrahman et al., 2024). The TOE and Institutional perspectives are the two main perspectives that elaborate on the antecedent conditions, explaining why organizations are implementing compliance initiatives by the interaction of internal enablers and external pressures (Lee et al., 2023). Nevertheless, such structures do not give much information about the process of maintaining and extending compliance after adoption. They are supplemented by the DC which explains the processual and transformative mechanism that compliance is embedded through repeated learning (Kiss, 2025; Samsudin & Ismail, 2019).

Figure 1 describes how SPC mediates the influence of contextual factors such as technological, organizational, and environmental factors (based on the TOE framework) and the institutional pressures, such as coercive, normative, and mimetic forces (based on the Institutional Theory) represented under environmental factors, on a firm's dynamic capabilities.

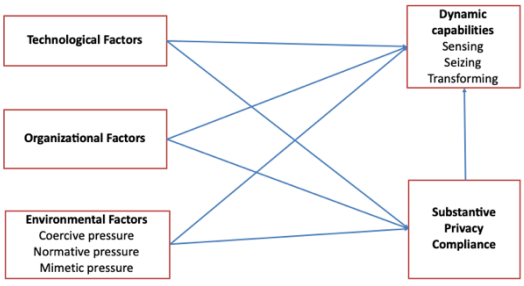


Figure 1: Proposed conceptual framework

4. Contributions

A number of implications are found in redefining the privacy compliance as DC to the theoretical advancement of privacy governance, and organizational compliance studies. First, the paper closes the divide between the privacy compliance and the DC theory, bringing the two together into a single conceptual framework. The incorporation of these areas provides this view with a stimulus to shift researchers out of the natural positions of silo thinking and interpret compliance as a dynamic organizational competency (Solaimani, 2024). Second, this stance opposes the existing perception of compliance as a reactive, punishment motivated act and suggests

a capabilities interpretation based on learning, adaptation and change. This change allows theorists to conceptualize compliance with privacy not only as the series of externally enforced norms of conduct but as a strategic resource capable of defining organizational resilience and value creation over time. Third, the DC lens offers a coping mechanism of privacy management how organizations develop, remain stable or even deteriorate with time. A DCV anticipates process of lifelong learning, which allows the richer empirical modelling and provides space to longitudinal, multilevel, process modelling research designs.

Managerially, considering privacy compliance a DC can urge executives and security leaders to reconsider the incorporation of privacy into the organization strategy and operations. Instead of handling privacy as a cost center whose main aim is to evade penalties, managers could position it as a capabilities focus which enhances customer security, facilitates digital transformation, and innovation. This view also shows how the investments should be directed at the technical controls and also to the organizational routines, cross-functional coordination and sustained training. Finally, considering privacy compliance as a dynamic capabilities gives managers the strength to develop resilience, competitive advantage based on trust, and synchronize privacy programs with the overall organizational objectives.

5. Future Directions and Conclusion

The focus on the privacy compliance as DC presents a number of potential research directions in the future. First, it is evident that there must be an effort to come up with measurement tools that can include the multidimensional character of the privacy DC. Second, empirical testing is needed to assess the way that dynamic privacy capabilities will be expressed in highly regulated industry, including fintech, health and startup companies. Third, the connection between the privacy incidents, organizational learning and capabilities enhancement is to be investigated in future research. Lastly, the advent of artificial intelligences (AI) and algorithms makes the issue of AI governance and its influence on privacy capabilities a new debate.

In conclusion, this paper suggests that privacy compliance should not be viewed as a very limited legal requirement or even a set of documented controls, but as an organizational dynamic capability, which changes regulatory requirements into organizational resilience.

Acknowledgement

The author owes a lot of credit to the direction and guidance of Dr. Minh Nhat Nguyen and Dr. Mai Thi Hoang Do, whose suggestions and positive criticism have significantly benefitted in shaping and refining this research.

Ethics declaration: This research involved human participants and received ethical approval from the RMIT, Human Research Ethics Committee. All participants provided informed consent prior to participation. The study was conducted in accordance with institutional guidelines and relevant ethical standards for research involving human subjects.

AI declaration: Artificial intelligence (AI) tools were used in a limited capacity during the development of this manuscript. Specifically, AI-assisted language tools were employed to support language refinement and clarity of expression. All conceptual development, theoretical framing, analysis, and interpretation were conducted independently by the author(s). The authors take full responsibility for the content of the manuscript.

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A Sociomaterial Framework for Orchestrating Knowledge Co-Creation in Expert Communities

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Abstract: Complex societal challenges increasingly require knowledge co-creation that unites diverse expertise across organisational and sectoral boundaries. Such collaboration does not usually arise spontaneously but requires orchestration practices to coordinate actors from different fields. Previous research on orchestration has examined networks, expert communities, digital platforms, collaborative processes, and material artifacts largely as separate streams of research. However, less attention has been paid to sociomaterial orchestration in voluntary expert communities on digital collaboration platforms. Therefore, the research question is "How is knowledge co-creation orchestrated in expert communities on a digital collaboration platform?" The empirical setting is based on the Fast Expert Teams model developed at LUT Business School, which invites volunteer experts from different sectors to engage in pro bono work on complex societal challenges through a four-week digitally mediated collaboration process. The study adopts a Participatory Action Research (PAR) approach and qualitative methods, through which the research team both implemented FET initiatives and conducted research. The empirical data consist of six FET collaboration processes, ranging from approximately 50 to over 100 participants, from which rich longitudinal qualitative data were collected. The study draws on process analysis and practice-based theorizing. The study develops a sociomaterial framework for orchestrating knowledge co-creation in expert communities. Sociomaterial orchestration aligns social, processual, technological, and material dimensions to enable collective outcomes. The framework is scalable and suitable for orchestrating initiatives across different forms of collaboration, from small-scale local projects to global networks.

Keywords: Sociomaterial orchestration, Knowledge co-creation, Digital collaboration platform, Expert community, Participatory action research (PAR)

1. Introduction

Complex challenges, such as climate change, require systemic multi-stakeholder collaboration across organisational boundaries (Briley et al, 2015). Experts can be invited to a digital collaboration platform to generate knowledge on an ad hoc basis for complex tasks that require integrating multiple perspectives (Kryzhanivska, Tuomisalo, Blomqvist, & Kuivalainen, 2025). Orchestration is defined as the management of network collaboration without hierarchical authority, coordinating the contributions of decentralized actors, and is realized through practices that build and manage multi-actor networks (Reypens et al, 2021).

Previous orchestration research has examined actors, platforms, collaborative processes, and artifacts as analytically separate phenomena. Network orchestration typically examines the coordination of actors, relationship management, and the steering of collaboration within networked structures (Dhanaraj & Parkhe, 2006; Hurmelinna-Laukkanen et al, 2022). Platform orchestration research has emphasized the role of digital platform affordances and AI-enabled functionalities in orchestrating distributed actors (Marchese et al, 2026; Treem & Leonardi, 2013; Leonardi, 2013).

Across these perspectives, social, technological, processual, and material elements often remain analytically separated, even though in practice they are constantly intertwined (Orlikowski & Scott, 2008; Hultin, 2019). A sociomaterial perspective would view the social and the technological as mutually constituting practices and relationships (Hultin, 2019). Therefore, this paper adopts a sociomaterial perspective and asks: "How is knowledge co-creation orchestrated in expert communities on a digital collaboration platform?"

The Fast Expert Teams model was developed at LUT University, which invites volunteer experts to co-create knowledge on a digital collaboration platform. These experts co-create knowledge in sub-teams over a four-week period to address themes of local, national, or international significance (Blomqvist, 2022a; OECD, 2021). The LUT team has served as a central actor by bringing together experts and participants from diverse sectors of society to address socially impactful themes (Ritala et al, 2023).

This study adopts the Participatory Action Research (PAR) approach, which involved the research team both implementing FET initiatives and conducting research. The cases presented in this paper are six Fast Expert Teams processes ranging from approximately 50 to over 100 experts from various sectors of society, including education, the public and private sectors, municipalities, ministries, local and international networks (Zandee & Coghlan, 2025). This study contributes to orchestration research by offering a sociomaterial perspective on

knowledge co-creation (Hultin, 2019). It develops a scalable framework that conceptualizes orchestration as the shaping of sociomaterial conditions.

2. Conceptual Framework: Sociomaterial Orchestration of Knowledge Co-creation in Expert Communities

A central company or key network actor typically acts as an ecosystem orchestrator, intentionally coordinating dispersed expertise and resources to create and capture value (Shen et al, 2024; Dhanaraj & Parkhe, 2006). Orchestrators are intermediaries that influence, coordinate, and shape relationships within the ecosystem (Ritala et al, 2023). Shen et al (2024) present key orchestration practices, such as strategic ecosystem planning, resource integration, technology utilization, innovation, and relational practices. Previous orchestration research has identified numerous practices for coordinating actors, resources, technologies, and collaborative activities (Dhanaraj & Parkhe, 2006; Reypens et al, 2021; Shen et al, 2024).

This study conceptualizes orchestration as the shaping of sociomaterial conditions that enable distributed knowledge co-creation. From a sociomaterial perspective, knowledge co-creation emerges through the entanglement of social, processual, material, and technological elements in practice (Reypens et al, 2021; Hultin, 2019; Orlikowski, 2002; Orlikowski & Scott, 2008). Sociomateriality holds that "the world is constituted by or comprised of ontologically distinct entities (social and technical) that interact or connect to produce organisational phenomena" (Priharsari & Abedin, 2021; Hultin, 2019, p. 91). This study proposes four interdependent dimensions of sociomaterial orchestration: expert community, knowledge co-creation process, digital collaboration platform, and artifacts and boundary objects. Together, these dimensions form the foundation of sociomaterial orchestration and provide the analytical structure for this study (Figure 1).

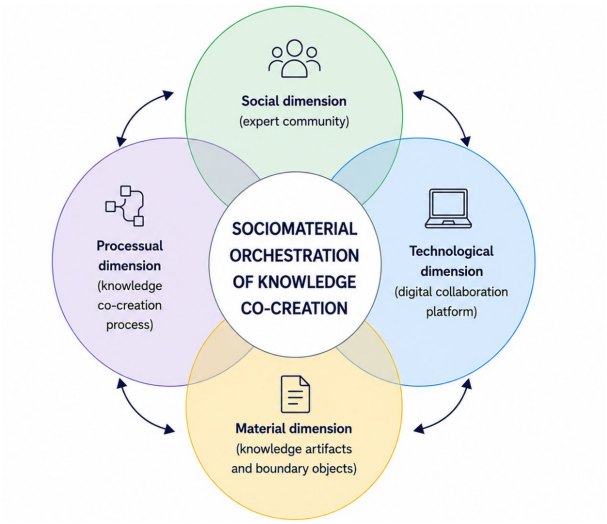


Figure 1: A framework of sociomaterial orchestration of knowledge co-creation in expert communities

2.1 Social Dimension: Expert Community

The expert community forms the social dimension of orchestration. Online communities are groups with shared goals that operate virtually despite geographic dispersion and enable knowledge sharing (Faraj et al, 2011; Faraj et al, 2015; Faraj et al, 2016). Priharsari and Abedin (2021) introduced the concept of communities of interest—online communities united by a common interest or passion. These communities comprise experts from various fields who contribute dispersed expertise to the shared co-creation process. Previous orchestration research has emphasized the importance of fostering trust, developing shared identity, promoting interorganisational socialization, and enabling knowledge mobility among participants to support collaboration and value creation (Dhanaraj & Parkhe, 2006; Reypens et al, 2021; Shen et al, 2024).

2.2 Processual Dimension: Knowledge Co-creation Process

The knowledge co-creation process constitutes the processual dimension of sociomaterial orchestration, as experts' tacit knowledge does not automatically become shared, explicit knowledge. Individual perspectives, experiences, and expertise must be made explicit, shared, refined, and gradually integrated into a shared understanding and collective solutions (Nonaka & von Krogh, 2009). Experts often come from diverse professional backgrounds and may therefore interpret problems differently. Participants use distinct concepts,

and may employ several approaches or practices, creating knowledge barriers that orchestrators have to actively bridge (Bechky, 2003; Carlile, 2004). Previous orchestration research has emphasized the importance of coordinating collaborative activities, aligning participants' contributions, and guiding collective processes toward shared goals (Dhanaraj & Parkhe, 2006; Reypens et al, 2021; Shen et al, 2024).

2.3 Technological Dimension: Digital Collaboration Platform

The technological dimension comprises digital collaboration platforms and technological tools. When experts work in distributed settings, they leverage technological affordances, turning the collaboration platform into a shared space for interaction (Faraj et al, 2011). Recent research on platform orchestration emphasizes the role of digital technologies in coordinating distributed actors, enabling ecosystem-wide collaboration, and supporting dynamic orchestration capabilities in digitally mediated environments (Marchese, Gastaldi & Corso, 2026). Digital technologies enable synchronous and asynchronous communication (Faraj et al, 2011; Marchese et al, 2026), while platforms can orchestrate autonomous actors in collaborative environments (Weber et al, 2025). They offer affordances such as visibility, editability, persistence, and association (Treem & Leonardi, 2013).

2.4 Material Dimension: Knowledge Artifacts and Boundary Objects

The material dimension consists of artifacts that function as carriers of knowledge and boundary objects between experts (Bechky, 2003; Carlile, 2004). From a sociomaterial perspective, knowledge is constructed through the intertwined interactions of people, technologies, and material artifacts, in which artifacts actively mediate and shape the knowledge (Orlikowski & Scott, 2008; Hultin, 2019). Material orchestration involves creating and leveraging artifacts and boundary objects that enable knowledge sharing across experts and communities.

3. Methodology

This study employs participatory action research, which enables the simultaneous examination of practice and the generation of scientific knowledge (Kemmis & McTaggart, 2000; Sandberg & Tsoukas, 2011; Zandee & Coghlan, 2025). This methodology is "based on a collaborative problem-solving relationship between researchers and clients. Its aim is to solve problems and create new knowledge" (Coghlan, 2011, p. 54). The approach intertwines research and practice, as when the study addresses questions of practical significance while producing practical and scientific outcomes (Sandberg & Tsoukas, 2011; Zandee & Coghlan, 2025).

3.1 Participatory Action Research as a Research Approach

Action research is tied to practice and involves iterative cycles of action and reflection (Orlikowski, 2002; Sandberg & Tsoukas, 2011). It is interventionist and context-bound, with data being inherently contextual and the researcher acting as an agent of change (Coghlan, 2011). Practitioners are viewed as co-researchers whose experiential and practical knowledge is central to knowledge creation (Zandee & Coghlan, 2025).

3.2 Research Setting: Fast Expert Teams

This study draws on six action research cases (Zandee & Coghlan, 2025) in which the research team built, implemented, orchestrated, and studied expert communities known as "Fast Expert Teams (FETs)" (Blomqvist, 2022a; 2022b). The Fast Expert Teams model has also been recognized in OECD work examining twenty-first-century knowledge co-creation initiatives (OECD, 2021). These communities worked on knowledge-related issues using a digital collaboration platform and technological tools (Table 1).

Table 1: Illustrative case examples of Fast Expert Teams processes under several themes

Case / Initiative	Theme	Key Objective / Outcome	Participants
Corona-FET 2020	Crisis response (COVID-19)	Rapid problem-solving during the pandemic; development of an FFP2/FFP3 respirator cleaning method and pilot facility	over 100 experts
Work2030 Hybrid Work and FET Model 2021	Future of work	Development of the FET operating model and hybrid work recommendations for the Ministry	92 experts
Work2030 Technology Industries of Finland, International Talent 2023	Talent mobility and integration	Development of a digitalized immigration and recruitment process, supporting integration into Finnish society and workplaces	50 experts

Case / Initiative	Theme	Key Objective / Outcome	Participants
Work2030 Growth Corridor 2023	Skills shortage and talent integration	Proposals for integrating international students into Finnish working life; enhancing interaction between education, employers, and society	62 experts
P2X Investments FET 2024	Energy transition (Power-to-X) and investment opportunities	Exploration of Power-to-X solutions and ecosystem-level opportunities in energy transition	65 experts
Civil Engineering FET 2026	Vision building for a new civil engineering program	Co-creation of future visions for civil engineering, integrating multidisciplinary expertise across sectors	79 experts

3.3 Data Sources and Empirical Material

Qualitative data were collected from the collaboration processes of six FETs, including interviews, digital traces, meeting transcripts, shared documents, and memos (Table 2). The orchestration practices reported in this study are based on the experiences of project managers, team leaders, and community facilitators and are grounded in empirical observations derived from action research (Orlikowski, 2002; Coghlan, 2011).

Table 2: Overview of data sources and analytical focus

Data source	Aim	Analysis
Digital trace data	Capturing behavioral data and actual knowledge co-creation process	Observing orchestration practices
Orientation interviews	Initial framing and participants' expertise	Identifying relevant themes and participants' interests
Individual interviews	Participants' experiences of FET processes	Qualitative research questions on participation, motivation and feedback
Focus group interviews	Collective reflection on FET processes	Analyzing group-level dynamics and collective learning
Meetings and memos	Capturing ongoing discussions	Contextual knowledge

3.4 Process-oriented Analysis

Data analysis is based on a process-theoretical approach (Langley, 1999), in which phenomena are viewed as chains of events unfolding over time (Van de Ven & Huber, 1990). Process data are multidimensional and context-dependent (Pettigrew, 1992; Langley, 1999). The analysis process is structured into temporal phases (temporal bracketing), which help identify the key stages of knowledge co-creation and the transitions between them (Langley, 1999). The analysis aims to identify the mechanisms and practices that guide the process forward. Theoretical understanding develops iteratively through cycles of action and reflection with theory-building and practical interventions intertwined throughout (Coghlan, 2011; Zandee & Coghlan, 2025). Theoretical concepts and proposals thus evolve through the interaction among practical interventions, empirical data analysis, and reflective interpretation (Figure 2).



Figure 2: Data analysis and implementation in participatory action research

4. Findings: Sociomaterial Orchestration of Knowledge Co-creation in Expert Communities

The key dimensions of sociomaterial orchestration are the social (community of experts), the processual (knowledge co-creation process), the technological (digital collaboration platform), and the material (artifacts and boundary objects). Orchestration is the coordination of these four interdependent elements, enabling the emergence of shared outcomes (Figure 3).

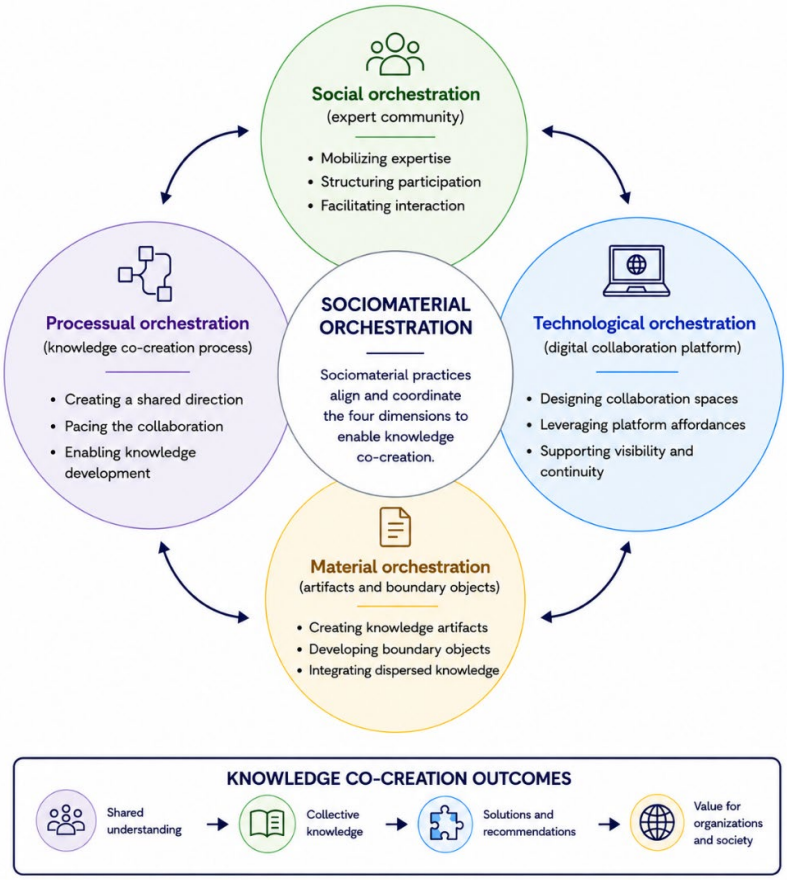


Figure 3: Sociomaterial orchestration of knowledge co-creation in expert communities

4.1 Social Orchestration: Building and Mobilizing the Expert Community

Mobilizing dispersed expertise: Social orchestration begins by identifying and inviting experts with diverse knowledge, experiences, and perspectives relevant to the focal challenge. Experts from different sectors are then invited to engage in a joint knowledge co-creation process. Fast Expert Teams have addressed diverse thematic topics, for example P2X investments, hybrid work, and visions for the future of education.

Structuring participation: Thematic sub-teams bring experts together around shared themes. These sub-teams create spaces for interaction where diverse expertise can develop ideas for systemic and complex phenomena. For example, in the P2X Fast Expert Teams process, the sub-teams focused on energy production, CO_2 capture, regulation, and investment conditions.

Facilitating interaction: Social orchestration also involves creating opportunities for interaction and dialogue among participants through organised meetings. Scheduled weekly meetings, summary discussions, and virtual morning-coffee sessions give rhythm to the community's work. In addition, breakout rooms and collaboration spaces are provided for teams to share their perspectives and discuss ideas. These interactions enable experts to exchange perspectives and combine dispersed expertise.

4.2 Processual Orchestration: Structuring and Sustaining the Knowledge Co-creation Process

Creating a shared direction: Since experts come from different organisations and backgrounds, it is important to establish a shared direction and understanding of the purpose, the community, and the teams' shared goals. Often, at the beginning of a collaboration, the direction can be vague, as the tasks to be solved are frequently

complex and can be approached from multiple angles. A preliminary sense of direction helps participants understand their own role in the collective effort.

Pacing the collaboration: Orchestration focuses on maintaining the rhythm and continuity of collaboration. The co-creation process is organised weekly. The content of the meetings is planned, and different types of meetings serve different purposes: morning coffee discussions spark new perspectives at the community level; weekly morning discussions define direction and purpose; wrap-up discussions conclude what has already been done; and, at team level, the focus is on concrete ideas and solutions. The digital collaboration platform enables continuous knowledge development between meetings through asynchronous interaction.

Enabling knowledge development: Process-oriented orchestration involves facilitating knowledge development by creating structures, phases, and opportunities for work that support co-creation at different stages of the process. As the process progresses, participants engage in tasks, discussions, workshops, and collaborative spaces that encourage knowledge sharing. In this way, orchestration creates the conditions for continuous knowledge development throughout the process.

4.3 Technological Orchestration: Designing and Utilizing the Digital Collaboration Platform

Designing collaboration spaces: Technological orchestration involves the design, construction, and maintenance of various collaboration spaces to meet the different needs of co-creation. Workspaces are designed to support the different stages of co-creation, and each page and collaboration space plays its own role in the process. Support pages provide instructions for using the platform, team-specific workspaces focus on developing themes, and community meeting pages bring together shared materials, recordings, and discussions.

Leveraging platform affordances: Technological orchestration also involves leveraging digital tools and platform features. Various collaboration spaces enable experts to work at both the community and team levels. Through these features, the platform supports collaboration and knowledge sharing among experts.

Supporting visibility and continuity: Technological orchestration supports the visibility of knowledge throughout the co-creation process. Discussions, materials, recordings, and other outputs remain available to participants, enabling them to review previous discussions and develop knowledge even between meetings. In this way, the digital collaboration environment forms an infrastructure that supports knowledge continuity.

4.4 Material Orchestration: Creating and Integrating Knowledge Artifacts

Creating knowledge artifacts: Material orchestration begins with the creation of knowledge artifacts through collaborative work. Experts participate in co-creation by producing content, sharing their perspectives, commenting on others' ideas, and developing ideas together. Discussions, documents, presentations, recordings, and other digital outputs externalize knowledge and make it accessible to other participants. Through these artifacts, knowledge can persist beyond individual interactions and enable the cumulative development of ideas over time.

Developing boundary objects: Material orchestration also involves developing boundary objects that enable the transfer and integration of knowledge. Team workspaces are visible to the entire expert community, allowing discussions to be followed and ideas generated in different teams to be combined. Visualizations, summaries, presentations, reports, and other shared artifacts serve as common reference points for experts to interpret, discuss, and develop knowledge together. In this way, artifacts help bridge the gaps between areas of expertise and perspectives.

Integrating dispersed knowledge: Material orchestration supports integrating distributed knowledge into collective knowledge. Meeting materials, recordings, notes, surveys, and AI-based summaries make the knowledge visible and easily accessible throughout the entire process. Through these artifacts, participants can revisit previous discussions, combine contributions made at different times, and continue developing the knowledge even between meetings. Through material orchestration, expert knowledge is gradually integrated into collective knowledge and shared outcomes.

4.5 Interrelationships Between Sociomaterial Orchestration Dimensions

Orchestration practices operate within the interplay of social, processual, technological, and material dimensions. For example, joint virtual meetings are conducted through technology. These meetings are part of social interaction in which collaboration and trust are built. Scheduled meetings also serve to maintain the process and generate recordings, notes, and summaries, which constitute the material dimension.

Orchestration practices therefore involve the continuous coordination of technological, processual, social, and material elements.

4.6 Challenges in Orchestrating Knowledge Co-creation in Expert Communities

Because participation is voluntary, commitment varies significantly among experts, making it difficult to fully leverage distributed expertise. Participants bring different perspectives, concepts, and areas of expertise to the process, so building a shared understanding does not happen automatically. Distributed work occurs at different times and locations, with varying intensity, making it challenging to coordinate collaboration and maintain shared progress. Experts generate many discussions, documents, and artifacts, and combining these into shared knowledge and concrete outcomes requires active orchestration.

5. Discussion

This study advances orchestration research by conceptualizing knowledge co-creation as a sociomaterial orchestration phenomenon emerging from the interplay of social, processual, technological, and material dimensions (Orlikowski & Scott, 2008; Hultin, 2019). Previous orchestration research has primarily focused on coordinating actors, relationships, and resources within networks and ecosystems (Dhanaraj & Parkhe, 2006; Reypens et al, 2021; Shen et al, 2024). This study extends that perspective by shifting attention from actor coordination to the orchestration of sociomaterial dimensions and their interrelationships through which knowledge co-creation emerges (Orlikowski & Scott, 2008; Hultin, 2019).

The results show that sociomaterial orchestration creates conditions for transforming dispersed expertise into shared knowledge and collective outcomes. Knowledge co-creation does not, therefore, arise automatically from bringing experts together or from the use of a digital platform. Instead, it requires orchestration practices that connect people, processes, technologies, and artifacts.

Previous studies have emphasized the affordances and technological features of platforms as enablers of collaboration (Majchrzak et al, 2013; Faraj & Azad, 2012). This study suggests that visibility, editability, persistence, and association offered by digital platforms become valuable when supported by practices of social, processual, and material orchestration (Treem & Leonardi, 2013).

Practically, the study offers a framework for evaluating and developing collaboration. The four domains of orchestration provide a tool for identifying the sources of challenges. Problems may relate, for example, to expert participation, process structure, the technological environment, or the development of knowledge artifacts. The framework helps identify challenges and direct interventions toward the dimensions where they are most needed.

6. Theoretical and Practical Implications

The framework provides an analytical lens for future research. It enables researchers to analyse different forms of collaboration through social, processual, technological, and material dimensions and to examine how these dimensions interact to enable or constrain knowledge co-creation. The practical contribution lies in providing a sociomaterial framework for orchestrating expert communities, which may be valuable for organisations, networks, and practitioners designing digital collaboration environments. The framework offers a scalable model for multi-stakeholder collaboration across contexts, including innovation networks, public sector development projects, research networks, and global expert communities.

7. Future Research

While this study identifies four sociomaterial dimensions of knowledge co-creation orchestration, it provides only an initial understanding of the complex interrelationships between them. Although the dimensions were presented separately for analytical clarity, the findings suggest that orchestration emerges through their continuous interaction and mutual influence. Future research could therefore examine how relationships between social, processual, technological, and material dimensions evolve over time and how different orchestration practices align these dimensions. Such work would provide a more dynamic understanding of sociomaterial orchestration.

8. Conclusion

This study argues that effective knowledge co-creation in distributed expert communities depends on the orchestration of sociomaterial dimensions through which dispersed expertise can be shared, developed, and integrated into collective outcomes. By introducing a sociomaterial perspective on orchestration, the study extends existing orchestration research beyond actor-centred coordination toward the creation of conditions that enable knowledge co-creation in digitally mediated environments.

Acknowledgements

I gratefully acknowledge all participants in the Fast Expert Teams processes for their active engagement and valuable contributions. I also thank the facilitators, project leaders, and collaborators involved in the design and implementation of each Fast Expert Teams process. I wish to express my sincere gratitude to Professor Kirsimarja Blomqvist and Emeritus Professor Matti Vartiainen for their valuable support and guidance. This research was funded by the Finnish Academy of Science and Letters, the Foundation for Economic Education, and the Finnish Cultural Foundation.

Ethics Declaration: Formal ethical clearance was not required for the research. This study was conducted in accordance with ethical principles. Prior to the study, participants were provided with a privacy notice and an informed consent form that outlined the study's purpose, data collection, and data security. Participation in the study was voluntary, and participants had the right to withdraw their participation at any time. All data were anonymized and stored in secure systems.

AI Declaration: The author used the Grammarly© application for language editing and proofreading. The tool was utilized solely to enhance grammar, clarity, and readability. The author developed conceptual models, analytical structure, and theoretical interpretations, while AI tools were used solely to support the figures' visual design.

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From Compliance to Integration: A Knowledge Management-based Maturity Model for Quality Culture in Portuguese Higher Education

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Abstract: Higher Education Institutions (HEIs) are increasingly required to move beyond formal compliance with Quality Management Systems (QMS) towards the development of genuine Quality Cultures — organisational environments in which improvement is collectively owned, evidence-based, and knowledge-driven. Yet, despite growing theoretical interest in the intersection of Knowledge Management (KM) and Quality Culture (QC), empirical investigation of this relationship remains notably scarce, particularly within the European context, where quality assurance research has historically prioritised structural and regulatory dimensions over the cultural and knowledge processes that sustain them. This paper presents the conceptual framework and preliminary empirical findings of an ongoing doctoral research project. The study makes two contributions: it empirically investigates the mediating role of KM processes — namely knowledge creation, acquisition, sharing, sensemaking, retrieval, and utilisation — in the relationship between TQM frameworks and QC within Portuguese HEIs; and it introduces the Quality Culture Maturity Model (QCMM), an inductively derived four-stage developmental framework grounded in the qualitative analysis of all 97 Portuguese HEIs' institutional evaluation reports. The study is grounded in Organisational Psychology, anchored in ISO 30401:2018 as a practical implementation reference, and addresses four core research questions concerning the extent to which KM processes are integrated into Portuguese HEIs' QMS, and how they shape QC. A sequential mixed-methods design is employed, comprising: (a) a Systematic Literature Review (SLR), registered in PROSPERO and following PRISMA protocol; (b) quantitative data collection via validated psychometric instruments administered to quality managers across all 97 Portuguese HEIs; and (c) qualitative triangulation through semi-structured interviews with institutional leadership, focus group with quality teams, and documentary analysis of strategic plans and institutional evaluation reports. Two sets of preliminary findings are reported. First, the SLR confirms that empirical research on the KM-QM relationship in HEIs remains geographically concentrated in non-European contexts, validating the relevance of this study. Second, documentary analysis of all 97 institutional evaluation reports from the Agency for Evaluation and Accreditation of Higher Education (A3ES) reveals a consistent pattern: institutions rated 'Good' or 'Very Good' by A3ES demonstrate a greater capacity for evidence-based decision-making, underpinned by more sophisticated — though often unrecognised — KM practices. From this analysis, a four-stage Quality Culture Maturity Model (QCMM) is inductively proposed, tracing institutional progression from *Compliance-Driven* through *Structural* and *Aligned* to *Integrated* Quality Cultures. A particularly distinctive finding is the prevalence of what we term 'unlabelled KM' — knowledge-sharing and sensemaking practices structurally embedded in institutional routines but neither formally recognised nor strategically leveraged. These findings suggest that the transition toward an integrated QC is fundamentally a knowledge challenge: institutions must develop the organisational capacity to transform raw data into actionable knowledge that informs strategic decision-making. This research contributes an original empirical and conceptual framework to a field marked by theoretical abundance but empirical scarcity, with direct practical implications for institutional leadership, quality managers, and European quality assurance policy.

Keywords: Knowledge management, Quality culture, Total quality management, Higher education institutions, Quality culture maturity model

1. Introduction

1.1 Conceptual Background: KM, TQM, and Quality Culture in Higher Education

Knowledge Management (KM) has multidisciplinary origins and a long-standing practice before its formal naming yet still lacks a universally accepted definition. At its core, KM treats organisational knowledge as a strategic asset — one that, unlike physical resources, is neither consumed by use nor depleted by sharing, yet remains vulnerable to loss through staff attrition and institutional forgetting (Dalkir, 2023).

KM is a central area of both academic study and professional practice, in which organisational knowledge is regarded as a strategic asset that enhances improvement, innovation, and competitiveness (Davenport & Prusak, 1998). A foundational contribution to this field is Nonaka and Takeuchi's (1995) SECI model, which explores the dynamic interplay between tacit and explicit knowledge through the processes of Socialisation, Externalisation, Combination, and Internalisation (Cardoso et al., 2005). This model has underpinned extensive theoretical development and empirical research (Von Krogh et al., 2000). Subsequent work has investigated the conditions for knowledge sharing (Wiig, 1993; Davenport & Prusak, 1998; Boisot, 1998), and the complexity of knowledge flows within uncertain environments (Snowden, 2002).

There is a broad recognition of the contextual nature of KM, highlighting the interaction between organisational culture, leadership, and motivation as critical factors that may either facilitate or inhibit its success (Zheng *et al.*,

2010; Shams & Belyaeva, 2019). Recent studies further demonstrate that the effectiveness of KM within HEIs is intrinsically linked to an organisational culture that values knowledge sharing and innovation. This requires effective leadership, appropriate incentives, and robust technological infrastructure (Herminingsih & Ratnasari, 2024). Consequently, KM constitutes a robust and dynamic research field with increasing scholarly attention directed towards its contribution to Quality Management (QM), particularly within the context of Higher Education (HE) (Manatos *et al.*, 2017).

QM — defined as a set of interrelated principles and processes designed to promote continuous improvement and enable organisations to meet stakeholder needs and expectations (International Organization for Standardization [ISO], 2015) — has been a cornerstone in the development and modernisation of Higher Education Institutions (HEIs), fostering accountability and excellence (Rosa & Amaral, 2007). Heightened public scrutiny, the expansion of the HE sector, and stringent regulatory requirements have bolstered the implementation of Quality Management Systems (QMS) (EUA, 2006; ENQA, 2015). However, despite QMS being mandatory, uncertainties persist regarding their applicability within HEIs. The literature identifies significant challenges associated with excessively bureaucratic systems focused on formalisms, which often fail to align QM with strategic management (Manatos *et al.*, 2017; Hildesheim & Sonntag, 2020; Ansmann & Seyfried, 2022).

Rather than relying solely on control mechanisms, the sustainability of QM in HE depends upon participation, self-evaluation, and a profound commitment to improvement (Sursock, 2011). This necessitates the development of a Quality Culture, described as an organisational culture dedicated to the continuous enhancement of quality. This concept is characterised by two distinct elements: 1) a cultural/psychological dimension (shared values, beliefs, expectations, and commitments regarding quality); and 2) a structural/managerial dimension (processes designed for quality improvement and the coordination of individual efforts) (EUA, 2006; Hildesheim & Sonntag, 2020). The concept of QC is inherently linked to Total Quality Management (TQM), a management philosophy that promotes continuous improvement by encompassing behavioural aspects, procedures, and techniques (Moura e Sá, 2022). Although KM and TQM are often treated as autonomous disciplines, they share common objectives and are mutually reinforcing (Akdere, 2009; Honarpour *et al.*, 2017; Abbas & Kumari, 2023).

To support the design and implementation of a knowledge management system, an international standard has been established – ISO 30401:2018. This standard determines requirements for KM systems within organisations — including HEIs — and mandates that organisations create, use, and maintain knowledge as an organisational asset (Carlucci et al., 2022). The current standard augments the requirements set forth in ISO 9001:2015, particularly concerning the management of organisational knowledge (Clause 7.1.6). It mandates that entities identify, maintain, and protect the knowledge assets required for process conformity and mission-critical objectives (ISO, 2015). Despite the relevance of ISO 30401, its uptake in European HEIs remains unexplored.

The present research project was designed to explore the relationship between KM, TQM, and QC in HE, while contributing to the implementation of ISO 30401 in HEIs in the European context, specifically in Portugal.

The Portuguese HE system is a binary network comprising 97 autonomous institutions, including public universities, polytechnics, and private entities. This structure accommodates over 450,000 students and is governed by the Legal Regime of Higher Education Institutions, ensuring a quality management framework aligned with the European Higher Education Area (EHEA) (Agency for Evaluation and Accreditation of Higher Education [A3ES], n.d.).

HEIs, in Portugal and across the world, are instrumental to economic and social development; however, they can only fulfil their mission if equipped with appropriate management models. This study is based on the premise that the effective synergy between KM and QM can enhance performance, foster continuous improvement, and support the strategic objectives of HEIs (Shehabat, 2017).

1.2 Research Gaps, Aims, and Contributions

Despite the growing theoretical literature at this intersection, critical empirical and practical gaps persist. Empirical investigation of the KM — QC relationship in HEIs has been notably limited and geographically skewed: most studies originate outside Europe, leaving the regulatory and cultural specificities of the European Higher Education Area unexamined. Although the concept of QC has attracted considerable theoretical interest, its operationalisation and systematic empirical investigation remain underdeveloped (Hildesheim & Sonntag, 2020). Existing research on KM and QM within HE tends to centre on academic staff perspectives, frequently overlooking the complementary roles of quality managers, institutional leadership, and technical teams — precisely those actors most responsible for QMS implementation. Finally, while institutions are formally

mandated to implement QMS underpinned by knowledge practices, structured implementation guidelines aligned with relevant standards — notably ISO 30401:2018 — remain absent from the European quality assurance landscape.

Against this backdrop, the primary aim of this research is to describe, analyse, and understand the relationship between KM and QC in the Portuguese HE sector, with the dual purpose of contributing to the KM–QM literature and producing actionable guidelines for institutional practice. The project unfolds across five sequential phases described in detail in section 2. The study is structured around four core research questions, each derived from the gaps identified above:

RQ1: What is the relationship between KM processes, TQM, and QC dimensions within Portuguese HEIs?

RQ2: Do Portuguese HEIs have KM processes integrated into their QMS?

RQ3: What are the primary dimensions of QC in Portuguese HEIs that have implemented KM and TQM processes?

RQ4: How do KM processes influence QC in Portuguese HE from the perspective of quality managers and institutional leadership?

This study makes two interrelated theoretical contributions. First, it moves beyond the established conceptual assertion that KM and TQM are mutually reinforcing (Akdere, 2009; Honarpour et al., 2017; Abbas & Kumari, 2023) to empirically examine the mechanisms through which KM processes mediate the translation of TQM frameworks into QC outcomes within a European HE context — a gap the SLR confirms has not been bridged. Second, the study introduces the Quality Culture Maturity Model (QCMM): an inductively derived four-stage framework (Compliance-Driven, Structural, Aligned, Integrated) that identifies, at each stage, the depth of KM integration required for progression. Unlike prior maturity models centred on procedural compliance, the QCMM positions KM capacity — specifically, the institutional ability to transform raw performance data into actionable knowledge — as the decisive variable in advancing QC, providing both an analytical lens and a practical diagnostic for institutional quality managers.

Figure 1 presents the study's conceptual framework, positioning KM processes as the mediating mechanism through which TQM frameworks are translated into QC outcomes. This mediation relationship — theorised by Honarpour et al. (2017) and Akdere (2009) but not yet empirically examined in the European HE context — is the central proposition this research is designed to test. The QCMM (right panel) operationalises QC as a developmental continuum rather than a binary state, providing the outcome variable against which KM integration is assessed across the full empirical programme.

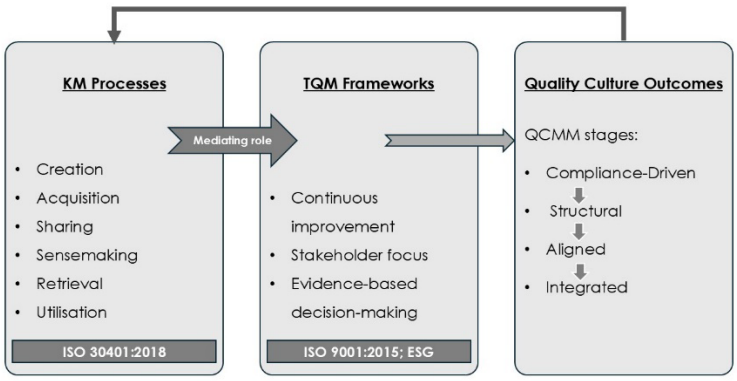


Figure 1: Study's conceptual framework — KM processes as the mediating mechanism between TQM frameworks (ISO 9001:2015, ESG) and the four-stage Quality Culture Maturity Model (QCMM)

2. Research Method

To address the research questions, this project employs a mixed-methods approach, combining the robustness of empirical data with contextual depth, to expand the understanding of the complex phenomena surrounding KM, QM, and QC in HE. By leveraging the complementary advantages of different research methods, the study aims to produce more robust, comprehensive, and reliable results.

To ensure transparency regarding the research timeline, Table 1 summarises the completion status of each phase at the time of submission.

Table 1: Completion status of each phase of the research project, at the time of submission:

Phase	Activity	Status
Phase 1	Systematic Literature Review (PROSPERO-registered; PRISMA protocol)	**Near completion**[1]
Phase 2	a) Documentary Analysis — 97 A3ES institutional evaluation reports	**Completed**
	b) Quantitative questionnaire administration to all 97 HEI quality managers	**Planned (June 2026)**
	c) Semi-structured interviews with institutional leadership	**Planned**
	d) Focus group with quality management technical teams	**Planned**
Phase 3	Multivariate statistical analysis and qualitative content analysis	**Planned**
Phase 4	Cross-method interpretation and critical discussion	**Planned**
Phase 5	Dissemination (publications, workshops)	**Ongoing**

2.1 Data Collection

Two data sources have already been collected and partially analysed at the time of this submission. The SLR (Phase 1) is nearing completion, and the documentary analysis of all 97 A3ES institutional evaluation reports (Phase 2a) has been completed, and its preliminary findings are reported in Section 3.

The remaining empirical phases are planned for 2026. Three online questionnaires will be administered simultaneously to quality managers across all 97 Portuguese HEIs via the LimeSurvey platform: the Knowledge Management scale (Cardoso & Peralta, 2011); the Quality Culture in Higher Education scale (Ali & Musah, 2012), adapted and validated for the European Portuguese context; and a sociodemographic instrument. These instruments have received a favourable opinion from the Data Protection Officer at the host institution and aim to capture quality managers' perceptions of KM and QC within their institutions, enabling the identification of patterns, trends, and statistical correlations.

The qualitative component comprises three complementary methods. Semi-structured interviews will be conducted with top and middle management — including Vice-Rectors and Directors — to explore leadership perceptions of strategic alignment. A non-probability purposive sampling strategy, based on explicit inclusion criteria (institutional role, scope of QMS responsibility, sub-sector representation), will be employed until thematic saturation is reached, encompassing both public and private institutions. Documentary analysis will involve an ongoing review of publicly available strategic plans and institutional evaluation reports, with the aim of identifying existing policy frameworks and guidelines within the scope of KM and QC. Finally, focus group will be conducted with quality management technical staff to contextualise the quantitative findings and capture shared understandings of KM practices at team level.

Table 2: Summary of instruments that will be used

Data type	Instrument	Participants	Linked RQ	Analytical method	Analysis goal
Quantitative	Online Questionnaires (Cardoso & Peralta, 2011; Ali & Musah, 2012)	Quality Managers of all 97 Portuguese HEIs	RQ1, RQ2, RQ3	Descriptive statistics; Pearson correlation; EFA; CFA; multiple linear regression (SPSS / R)	Identify patterns, trends, and statistical relationships between KM processes, TQM, and QC dimensions
Qualitative	Semi-structured Interviews	Top/Middle Management (Vice-Rectors, Directors); non-probability purposive sampling to saturation	RQ1, RQ4	Reflexive thematic analysis* (MAXQDA) (*Braun & Clarke, 2022)	Explore strategic alignment and leadership perceptions of KM–QC integration

[1] Phase 1 finalisation is expected by June 2026

Data type	Instrument	Participants	Linked RQ	Analytical method	Analysis goal
Qualitative	Documentary Analysis (A3ES evaluation reports, strategic plans)	All 97 HEI institutional evaluation reports (most recent A3ES cycle)	RQ2, RQ3	Qualitative content analysis** (MAXQDA) (**Bardin, 2016)	Identify KM-adjacent practices and QMS maturity patterns within formal quality documentation
Qualitative	Focus Group	Technical quality management staff in Portuguese HEIs (max. 15 participants)	RQ3, RQ4	Reflexive thematic analysis* (MAXQDA) (*Braun & Clarke, 2022)	Contextualise quantitative findings; capture shared team-level understandings of KM practices

2.2 Data Analysis

The analytical choices are directly responsive to the research questions and the properties of the instruments employed, as summarised in table 2. Exploratory Factor Analysis (EFA) is used to examine the factor structure of the adapted Quality Culture scale in the Portuguese HE context, where validation data for this population do not yet exist; Confirmatory Factor Analysis (CFA) then tests the stability of the emergent structure (RQ3). Pearson correlation and multiple linear regression are applied to test the directional relationships between KM processes, TQM implementation levels, and QC dimensions — directly addressing RQ1 — while descriptive comparison across institutional types enables assessment of integration levels (RQ2). Regarding qualitative strands, reflexive thematic analysis (Braun & Clarke, 2022) for the interviews and focus group, and qualitative content analysis (Bardin, 2016) for the documentary corpus are used to identify emergent themes regarding how KM shapes institutional quality culture trajectories (RQ4). Triangulation across quantitative and qualitative strands is not merely additive: each method provides a distinct lens on the same phenomenon, reducing the risk of method-specific bias and enhancing the interpretive depth of findings, particularly for RQ4, which concerns the perceptions and sensemaking of institutional actors.

3. Preliminary Results

3.1 Preliminary Results from Phase 1 — SLR

The SLR, registered in PROSPERO and following PRISMA protocol, searched Web of Science and Scopus using the terms 'KNOWLEDGE MANAGEMENT' and 'QUALITY MANAGEMENT' (or equivalent expressions) returning 21 retrieved papers after full-text screening and eligibility assessment against pre-registered inclusion criteria.

This SLR reveals that the volume of empirical research specifically investigating the link between KM and QM in HE remains limited and is geographically skewed towards non-European contexts. The central finding of the SLR is that the relationship between KM and QM is one of integration and mutual support, rather than a mere co-existence — evidence suggests that KM often functions as the primary engine facilitating the translation of QM frameworks into practical, impactful organisational actions that enhance institutional performance.

3.2 Preliminary Results from Phase 2 — Documentary Analysis

The following results derive from the documentary analysis component of Phase 2, which comprised the qualitative analysis of 97 institutional evaluation reports and Board of Directors' decisions from the most recent institutional evaluation cycle conducted by A3ES — this represents complete population coverage of the Portuguese HE sector, eliminating selection bias and permitting sector-level pattern detection rarely available in HE quality research. In this study, A3ES institutional evaluation reports are operationalised as a window onto QC: they constitute standardised outputs of the mandatory quality assurance cycle under European frameworks and provide publicly available evidence of QMS practices, data use, and improvement processes — making them a relevant and accessible source for identifying KM-adjacent behaviours.

The research (to be published) identifies a developmental trajectory for HEIs through a proposed four-stage Quality Culture Maturity Model: *Compliance-Driven*, *Structural*, *Aligned*, and *Integrated*. This model differentiates institutions that merely "possess" a system from those that "live" a Quality Culture. The progression between these stages is fundamentally connected to KM, as seen in Figure 2:

- Lower Maturity (Compliance/Structural): Characterised by "structural silos" and "decoupling," where formal procedures exist but remain disconnected from daily academic operations.
- Higher Maturity (Aligned/Integrated): Defined by "cultural internalisation," where quality is a shared responsibility and knowledge flows transversally across the institution.

A core finding is the critical role of KM in advancing QMS maturity. Institutions rated 'Good' or 'Very Good' consistently demonstrate the capacity to 'close the loop' — moving from passive data collection to active data utilisation — whereas institutions rated 'Sufficient' typically do not. While the documentary body does not permit a causal claim, the pattern is robust across the 97 reports and supports the QCMM hypothesis that KM integration is associated with higher QMS maturity.

Figure 2 depicts the four-stage QCMM as a developmental trajectory derived inductively from the documentary analysis of all 97 A3ES institutional evaluation reports. Crucially, the distinction between stages is not merely structural but epistemological. Compliance-Driven and Structural institutions treat knowledge primarily as a by-product of quality reporting: data are collected, procedures are documented, but the loop between data and institutional decision-making remains largely closed. Aligned and Integrated institutions, by contrast, demonstrate the capacity to transform performance data into actionable knowledge — what the documentary analysis terms the “closing of the loop” — enabling evidence-based strategic decisions that are visibly informed by what the institution knows about itself.



Figure 2: The Quality Culture Maturity Model (QCMM) four-stage developmental trajectory from Compliance-Driven through Structural and Aligned to Integrated Quality Cultures, with associated KM-integration depth at each stage

A key finding is the prevalence of knowledge-sharing and sensemaking practices that are structurally embedded in institutional routines but are neither formally recognised as KM nor strategically leveraged as such. The QCMM thus not only describes where institutions currently stand but diagnoses what is required — specifically, deliberate recognition and strategic alignment of existing knowledge practices — to advance to the next stage.

4. Conclusions, Limitations, and Next Steps

This paper reports the conceptual and initial empirical work of a doctoral project investigating the intersection of KM and QC in Portuguese HEIs. Although the full multi-method fieldwork is still underway, the preliminary findings derived from the SLR (Phase 1), and documentary analysis (Phase 2) already offer substantive contributions to the four core research questions structuring this project.

Regarding RQ1 — the relationship between KM processes, TQM, and QC — the SLR confirms what Honarpour et al. (2017) and Akdere (2009) have theorised: KM and TQM are mutually reinforcing, with KM functioning not merely as an operational tool but as the primary engine through which quality frameworks are translated into institutional practice. Crucially, however, the SLR reveals that this relationship has been empirically examined almost exclusively outside Europe — of the 21 retrieved papers, only 3 originate in European institutional contexts — a gap this study directly addresses.

Regarding RQ2 and RQ3 — whether KM processes are integrated into Portuguese HEIs' QMS, and what QC dimensions characterise those that have done so — the documentary analysis of all 97 A3ES institutional evaluation reports provides a compelling preliminary answer. The proposed Quality Culture Maturity Model identifies a four-stage developmental trajectory — Compliance-Driven, Structural, Aligned, and Integrated — that differentiates institutions that merely possess a QMS from those that genuinely live a Quality Culture (EUA, 2006; Hildesheim & Sonntag, 2020). A decisive factor at each transition is the depth of KM integration: specifically, the institutional capacity to move from passive data collection to active knowledge utilisation in evidence-based decision-making.

A particularly significant finding, which also speaks to RQ4 — how KM processes influence QC — is the widespread presence of what may be termed as “unlabelled KM”: knowledge-sharing and sensemaking practices that are structurally embedded in institutional routines but are neither formally recognised nor strategically

leveraged as KM. This finding reframes a key challenge facing Portuguese HEIs: the barrier to QC advancement is not primarily the absence of knowledge processes, but their invisibility. As noted by Zheng et al. (2010), the alignment between organisational culture, structure, and KM strategy is decisive for institutional effectiveness — and it is precisely this alignment that appears to remain underdeveloped in compliance and structural-stage institutions.

Taken together, these preliminary results support the core argument of this research: that KM processes act as essential mediators between TQM frameworks and QC, and that advancing institutional maturity requires the deliberate recognition, formalisation, and strategic alignment of knowledge practices — a process for which ISO 30401:2018 offers a practical normative anchor currently underutilised in the European HE context.

This study acknowledges two key limitations at its current stage. First, the empirical focus is restricted to the Portuguese HE system, which may constrain the generalisability of findings to other European or international contexts governed by different regulatory frameworks. Second, the results presented here are based primarily on secondary data sources — documentary analysis and SLR — rather than the full multi-method fieldwork, which limits the depth of inference possible at this stage.

To fulfil the research objectives, the project will proceed with questionnaire administration (Phase 2b, planned to occur in June 2026), semi-structured interviews, focus group, and multivariate analysis, culminating in actionable KM implementation guidelines aligned with ISO 30401:2018. Findings will be disseminated through peer-reviewed publications and practitioner workshops.

In its current form, the QCMM offers institutional quality managers a diagnostic instrument for locating their institution's stage and a developmental map for advancing it; subsequent phases will refine and validate the model against multi-method empirical evidence.

Acknowledgements

The author wishes to express sincere gratitude to her doctoral supervisors, Professor Leonor Pais and Professor Patrícia Moura e Sá, for their guidance, expertise, and continued support throughout this research, conducted at the University of Coimbra, Portugal.

Ethics and Integrity: The study complies with GDPR and institutional ethics requirements, including Data Protection Officer approval and Ethics Committee review. Informed consent will be obtained from all participants before interviews and focus group.

AI Declaration: The author acknowledges the use of Artificial Intelligence (AI) tools, specifically Gemini Pro, NotebookLM, and Claude, during the preparation of this manuscript. AI was employed to assist in the following tasks:

- Translation and Linguistic Refinement: to support the translation of the text into English, ensuring the linguistic precision and rigour expected for submission to a scientific conference.
- Literature Review Support: to assist in the literature review process, specifically by providing summaries of certain bibliographical references consulted during the research.
- Reference Management: to review the final list of bibliographical references to ensure strict adherence to the Harvard referencing style.

The author declares that the core conceptual framework, research design, and project ideas are entirely original and the result of the research team's intellectual work. The author has critically reviewed all AI-generated outputs and remains fully responsible for the final content, accuracy, and integrity of the paper.

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Educational Integration, Social Inclusion and Transition to Work: A Scoping Review of Conceptual Frameworks

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Abstract: This study examines frameworks that describe educational integration, social inclusion, and the transition to working life among students with immigrant backgrounds in higher education. A scoping review of 14 studies identified three framework clusters: social inclusion, educational support, and transition to working life. The findings show overlap but limited integration, particularly in linking pedagogy to labour market outcomes. A multi-level model (micro, meso, macro) is proposed, interpreted through the lenses of educational integration, social inclusion, and knowledge management, highlighting the need for more integrated approaches.

Keywords: Educational integration, Social inclusion, Knowledge management, Higher education, Immigrant students, Transition to working life

1. Introduction

International mobility has increased the diversity of student populations in higher education (OECD 2025a), placing pressure on institutions to respond to labour market demands and support the integration of students with immigrant backgrounds into both working life and academic communities (OECD 2025b). This paper examines conceptual frameworks describing educational integration, social inclusion, and transition to work, aiming to develop a multi-level understanding across individual, institutional, and structural levels.

Existing research has addressed these perspectives separately, with limited attention to their interconnections. In previous research, education integration, social inclusion, and the transition to working life have often been examined from the perspectives of different disciplines. While educational research has primarily focused on student integration and retention, as an example Tinto's (1975) theory of student integration, sociological studies have emphasized social inclusion, social capital, and inequality, as an example Bourdieu's (1977) theory of capital. Research on labour market integration has examined employability and transition-to-work processes, often grounded to human capital theory by Becker (NBER 2020). A central challenge, therefore, lies in balancing scalable institutional strategies with the need for flexible, student-centered support that promotes equitable inclusion and meaningful labour market integration for students with immigrant backgrounds.

This scoping review maps conceptual frameworks describing educational integration, social inclusion, and knowledge management and identifies key concepts, theoretical approaches, and knowledge gaps (Pollock et al. 2024). The review indicates that the primary conceptual and practical challenge concerns how higher education institutions can reconcile institutional efficiency and standardized integration practices with equitable, context-sensitive, and student-centered inclusion strategies.

2. Conceptual Background

In this study, educational integration, social inclusion, and knowledge management are understood as complementary and interconnected concepts (Figure 1). Educational integration provides a framework for examining how students with immigrant backgrounds become academically and socially attached to higher education institutions. Social inclusion broadens this perspective by highlighting how access to cultural, social, and economic capital influences students' opportunities for participation, belonging, and success in both higher education and the labour market. Knowledge management contributes an organisational perspective by explaining how higher education institutions can identify, create, share, and utilise knowledge to develop effective support services, guidance practices, and stakeholder collaboration.

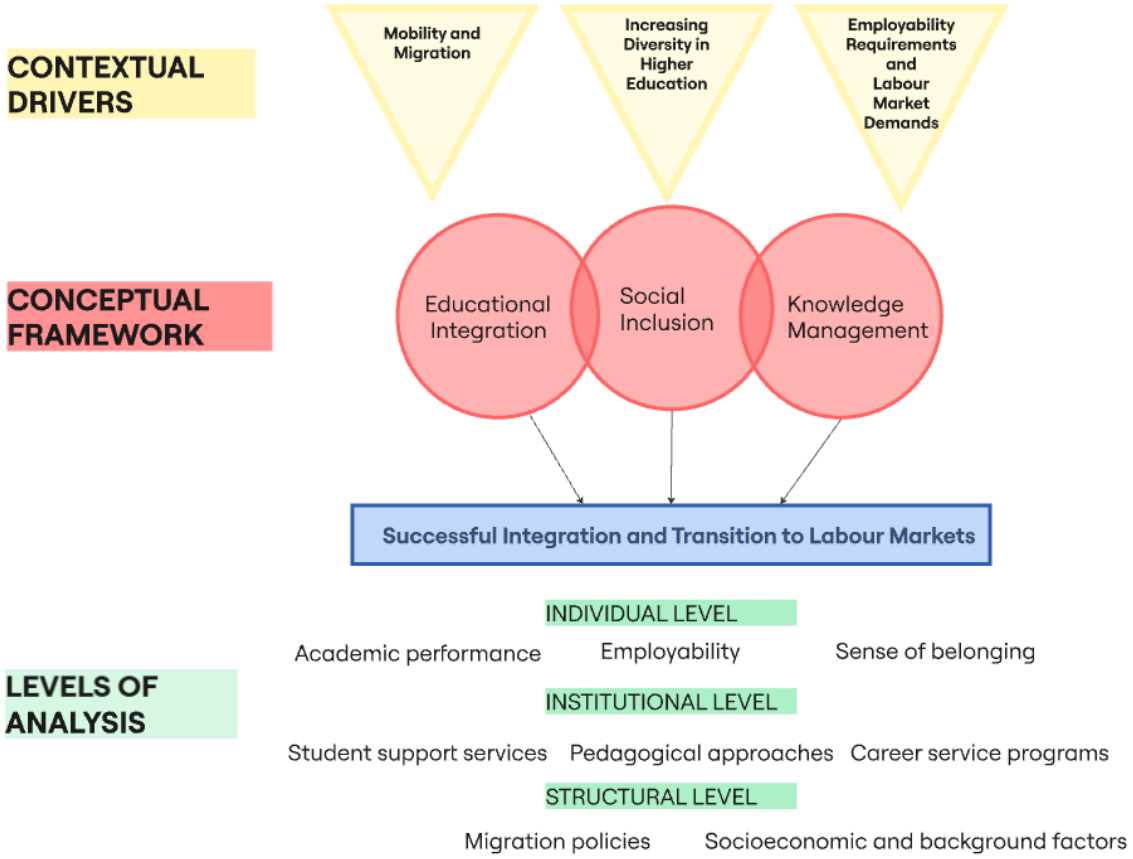


Figure 1: Conceptual Framework. Source: Authors' own elaboration.

Educational integration is understood as a process in which a student becomes attached to a higher education institution both academically and socially. Tinto's (1975) classical theory conceptualises student integration as a framework in which academic and social integration influence students' attachment to their studies. Higher education institutions should promote integration through various support mechanisms, such as early-stage orientation, the development of academic advising services, mentoring, and fostering participation in social activities (Samoila & Vrabie, 2023). Tinto's framework focuses primarily on students' academic and social engagement within higher education institutions; broader structural and societal factors also shape integration processes. Globalisation, increasing international mobility, and growing student diversity have transformed education approaches worldwide, creating new demands for education policies and institutional practices. Research suggests that international organisations, particularly the OECD, have played a significant role in shaping educational governance through policy recommendations, performance indicators, and standardised approaches aimed at improving migrant students' educational outcomes (Hajisoteriou and Neophytou 2022).

Social inclusion in Bourdieu's (1977) theory is defined by three forms of capital: cultural capital, social capital, and economic capital. Cultural capital includes, for example, language skills, education, and behavioral norms; social capital refers to networks and relationships; economic capital consists of resources and wealth. Students with immigrant background may face unequal access to these forms of capital. It may influence their integration into higher education and their transition to the labour market. When comparing these two theoretical perspectives: educational integration and social inclusion, it can be argued that educational integration explains student persistence as a function of academic and social integration, whereas social inclusion highlights how unequal access to cultural and social capital shapes students' ability to integrate into higher education. Together, these two perspectives provide an understanding of how higher education institutions and employers can support inclusion, belonging, educational success, and successful transition into employment among students with immigrant background.

Knowledge management focuses on how organizations create, utilize, and share knowledge to develop their practices and decision-making. In the higher education context, knowledge management is reflected in the

development of student support services based on student individual needs, which emphasizes the heterogeneity and diversity of students, and collaboration between stakeholders (Alisaari et al. 2025). Successful integration also requires higher education institutions to effectively manage and apply knowledge. Collaboration between universities and employers can facilitate students' transition to working life (Tzavidas et al. 2020).

3. Methods

3.1 Study Design

This study was conducted as a scoping review to map research on conceptual frameworks describing educational integration and social inclusion in higher education, and their role in supporting students with migration backgrounds in the transition to working life. Scoping reviews are suitable for examining complex or unclear phenomena, providing a broad overview of existing knowledge (Pollock et al. 2024). They address broader questions and apply more inclusive criteria, enabling the identification of diverse evidence (Munn et al. 2018). The review followed the relevant reporting principles of PRISMA 2020, to ensure transparency in study identification, screening, eligibility assessment, and inclusion (see Figure 2).

3.2 Eligibility Criteria

Studies were included if they explicitly referred to integration and/or social inclusion and focused on the higher education context and transition to working life. Studies needed to be peer-reviewed journal articles. Studies were excluded if they did not include a conceptual or theoretical framework, were purely descriptive without analytical contribution, or focused on context unrelated to higher education.

3.3 Information Sources and Search Strategy

The search strategy combined keywords related to integration, inclusion, education, labor markets, and conceptual frameworks. The literature search was conducted in the Scopus database. The search-query reads as: (immigrant* OR migrant* OR refugee* OR "international student*" OR "ethnic minorit*" OR "minority student*" OR "culturally diverse") AND ("higher education" OR universit* OR "tertiary education" OR "postsecondary education") AND (integration OR inclusion OR "social inclusion" OR belonging OR participation OR acculturation) AND (employ* OR employability OR "transition to work" OR "school-to-work" OR career* OR "labour market" OR "labor market") AND (approach* OR intervention* OR strateg* OR program* OR support* OR model* OR framework* OR practice* OR pedagog* OR curriculum). The search was limited to peer-reviewed publications, which were published between 2016 and 2026 to ensure the inclusion of recent and accessible research. This limitation was also motivated by the aim to capture contemporary pedagogical approaches and developments, especially those influenced by the increasing role of digitalization and the digital leap in higher education, including the expansion of digital learning environments and hybrid pedagogies. The included studies were published in journals published by Elsevier, Taylor & Francis, and Springer Nature. These publishers were selected because they are among the leading international academic publishers in the fields of education, social sciences, and migration studies, and their journals maintain rigorous peer-review standards and broad international visibility. Publisher was not used as an independent quality criterion; instead, studies were assessed against the predefined eligibility criteria, including peer-review status, and relevance to the research question. Only publications written in English were considered.

3.4 Selection Process

The article selection process followed PRISMA guidelines. Through database searches, a total of 2673 records were identified. After the removal of 794 duplicate records, 1,879 records remained. The titles of these records were screened against the eligibility criteria, resulting in the exclusion of 1,614 records and the retention of 265 records for abstract screening. Following abstract screening, 46 articles were retained for full-text assessment. All 46 full-text articles were retrieved and assessed for eligibility. During this stage, 32 articles were excluded for reasons including the lack of a higher education context, insufficient relevance to transition to working life and the absence of a pedagogical, integration, or social-inclusion perspective. Screening was conducted by the first author. Any disagreements concerning eligibility were resolved through discussion with a second author. The complete study-selection process is presented in Figure 2.

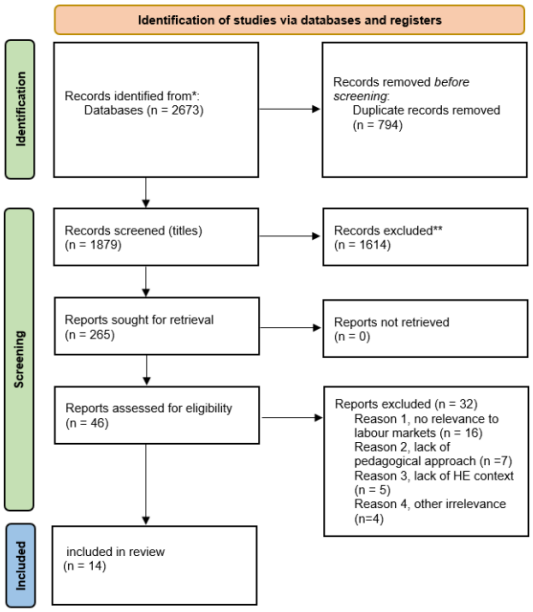


Figure 2: PRISMA flow diagram of the study-identification and selection process. Source: Authors' own elaboration

3.5 Data Analysis

The 14 included articles were systematically coded using a predefined analytical framework comprising the following categories: definitions of integration into culture and/or working life, definitions of inclusion, conceptualizations of pedagogy, research methods, study type, theoretical or conceptual frameworks, and key findings. The coded data were analyzed using a thematic synthesis approach (Thomas & Harden, 2008), whereby concepts and findings were compared across studies and grouped into descriptive themes. Through an iterative process of constant comparison, these themes were further refined and organized into higher-order conceptual clusters. This enabled the development of an analytical synthesis that identifies common patterns and differences in how higher education, inclusion, integration, and transitions to working life are conceptualized within the reviewed literature.

4. Results

4.1 Characteristics of the Included Studies

The 14 included articles (see References, list of included articles) were conducted across diverse geographical regions worldwide. A structured data-charting form was used to record information consistently across the included studies. They included immigrant and international students facing barriers to participation in higher education and employment. Exchange students were excluded from the study because their integration into the labour market of the host country was not relevant. The articles were coded for definitions of integration into education, culture, or working life; definitions of inclusion: definitions related to pedagogy; and key findings, based on which the main characteristics and key concepts were identified (Table 1). In addition, the population, and the country in which each study were coded. Of the included studies, seven were qualitative, three were quantitative, three used mixed methods, and one was a comparative analysis.

Table 1: Main characteristics and key concepts of the included articles. Source: Authors' own synthesis based on the reviewed studies.

Author (Year)	Country	Method	Context/population	Key Concepts
Lin, Yuqi (2025)	Australia/China	Comparative analysis	International graduates	Opportunities, participation
Zhang et. al (2025)	Malaysia	Quantitative	Immigrant students	Language and cultural training, provider of skills
Chiu et. al (2025)	UK	Qualitative	Immigrant students	Belonging, participation in academic life

Author (Year)	Country	Method	Context/population	Key Concepts
Hun Debo (2023)	Norway	Quantitative	Immigrant students	Social integration, participation in labour markets
Hu, Lue (2025)	United States	Qualitative	Immigrant students	Belonging, participation, equal opportunities for engagement in studies
Coustere et. al (2024)	Canada	Qualitative	Immigrant students	Migration policies, career pathways, participation in on campus
Brotherhood et al. (2024)	Japan	Mixed methods	Immigrant students	Participation in on-campus, participation in academic society, social integration
Ennerberg, Economou (2022)	Sweden	Qualitative	Migrant teachers	Migration policies, career pathways, participation in labour markets, opportunities
Chen (2022)	Japan	Qualitative	International University faculty members	Participation, belonging, social integration
Hsu, Chen (2021)	Taiwan	Quantitative	Immigrant working students	Participation, language and culture training during studies, migration policies, access to labour markets
Cerna, Chou (2023)	Global	Literature review	Literature review	Mobility opportunities, transition to working life, migration policies, participation in academic society
Rosvall et al. (2022)	Sweden	Qualitative	Immigrant students, immigrant employers, education, and employment professionals	Participation, belonging, participation in academic society, migration policies, access to education and labour markets, language, and culture learning
Samaluk (2025)	Slovenia	Qualitative	Immigrant workers from different career stages	Access to labour markets from education, participation in labour markets
Mathies, Karhunen (2021)	Finland	Quantitative	Immigrants' graduates follow -up.	Belonging, opportunities, participation in labour markets, adapting

Identified Frameworks and Models

The synthesis identifies three framework categories describing educational integration, social inclusion, and transition to work. Many studies included concepts from multiple frameworks, so articles were not confined to a single category.

Social Inclusion Frameworks: This framework identifies the social factors that influence an individual's integration into society. It emphasizes the importance of belonging, participation, and social integration (Chen 2022; Chiu et al. 2025; Hsu & Chen 2021; Hundebo 2023; Rosvall et al. 2022; Xu & Lue 2025; Zhang et al. 2025). Social inclusion is facilitated by individuals' ability to interact and communicate effectively, highlighting the importance of learning the local language (Brotherhood & Patterson 2024; Rosvall et al. 2022; Zhang et al. 2025). Acceptance by members of the academic and/or work community is considered essential for successful inclusion (Chen 2022; Coustere et al 2024). Together, these factors support individuals' adaptation to institutional and organizational requirements.

Educational Support Frameworks: This framework identifies the needed actions from higher education institutions to support individuals' integration to social inclusion, transition into the labour market, and integration. It emphasizes the importance of individuals' participation both on campus and within the broader academic community (Hu & Lue 2025; Chen 2022). Higher education institutions are viewed as a provider of essential skills and support, including language and cultural training during studies (Hsu & Chen 2021; Hu & Lue 2025; Lin 2025; Zhang et al. 2025). The recognition of competencies, mobility opportunities, and equal opportunities for engagement in academic activities play a crucial role in supporting successful studies and facilitating the transition into working life (Chiu et al. 2025; Hu & Lue 2025; Hundebo 2023; Rosvall et al. 2022).

Transition-to-working-life Frameworks: The framework identifies the factors required for a successful transition into the labour market. It emphasizes the importance of access to and participation in both higher education and working life. Individuals' opportunities for inclusion are shaped by migration policies and the availability of educational and employment opportunities (Cerna & Chou 2023; Coustere et al. 2024; Ennerberg & Economou 2022; Hundebo 2023; Li 2025; Rosvall et al. 2022; Samaluk 2025) Labour market participation and adaptation in work environments are viewed as a key factor in supporting the development of meaningful career pathways and facilitating long-term social and economic integration (Cerna & Chou 2023; Coustere et al. 2024; Ennerberg & Economou 2022; Hsu & Chen 2021; Mathies & Karhunen 2021). Conceptual clustering of identified frameworks is presented in Table 2.

Table 2: Conceptual clustering of identified frameworks. Source: Authors' own synthesis based on the reviewed studies

Study	Key Concepts	Framework Category
Lin, Yuqi (2025)	Opportunities, participation	Social inclusion, Transition -to-working-life
Zhang et. al (2025)	Language and cultural training, provider of skills	Educational support
Chiu et. al (2025)	Belonging, participation in academic life	Social inclusion, educational support
Hundebo (2023)	Social integration, participation in labour markets	Social inclusion, educational support
Hu, Lue (2025)	Belonging, participation, equal opportunities for engagement in studies	Educational support
Coustere et. al (2024)	Migration policies, career pathways, participation in on campus	Transition-to-working life, educational support
Brotherhood et al. (2024)	Participation in on-campus, participation in academic society, social integration	Educational support, social inclusion
Ennerberg, Economou (2022)	Migration policies, career pathways, participation in labour markets, opportunities	Transition-to-working-life
Chen (2022)	Participation, belonging, social integration	Social inclusion
Hsu, Chen (2021)	Participation, language and culture training during studies, migration policies, access to labour markets	Educational support, transition-to-working-life
Cerna, Chou (2023)	Mobility opportunities, transition to working life, migration policies, participation in academic society	Transition-to-working life, educational support
Rosvall et al. (2022)	Participation, belonging, participation in academic society, migration policies, access to education and labour markets, language, and culture learning	Social inclusion, educational support, transition-to-working-life
Samaluk (2025)	Access to labour markets from education, participation in labour markets	Educational support, transition-to-working-life
Mathies, Karhunen (2021)	Belonging, opportunities, participation in labour markets, adapting	Social inclusion, transition-to-working-life.

5. Discussion

The discussion synthesizes the findings by examining how the identified framework clusters contribute to understanding the integration of students with immigrant backgrounds. It outlines three key dimensions (social inclusion, educational support, and transition to working life) and explores how they intersect to shape integration. It also considers disciplinary perspectives and their convergence, and identifies key gaps, particularly in linking educational practices, labour market outcomes, and long-term integration processes.

5.1 Findings

Social inclusion frameworks examined the integration of students with an immigrant background as a process of belonging, inclusion, and participation/engagement. These frameworks emphasize the individual's opportunities to participate in academic and professional communities, as well as their ability to communicate and be an active member of society.

Educational support frameworks focused on the factors that can promote the integration of students with an immigrant background into the higher education environment, learning culture, and collaboration with working life during their studies. These frameworks highlighted the importance of various support services, the creation of learning environments that foster pedagogy tailored to students with immigrant backgrounds, as well as mentoring, guidance, and language support.

In addition, other mechanisms were identified, such as the use of artificial intelligence in education (Zhang et al. 2025), which can support students' academic success, inclusion, and engagement with their studies. Although educational support was often considered a prerequisite for successful integration, clear pedagogical models linking teaching methods to broader integration outcomes were rarely identified in the research data.

Transition-to-working-life frameworks extended the analysis beyond education, while at the same time bringing together the significance of educational and societal integration during the transition to working life. These frameworks emphasized the importance of access to the labour market, which was seen as achievable when collaboration with working life was established during studies and when national immigration policies supported the employment of individuals with an immigrant background. Additionally, the importance of the social environment, such as family reunification, was also highlighted within these frameworks as a factor that facilitates commitment to work. In these frameworks, structural conditions and integration into workplace communities were particulary emphasized.

5.2 Multi-Level and Interdisciplinary Integration of the Findings

When examined together, the reviewed frameworks revealed considerable conceptual overlap, but only limited theoretical and practical integration across disciplines. Social inclusion frameworks emphasize belonging and participation at the societal level. Educational support frameworks emphasize various education-related factors that facilitate inclusion and integration. However, a clearly pedagogical framework or pedagogical approach that systematically connected to these factors was absent from the literature. Frameworks describing the transition to working life extended these processes by focusing on access to labour markets, labour market participation, and the factors that support individuals in establishing themselves within working life.

Based on this synthesis, the findings can be integrated into a multi-level conceptual model comprising micro, meso, and macro levels. At the **micro level,** integration is understood as individual experiences of belonging, and participation. Students' abilities to participate and later engage in social, academic, and professional environments are factors that contribute to successful integration. At the **meso level**, higher education institutions are key facilitators of integration. Employers, in collaboration with higher education institutions, also play a significant role in the transition to the labour market. Institutional pedagogical practices, guidance, mentoring, language support, career services, and employer collaboration form interconnected parts of the student integration process. Knowledge management is particularly relevant at this level because it can support the collection, sharing, and application of knowledge across institutional units and external stakeholder networks. At the **macro level**, structural conditions, such as labour market policy, immigration systems, qualification-recognition practices, anti-discrimination measures, and national education policies, create a broader context. Access to employment and supportive policy environments is critical for enabling long-term integration and commitment to society, education, and working life.

Integration depends on alignment across the three levels; weak coordination may undermine the integration process. This highlights the need for more comprehensive models that explicitly connect to these levels.

Across disciplines, the findings revealed shared conceptualizations of integration. From a sociological perspective, integration was framed through inclusion, participation, and societal belonging, which is connected to Bourdieu's (1977) theory of three forms of capital. Educational research emphasized academic integration, learning environments, and student support mechanisms, which aligns with the findings of Samoila & Vrabie (2023) regarding the role of higher education institutions in promoting student support mechanisms. Labour market–oriented studies focused on access to employment, employability, and integration into workplace communities. These aspects can also be understood as part of effective knowledge management.

The analysis indicates that integration is understood across disciplines as a multidimensional, relational, and processual phenomenon. Social environments, educational factors, and structural conditions, such as migration and labour-market policies, interact across the identified frameworks. An interdisciplinary approach is needed to connect sociological understandings of inclusion and inequality, educational perspectives on

student engagement and institutional support, labour-market perspectives on employability and access to work, and knowledge-management perspectives on organisational learning and stakeholder collaboration.

5.3 Gaps and Implications

A notable gap concerns the limited integration of pedagogical approaches with transition to work models. While educational support mechanisms were discussed, their relationship to employment outcomes was not addressed.

Another notable gap concerned leadership and its role in supporting the transition of individuals with immigrant backgrounds into working life and their long-term integration within the workplace. Furthermore, there was limited discussion of collaboration between higher education institutions and employers, despite its potential importance in facilitating successful transitions from education to employment as can be seen in connection with education-related factors and transition to working life factors.

From a research perspective, the results highlight the need for more interdisciplinary frameworks. Studies should focus on developing conceptual models that explicitly connect pedagogical practices with integration processes and employment outcomes. From a practice perspective, higher education institutions should develop pedagogical approaches that support students' integration and facilitate the rapid adoption of higher education culture, thereby enabling a successful transition to working life. These aspects should also be explicitly considered in curriculum design. In addition, knowledge management practices within higher education institutions should support mentoring, language learning, and collaboration with working life during studies to enhance students' opportunities for societal participation and their sense of cultural belonging. From a policy perspective, findings emphasize the importance of bridging higher education and employment systems. This requires policies that promote cooperation between higher education institutions and employers, as well as structural conditions that support labour market access and long-term integration for individuals with migrant backgrounds.

5.4 Strengths and Limitations

This paper provides a comprehensive synthesis of existing conceptual frameworks related to social inclusion, educational support, and transition to working life. The study offers an integrative perspective across disciplinary boundaries. A key strength of this paper is its interdisciplinary perspective, which integrates concepts from higher education, sociology approaches, labour market approaches, and knowledge management. The scoping review approach captures a broad range of perspectives and identifies key patterns across literature. The study addresses the research question by clarifying how different conceptual frameworks have been used to describe integration processes and their interconnections.

However, limitations are acknowledged. First, the review is limited to a single bibliographic database, Scopus, as well as the specified publication period and eligibility criteria, which may have excluded relevant studies. Second, while the study identifies conceptual patterns, it does not test the relationships between integration processes and outcomes. Third, the limited availability clearly defines pedagogical models in the literature and constrains the ability to draw firm conclusions about effective educational practices. Finally, the geographical and institutional diversity of the studies may limit direct comparison because concepts such as integration, inclusion, and employability are shaped by different national and regional contexts.

6. Concluding Remarks

The aim of this study was to examine what conceptual frameworks have been used to describe the educational integration, social inclusion, and transition to working life of students with immigrant backgrounds in higher education. The findings indicate that, although these phenomena have been addressed across different disciplines, they remain fragmented across disciplines. Three main framework clusters were identified: social inclusion frameworks, educational support frameworks, and transition-to-working-life frameworks. The synthesis revealed conceptual overlaps between the frameworks, but only limited integration between them. Pedagogical approaches, institutional support, and concrete models of collaboration between higher education institutions and working life were often insufficiently addressed.

The multi-level conceptualisation developed in this study can be interpreted through the combined lenses of educational integration, social inclusion, and knowledge management. At the micro level, Tinto's (1975) concept of educational integration helps explain students' academic and social attachment, while Bourdieu's (1977) theory of capital highlights inequalities in the resources that shape participation and outcomes. At the meso level, knowledge management explains how higher education institutions can collect, share, and apply

knowledge to develop pedagogical support, guidance services, and stakeholder collaboration. At the macro level, immigration policies, labour-market structures, and education systems shape students' opportunities for long-term inclusion and employment. Effective integration therefore depends on coordination and alignment across all three levels.

A central challenge in the existing literature is the trade-off between institutional efficiency and equitable inclusion. Higher education institutions aim to implement scalable and efficient integration models that support students' transition into working life, yet standardized institutional practices do not always respond adequately to the diverse social, cultural, linguistic, and labor-market realities faced by students with immigrant backgrounds.

Future research should focus on developing and empirically testing integrated models that connect pedagogical practices, institutional strategies, and labour market outcomes, as well as examining how knowledge management can be operationalised to support these processes and how pedagogical development can better respond to and support student diversity. Overall, the study demonstrates that integration is a multi-level phenomenon requiring coordinated development across individual, institutional, and structural dimensions.

Acknowledgements

The author would like to express sincere gratitude to her supervisors for their continuous support and valuable guidance throughout the research process, particularly Dr Maud Reveilhac and Dr Henri Hussinki. Appreciation is also extended to LAB University of Applied Sciences and LUT University for their support.

Ethics Declaration: This study did not involve human participants, personal data, or ethical risks requiring formal ethical approval. Therefore, ethical clearance was not required.

AI Declaration: The author used generative AI tools (ChatGPT, OpenAI) to support language refinement, structuring, and condensation of the manuscript. All content, interpretations, and final decisions remain the responsibility of the author.

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Deriving Uncertain Knowledge in Knowledge Graphs Under Theoretical Mapping of Heuristics

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Abstract: This paper proposes a deterministic, explainable framework for validating uncertain entities during Knowledge Graph (KG) expansion. The contribution is conceptual and formal: we present the framework and demonstrate its internal mathematical coherence, while empirical evaluation is explicitly deferred to future work. Since adding unverified nodes is trivial but removing structurally corrupted data afterwards is computationally hard, the multiphase Let's Build Knowledge (LBK) Framework acts as a gatekeeper that prevents such corruption at the point of entry. Drawing on cognitive heuristics, molecular data patterns, and meta-reasoning, LBK offers a deterministic alternative to prevalent stochastic and embedding-based approaches in Explainable AI (XAI): it integrates Formal Concept Analysis (FCA) with a localized adaptation of Byzantine Fault Tolerance (BFT) to scrutinize incoming structures, enabling loss-free, rule-based verification of new entities before global integration. We provide a precise specification of this hybrid model and demonstrate its formal capacity for deterministic uncertainty management, without claiming empirical validation.

Keywords: Knowledge, Uncertainty, Subgraphs, Isomorphism, FCA, Hyperedge

1. Introduction

This paper pursues a single, clearly bounded goal: to design and formally justify a method that validates newly added, uncertain entities in a Knowledge Graph without resorting to probabilistic embeddings. In doing so, we extend a quality-based, terminological tradition in which uncertain concept hypotheses are legitimized or refuted by logic-based meta-level assessment rather than stochastic estimation (Hahn and Schnattinger 1998; Schnattinger and Hahn 1996), transferring this principle from text-driven concept acquisition to graph-structured entity validation. Concretely, we (i) propose the Let's Build Knowledge (LBK) Framework, (ii) demonstrate that Formal Concept Analysis and a localized Byzantine consensus can validate uncertain nodes deterministically within a bounded neighborhood, and (iii) specify a transparent, reproducible validation function. In design-science terms, the contributed artifact is a method whose utility is argued analytically; the paper's claim is thus the design and formal justification of the method, not its empirical confirmation (Gregor and Hevner 2013). The remainder of this introduction motivates the need for such a deterministic alternative; Sections 2–3 develop the formal model, whose mathematical coherence is demonstrated while empirical benchmarking remains future work.

The need for such validation arises from a concrete problem. In today's digital transmission of knowledge, inconsistent or false information is increasingly conveyed, leading to severe structural uncertainties (Zhou et al. 2022). Generative AI has accelerated this challenge: AI-generated content amplifies disinformation at scale, making synthetic text and fabricated media hard to distinguish from authentic sources (Cazzamatta and Sarısakaløğlu 2025), regardless of the medium (Broda and Strömbäck 2024). LLMs remain highly prone to hallucination and weak reasoning in domain-specific contexts (Ma et al. 2025), motivating the integration of structured Knowledge Graphs (KGs) for factual grounding and explicit reasoning paths (Zhang, Zhou, and Yang 2025).

KGs are the structural answer to these limitations but introduce a validation problem of their own. Within KGs such as Wikidata (Vrandečić 2012), semantic structures enable critical applications like semantic search (Noy et al. 2019), Graph Neural Networks for recommender systems (Wang et al. 2019), and advanced question answering (Huang et al. 2019; Ma et al. 2025). Yet handling new, unverified data within a semantic triple remains fundamental, as every newly generated node is initially uncertain (Schnattinger and Hahn 1996; Jarnac, Chabot and Couceiro 2025). Current embedding methods address this probabilistically, which limits interpretability, factual precision, and deterministic validation (Cao et al. 2024).

These probabilistic limitations are precisely what the stated goal seeks to avoid; for a deterministic alternative, we turn to cognitive science as a theoretical foundation for uncertainty resolution. Substituting stochastic estimation with a graded, evidence-quality assessment of competing hypotheses has already been

operationalized in a purely symbolic, terminological setting (Hahn and Schnattinger 1998), which we take as a direct methodological precedent. In psychology, humans resolve factual uncertainties even without explicit prior knowledge through learned patterns known as eristic reasoning (Kurdoglu, Jekel, and Ateş 2023): such heuristics act as cognitive shortcuts that enable rapid judgment by substituting complex structural assessments with simpler, related properties (Tversky and Kahneman 1974). Because this pattern matching operates independently of formal stochastic reasoning, it is an ideal blueprint for machine-based, explainable uncertainty resolution in knowledge graphs (Spiliopoulos and Hertwig 2024). Inspired by this, we introduce the Let's Build Knowledge (LBK) Framework, which rejects opaque vector embeddings and instead applies meta-heuristic, structural information to deterministically legitimize or refute uncertain knowledge units and question-answer relationships.

Our goal and contributions are guided by one central research question:

Research Question (RQ): How can unverified, newly introduced entities within an expanding Knowledge Graph be validated in a deterministic, explainable, and computationally bounded manner without relying on probabilistic embeddings?

To answer it, the paper makes three theoretical contributions to Explainable AI (XAI), each stated as what we propose, demonstrate, or establish, not as an empirically proven result:

1. Topological Quarantining**:** a method to structurally isolate uncertain data into localized subgraphs, bounding the processing scope to a constant execution radius $2 \leq dist(x, v) \leq 4$.
2. Deterministic Pattern Derivation: showing how Formal Concept Analysis (FCA) and Galois connections map multidimensional node attributes into a lossless formal context lattice.
3. Consensus-Driven Reintegration**:** a mathematical validation function $\big(\Psi(x)\big)$ based on an algorithmic transfer of Byzantine Fault Tolerance (BFT) to formal concepts, enforcing a strict 75% threshold for deterministic graph expansion.

2. Related Work

2.1 State of the Art

Against the delimitation from LLM-based reasoning, the state of the art cannot be identified unambiguously. Knowledge Graph Completion (KGC) is closely related, as both approaches address incompleteness in knowledge graphs, but their objectives differ fundamentally: KGC estimates the probability of missing relations between already accepted entities and predicts plausible links from learned embeddings (Hou et al. 2025), whereas the proposed approach evaluates whether a previously unknown candidate node should be accepted at all. LBK thus inverts the setting — it does not score the plausibility of a relation but decides the admissibility of a newly arriving, unverified entity before it may participate in the graph: KGC answers which edge is probable, LBK whether the node may enter, a deterministic gatekeeping decision with an auditable justification rather than a probabilistic ranking. A more closely related, logic-based approach is given by Delfino, Lenzerini and Poggi, who define a formal-logical semantics for RDFS-based knowledge graphs (RKGs) — including their metamodeling features — and analyze query answering, showing in particular that such graphs need not possess a universal model (Delfino, Lenzerini, and Poggi 2025).

2.2 Hyper-reasoning

A fundamental problem in abstracting and validating newly added nodes is the purely binary, incident nature of edges: while edges define connections, in isolation they hardly transfer complex information. Ontologies offer a first semantic enrichment by formalizing relationships as RDF triples (Stuckenschmidt 2011). To extend the reasoning chain further, this work breaks up the binary relation between two nodes through hyper-reasoning. Decisively shaped by Gao and Zhang, this technique generates a set of edges together with their attributes and declares them a hyperedge (Gao et al. 2021). Such a hyperedge does not alter the fundamental graph structure but enables a more differentiated perspective: rather than evaluating purely binary constellations, it groups nodes into a common set via connected relations — for the subgraph construction presented here, an essential step to ensure the injective mapping of information.

Even though current analyses partly question the superiority of Hypergraph Neural Networks (HGNN) over conventional Graph Neural Networks (GNN) (Kim et al. 2024), hypergraph structure is fundamental to the reasoning approach chosen here, since without it the correct, injective representation of complex ontological relationships could not be guaranteed. Modern hyper-reasoning performs well given high computational

resources but fails in real-time scenarios, as it processes the graph globally — impractical for on-demand decisions. Crucially, our use of hypergraphs differs in kind, not only scale: HGNNs embed higher-order structure into a learned vector space and propagate messages globally (Gao et al. 2021; Kim et al. 2024), drawing their power from this global, statistical aggregation, whereas LBK uses the hyperedge only as a non-learned structural carrier guaranteeing an injective, loss-free grouping of local context, with no embedding or message passing at all. We thus deliberately trade representational expressiveness for locality, determinism, and explainability — a trade-off mainstream hypergraph reasoning does not make. By combining hyper-reasoning with a strict limitation of hops, LBK confines validation to a localized neighborhood ($2 \leq dist(x, v) \leq 4$), drastically reducing the required computing power and enabling instant, operational decisions.

2.3 Meta-reasoning

Since every newly added node is initially interpreted as uncertain, the definition of "validity" must be derived congruently. To this end, meta-reasoning is applied within the isolated subgraph: because its injective mapping endows every node with a specific set of properties, these can be mapped into property classes via Formal Concept Analysis (FCA) and treated as reasoners on a meta level (Ganter and Wille 2024). A related terminological meta-reasoning perspective is given by Hahn, Klenner and Schnattinger, who formalize meta-level abstractions to validate uncertain or heterogeneous knowledge sources (Hahn, Klenner, and Schnattinger 1996). Methodologically related, Mandal and Medya show that meta-learning in Graph Neural Networks (GNNs) significantly improves speed and accuracy (Mandal et al. 2021) — but where they use statistical embeddings for classification, the present work is purely logic-based. A further line interprets node contents as a meta level to exploit structural (graph-theoretic isomorphism) similarities for reasoning in LLMs, serving a different discipline (Yuan et al. 2025); such works underline the need for meta-level abstractions, which this publication addresses through FCA.

The decisive difference is that the present model is purely symbolic: validation is carried out entirely by FCA and Byzantine consensus, with no learned component anywhere in the pipeline. Neural-symbolic systems gain generalization from their statistical part but inherit its opacity and dependence on training data; LBK relinquishes generalization to keep every validation step inspectable and reproducible, continuing a strictly symbolic line of terminological meta-reasoning (Hahn, Klenner, and Schnattinger 1996). As "meta-reasoning" has no universal definition, FCA is chosen as the abstraction level that formally safeguards validation. LBK also takes a deliberately different stance on uncertainty: whereas surveys describe quantifying and propagating it through probabilities, fuzzy degrees, or confidence weights on triples (Jarnac, Chabot, and Couceiro 2025), LBK resolves it categorically — each candidate is mapped, through local consensus, to a discrete admissibility decision, eliminating uncertainty at the point of entry rather than carrying it forward as a graded annotation. This continues a quality-based terminological tradition in which uncertain hypotheses are graded by discrete quality labels rather than numeric likelihoods (Schnattinger and Hahn 1996).

2.4 Byzantine Fault in Knowledge Graphs

Within this work, a knowledge graph is assumed to represent the mathematical representation of a distributed network. Based on this analogy, the theory of Byzantine Fault Tolerance (BFT) can be transferred to the validation of knowledge structures (Lynch 1997). Here, a network message corresponds to the triple content (semantics) within the ontology, while the edges act as communication paths via which the context (meta information) contributes to consensus formation at the dummy vertex. Byzantine Fault Tolerance is generally represented by the condition $n \geq 3f + 1$; its safety factor of 3 enables a system – in this context the graph – to make an autonomous decision about the validity of information (Pease, Shostak, and Lamport 1980). The original implementation of BFT, however, does not investigate vagueness, and traditional BFT approaches rely strictly on Boolean indicators to verify nodes, making them incapable of evaluating complex, non-binary semantic structures. Due to the increased vagueness within heuristic approaches, a safety factor of 4 is chosen in the further course of this work ($n \geq 4f + 1$). This deliberate expansion of the fault-tolerance ceiling counters the non-binary entropy of semantic data, providing the formal mathematical justification for the consensus thresholds executed in the subsequent validation phases.

2.5 Provenance and Delimitation of the Dummy-vertex Model

The use of so-called dummy nodes originates primarily in medical research, mainly within computer-aided antibiotic modelling, where the dummy node represents a potential new molecule within an existing chemical application chain. Mathematically, an initially empty node is added to an original graph G, its interaction potential defined by the topological neighborhood and the corresponding edge relations $E \subseteq V \times V$. Since the

empty node initially exerts no intrinsic influence on the overall system, it allows the isolated simulation of connections to target nodes.

Complementarily, the dummy- or virtual-node construct itself has a direct precedent in graph-based machine learning. Pham et al. augment an attributed graph with an initially empty node connected to the existing nodes, whose representation captures latent aspects not immediately available from the local attributes and connectivity structure (Pham et al. 2017). Because this construct was validated, among other tasks, on predicting the bioactivity of chemical compounds, it substantiates the isolation-and-trial-embedding principle that the present work projects onto knowledge-graph validation. A closely related line in biochemistry applies such trial embeddings to assess the influence of altered active substances on a target node (Gilmer et al. 2017). Methodologically, however, the present approach differs clearly: rather than the learned message passing and vectorization used there to derive Euclidean embeddings, the LBK Framework employs the dummy node solely as a non-learned structural carrier for local, logic-based legitimation.

Further differentiation concerns Cui and Abdelzaher (2024), where dummy nodes serve as anchor points to approximate incomplete knowledge via virtual paths; in contrast, the method presented here does not focus on statistical approximation but on the explicit validation of vague knowledge units through Byzantine consensus.

3. Formal Representation

3.1 Formal-theoretic Approach

Assumptions. Before the formalization, we fix the assumptions used throughout. (A1) Every newly arriving entity x is initially treated as uncertain and must be validated before global integration. (A2) The accepted graph $G = (V, E)$ is regarded as a trusted distributed system, so that a Byzantine-style consensus over neighbouring evidence is meaningful. (A3) Information transfer from G into the local subgraph is injective and therefore loss-free. (A4) Only the bounded neighbourhood $2 \leq dist(x, v) \leq 4$ is consulted; a candidate with no admissible neighbor is rejected. (A5) Attributes are discrete, so that the incidence relation of the formal context is well-defined and the Galois derivations are exact. These assumptions delimit the scope of every definition and result below.

This work validates uncertainties in a knowledge graph by transferring heuristic ways of thinking to a machine. This requires both establishing the factorization for validation and validating the node resource-efficiently even within a large graph. To this end, a new node is inserted into an existing graph, an attribute signature is derived in its context, and — via this signature and a fixed number of neighbors — a validation set of nodes is spanned. To map this set context specifically, the hyperedge approach is used; within it, the edge contents follow transitivity and reflexivity derived from the established attribute signature. The spanned space is limited to a maximum neighborhood of 4 nodes, while a neighborhood must nonetheless be present, since a disjoint node implicitly corresponds to untruth and cannot be incorporated into the original graph.

This validation space of edge and node relationships is mapped within a subgraph, guaranteeing performance and allowing large amounts of data to be considered in an isolated, context-specific manner; due to the injective property of the graph, information transfers into the subgraph without loss. There, Formal Concept Analysis serves as the validation operator: by the Galois derivation applied to the semantic sets according to Ganter and Wille, the common attributes between the surrounding nodes and the node to be validated are derived via intersection. For robustness Byzantine Fault Tolerance then validates this intersection against the totality of attributes, which must reach a threshold of at least 75%; meeting it validates the new node within its context and renders it robust with respect to the graph.

If the dummy node is classified as robust, it can be integrated into the original graph. The reason for this is that subgraphs can always be traced back to the original graph.

3.2 Mathematical Representation

Table of Annotation		
Annotation	Definition	Context
$\boldsymbol{G = (V, E)}$	Representation of KG	Existing as true accepted KG
$\boldsymbol{x = V_{dum}}$	Vague Dummy Node	New to enter and unverified entity

Table of Annotation		
$\boldsymbol{\mathcal{X}}$	Isolated Subgraph set	Set of neighborhood hops within the radius $2 \leq dist(x, v) \leq 4$
$\boldsymbol{K = (O, A, I)}$	Formal context (FCA)	O = Object, A = Attributes, Incidence relation $I \subseteq O \times A$
$\boldsymbol{M_x}$	Attribute set of x	Set of Attributes contained in x
$\boldsymbol{M_x'}$	First Galois derivation	Set of objects O that consistently contain all attributes of M_x
$\boldsymbol{M_x''}$	Second Galois derivation	Set of attributes A consistently shared by the neighborhood objects in M_x'
$\boldsymbol{n}$	Cardinality of M_x''	Total cardinality of the validated attribute consensus set $n = \lvert M_x'' \rvert$
$\boldsymbol{f_{obs}}$	Attribute deficit	Number of missing or deviating attributes $\lvert M_x'' \backslash M_x \rvert = n - \lvert M_x \rvert$
$\boldsymbol{\Psi(x)}$	Validation function	Calculated consensus score for the dummy node
$\boldsymbol{\Gamma}$	Absolute threshold	Baseline barrier for reintegration (initially set to 0.75)

The fundamental formal representation of an original graph is henceforth defined as $G = (V, E)$. It should be noted beforehand that the conventional graph structure as well as the graph modification refer to the teachings of Reinhard Diestel and all approaches are taken from the book Graph Theory (Diestel 2025). As usual, $e \in E$ represents an edge, while $v \in V$ represents a node in a graph. The dummy vertex is expressed in a simplified manner as x, or $V_{dum} = x$. To integrate x into an existing graph, the following holds:

$$G' = (V', E') \mid V' = V \cup \{x\}, E' = E \cup \{e_x\}$$

In general, the neighborhood relation is defined over the edge set e_x, where $e_x = e_{x_N}$. The attribute signature of the candidate node $x$is denoted by $\Sigma_{\text{Features}_{\text{dummy}}} = M_x$. Following Diestel, neighborhoods can be characterized by shortest-path distances. In this work, however, the direct neighborhood is defined as

$$N(x) := \{v \in V \mid \text{label}(x, v) = \text{true}\}.$$

Furthermore, the admissible hull of x is defined as

$$H(x) := \{v \in V \mid 2 \leq \text{dist}(x, v) \leq 4\}.$$

The direct 1-hop neighborhood is intentionally excluded from the validation process to avoid trivial confirmation and circular validation effects. Consequently, only vertices at distances two to four contribute to the derivation of the consensus attribute set. Since the hull of the subgraph and the relationship of the nodes within this subset have now been explained, the mapping m is established in the following. Diestel describes the mapping of an injective graph by $G' \subseteq G$. Since, in the present case, G' is declared through the addition of the information, the mapping follows as

Let: $m: G' \rightarrow G''$ whereby m is strictly bound to the neighborhood filter $H(x)$.

Substructure mapping (clarification). To avoid overloading the symbol G, we write $G'' \preccurlyeq G' \subseteq G$: G' is the graph after tentatively inserting x, and G'' the local validation subgraph. Inside G'' every node v carries its attribute set $M_v \subseteq A$ and every edge its incidence, and I is restricted to $V(G'') \times A$; this restriction is what makes the Galois machinery applicable locally.

The construction of the subgraph G'' is at the same time the activation function of the validation process; therefore G'' is equated. Within the local subgraph $G'' = (V'', E'')$, the formal context $K'' = (O, A, I)$ is induced by setting

$$O := V'', \qquad A := \bigcup_{v \in V''} M_v, \qquad I := \{(v, a) \in O \times A \mid a \in M_v\}.$$

This construction makes the incidence relation well-defined and the Galois derivations on K'' exact, so that the application of Galois theory to the nodes and edges within the subgraph is ensured.

We assume $x \notin O$. If x were already contained in the formal context the validation function would evaluate trivially to $\Psi(x) = 1$.

Now, the node to be validated is defined as x with the features M_x, and the validation set as M_x''. This step leads to the following result: M_x is the set of attributes of x. Through the first Galois derivation M_x, the set of matching nodes from the total set G in the subgraph G'' is formed. Subsequently, M_x is checked against M_x', whereby the result would have to equal 1 for an equality. Due to ontological vagueness, reaching 1 is nearly impossible, which is why ≈ 1 represents a perfect result. For the case that a perfect result is not possible, the approximation and the threshold are defined in the following:

$$M' = \{o \in O \mid \forall a \in A(x) : \{o, a\} \in I\}$$

$$M'' = \{a \in A \mid \forall o \in M' : \{a, o\} \in I\}$$

The validation function is defined as

$$\Psi: \{x\} \to [0,1],$$
$$\Psi(x) := \frac{|M_x \cap M_x''|}{|M_x''|}.$$

If ${M_x}'' = \emptyset$, the validation is undefined and therefore $\Psi(x) := 0$.

The admissible deviation is derived from the Byzantine fault tolerance assumption

$$n \geq 4f + 1,$$

where

$$n := |M_x''|$$

denotes the size of the consensus attribute set and f the maximum tolerated deviation. Solving for f yields

$$f_{max} \leq \frac{n-1}{4}.$$

The corresponding relative deviation threshold is defined as

$$\Gamma' := \frac{f_{max}}{n}.$$

Consequently, a candidate node is automatically accepted if

$$\Psi(x) \geq 1 - \Gamma' \ \ or \ \ \Psi(x) \geq \Gamma.$$

where Γ' accounts for discrete boundary effects in small attribute sets.

For sufficiently large values of n, this corresponds to the practical threshold

$$\Psi(x) \geq \Gamma.$$

If the condition is satisfied, the candidate node is integrated into the graph:

$$G_{\text{new}} = (V \cup \{x\}, E \cup \{e_x\}).$$

Otherwise,

$$G_{\text{new}} = G.$$

3.3 Adaptive Decision Policy

One of the existing problems is still the error handling of the threshold value. To be able to address such an issue in the given problem setting, the proposal of adaptive logic is implemented. A candidate is admitted automatically (unsupervised) if $\Psi(x) \geq 0.75$, routed to human expert review (supervised) if $0.5 < \Psi(x) < 0.75$, and rejected (isolation) otherwise, i.e. if $\Psi(x) \leq 0.5$. Formally:

$$\begin{aligned} \Psi(x) \in [0.75,\ 1] &\quad \Rightarrow \text{ unsupervised,} \\ \Psi(x) \in (0.5,\ 0.75) &\quad \Rightarrow \text{ supervised,} \\ \Psi(x) \in [0,\ 0.5] &\quad \Rightarrow \text{ isolation.} \end{aligned}$$

4. Conclusion and Critical Reflection

In summary, this section presented a deterministic, semantics-based framework for relationship validation in Knowledge Graphs. By combining Formal Concept Analysis (FCA) with localized Byzantine consensus, the LBK model derives ontological structure that preserves local context without opaque probabilistic embeddings, and by confining evaluation to a tightly bounded neighborhood it keeps runtimes low and scales to high-dimensional graphs across domains without domain-specific retraining.

A critical reflection nonetheless exposes two structural dependencies. First, capping the search radius at four hops makes the method vulnerable to data sparsity: in fragmented regions the local subgraph may not yield enough objects ($|G|$) and attributes ($|M|$) for Galois derivation to expose meaningful symmetries; future work will therefore explore adaptive radius scaling. Second, the strict absolute threshold (0.75) guards against semantic vagueness but, as a static barrier in non-binary semantic spaces, risks rejecting valid yet weakly connected knowledge units, which motivates investigating symmetric similarity matching between node literals to accommodate gray areas of vagueness.

To test these boundaries empirically, upcoming work will use the GDELT benchmark, injecting flagged true and false information into the local topology to measure runtime, structural stability, and validation precision, and will extend the multiphase architecture with a formalized Human-in-the-Loop verification step to bridge strict algorithmic consensus and nuanced contextual semantics.

Complexity. Because validation is confined to the bounded neighborhood $2 \leq dist(x, v) \leq 4$, the formal context has at most N_{max} objects and $|A|$ attributes, both independent of the global graph size $|V|$. Computing the two Galois derivations is $O(N_{max} \cdot |A|)$, and materializing the local concept structure follows the known bounds for concept computation, which depend on the density of the context rather than on $|V|$ (Kuznetsov and Obiedkov 2002). The per-insertion cost is therefore constant with respect to the global graph; the method scales to large KGs by construction, and the cost is paid locally.

Scalability and worst case. The constant-per-insertion cost assumes sparse-to-moderate neighborhoods. In the worst case – a densely connected hub with a large admissible neighborhood and a dense context – the number of formal concepts can grow exponentially in $|A|$ (Kuznetsov and Obiedkov 2002), so validations near hubs may become expensive even though global scaling is preserved. Bounding the radius mitigates but does not remove this; an attribute cap or a concept-count budget would be required for hard real-time guarantees.

Failure cases. Beyond sparsity, three failure modes deserve attention. (i) Generic-attribute admission: a candidate declaring only a few widely shared attributes can attain $\Psi(x) = 1$ trivially, because its small attribute set is already closed; the consensus then certifies under-specification rather than correctness. (ii) Adversarial attribute stuffing: a malicious node can copy the attributes prevalent in a target neighbourhood to manufacture consensus, since the test rewards agreement, not provenance. (iii) Homogeneous neighbourhoods: where neighbours are near-identical, almost any candidate passes and the discriminative power of Ψ collapses. These cases show that the consensus test certifies local structural conformity, not factual truth – an intrinsic limitation of any purely structural validator.

Limitation of the BFT analogy**.** The Byzantine Fault Tolerance analogy is a theoretical modelling assumption rather than an absolute guarantee. Since related attributes in a Knowledge Graph tend to co-occur, the 75% threshold serves as a principled heuristic. The formal study of consensus under such correlated evidence is therefore left to future work.

AI Declaration: An AI tool (Large Language Model) was used during the development of this paper specifically to assist with the structural formatting and stylistic alignment of the document according to the conference requirements. The AI tool was utilized to reformat existing text blocks and mathematical formalizations into the required Word structure. All conceptual ideas, logical derivations, and the final intellectual content were produced and verified by the author.

Ethics Declaration: The author(s) confirm that ethical clearance was not required for the research presented in this paper, as the study involved the theoretical development of a mathematical framework and did not involve human participants, animal subjects, or the collection of sensitive personal data. All research was conducted in accordance with standard academic integrity guidelines.

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From Vision to Knowledge Flow: How Transformational Leadership Fosters Knowledge Sharing in the Polish Film Industry

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Abstract: This study examines how transformational leadership fosters knowledge sharing in the Polish film industry, focusing on the mechanisms through which trust-based relationships, mentoring practices, and adaptive responses to disruption shape knowledge flows in film production teams. The research is grounded in the transformational leadership framework of Bass and Riggio (2006) and integrates Nonaka's (1994) distinction between tacit and explicit knowledge with project-based organization research and developmental network theory. The methodology comprises eleven semi-structured interviews with film producers selected through purposive sampling from the membership directory of the Krajowa Izba Producentów Audiowizualnych (KIPA), and analysed through three-stage grounded coding, yielding 221 first-order codes and 18 second-order categories. The findings show that transformational leadership in film production is enacted primarily through relational mechanisms — role modelling, reputational sanctioning, vision-based partner selection, and leader presence — which form the foundation for knowledge sharing in long-cycle creative projects. Mentoring operates predominantly outside formal pathways and relies on distributed developmental networks and situated learning, while leadership behaviours adapt to technological disruption and project-based uncertainty. The study contributes to transformational leadership theory by extending its application to project-based creative industries and to the knowledge sharing literature by clarifying the conditions under which trust and adaptive leadership facilitate knowledge exchange.

Keywords: Knowledge sharing, Transformational leadership, Trust, Mentoring, Project-based organization, Film industry, Creative industries

1. Introduction

Leadership remains a central construct in management and organizational research because it shapes employee attitudes, behaviours, and overall effectiveness (Hughes et al., 2018; Banks et al., 2016). In increasingly project-based and creative work, the leader's role extends beyond task coordination to the construction of shared meaning, the orchestration of knowledge flows, and the sustaining of trust under structural uncertainty (Sydow et al., 2004; Bechky, 2006). The way in which leadership behaviours produce these effects, and the contextual conditions that shape them, have therefore become central questions for contemporary research on leadership and knowledge management.

Within the leadership discourse, transformational leadership is contrasted with transactional leadership grounded in contingent rewards. Transformational leadership emphasizes the leader's ability to inspire, intellectually stimulate, and develop followers, generating outcomes that exceed routine performance (Bass and Riggio, 2006; Burns, 1978). Meta-analytic evidence confirms its positive effects on follower attitudes, innovation, and team performance (Banks et al., 2016; Hughes et al., 2018), though critical scholarship has drawn attention to pseudo-transformational leadership and its dark-side manifestations (Bass and Steidlmeier, 1999; Tourish, 2013). Recent empirical work continues to specify the mediating mechanisms through which transformational leadership translates into knowledge sharing behaviour, including perceived organizational support (Chen, Chang and Tian, 2024), organizational commitment (Amin and Sudarmiatin, 2024), and team communities of practice (Matsuo, 2025).

Transformational leadership also shapes knowledge processes, creativity, and innovation. It fosters both individual skill development and collective knowledge sharing, especially in knowledge-intensive sectors (Dong et al., 2016; Hughes et al., 2018). This relationship is particularly salient in creative industries, where production depends on integrating tacit and explicit knowledge across specialized roles, and where leaders enact vision through long-term project cycles (Grabher, 2002; Manning, 2017). The Polish film industry offers an instructive setting that combines a project-based logic, craft traditions, and a fragmented institutional environment characterized by lottery-like state funding mechanisms, dense informal networks, and limited formal accountability.

This study addresses three research questions: (1) How do project leaders in the Polish film industry build and sustain trust-based relationships that enable knowledge sharing in long-cycle film projects? (2) Which mentoring practices and knowledge-sharing mechanisms transmit professional knowledge in the Polish film industry, given the absence of formal pathways into the profession? (3) How does transformational leadership shape knowledge sharing under conditions of technological disruption and project-based uncertainty? By integrating the

transformational leadership framework with knowledge sharing theory and project-based organization research, the paper contributes to a more nuanced understanding of leadership in creative industries and offers empirically grounded insights into the mechanisms that connect vision, trust, and knowledge flow.

2. Transformational Leadership Definitions

This section reviews the conceptual foundations of transformational leadership theory, its operationalization through the Four I's model, and its relevance to the distinction between explicit and tacit knowledge that underpins the analysis of film production teams.

2.1 The Essence of Transformational Leadership

Transformational leadership refers to the ability of leaders to exert a lasting influence on the attitudes, values, and aspirations of followers (Burns, 1978; Bass, 1985). It is defined as a process of social influence in which leaders elevate followers beyond immediate self-interest, foster commitment to a shared vision, and stimulate higher-order needs for achievement and meaning at work. Unlike transactional leadership, it operates through the moral, emotional, and cognitive engagement of followers, producing outcomes that exceed formal organizational expectations (Bass and Riggio, 2006). The construct has been extensively validated across organizational settings and remains one of the most influential leadership theories in contemporary management research.

Recent reviews confirm that transformational leadership is associated with innovation, knowledge sharing, employee creativity, and organizational commitment (Banks et al., 2016; Hoch et al., 2018). Its effects are contingent on contextual factors such as task complexity, the temporal structure of work, and the institutional environment (Oreg and Berson, 2019). In project-based organizations and creative industries, temporal compression of work, recurring team formation and dissolution, and reliance on tacit knowledge create distinctive conditions under which transformational behaviours acquire specific operational meaning (Sydow et al., 2004; Bechky, 2006; Keegan and Den Hartog, 2004). Bai (2025) further demonstrates that the effect of transformational leadership on career growth is mediated by self-efficacy and psychological capital, suggesting that follower-level mechanisms are integral to understanding how transformational behaviours generate lasting outcomes.

2.2 The Core Dimensions: The "Four I's" Model

Bass's operationalization of transformational leadership identifies four dimensions — idealized influence, inspirational motivation, intellectual stimulation, and individualized consideration (Bass and Riggio, 2006). These dimensions co-occur and mutually reinforce one another in practice (Banks et al., 2016; Tan et al., 2025).

Idealized influence refers to the leader's ability to serve as a role model. Leaders demonstrating this dimension are perceived as credible, ethical, and consistent in their actions, fostering trust and identification (Bass and Riggio, 2006; Brown and Treviño, 2006). Only leaders whose values align with the collective good can sustain idealized influence over time (Bass and Steidlmeier, 1999). In project-based organizations, where formal hierarchies are flattened, idealized influence is built and tested in micro-interactions that signal the leader's commitment and willingness to absorb personal cost on behalf of the collective.Inspirational motivation refers to articulating a compelling vision and communicating it in ways that energize followers. Transformational leaders foster optimism, enthusiasm, and shared purpose (Bass and Riggio, 2006). It operates through self-concept-based mechanisms in which followers identify their aspirations with the collective project (Shamir et al., 1993; Tan et al., 2025). In creative industries, where projects span years and meaning is tied to artistic significance, inspirational motivation is enacted through the selection of partners, themes, and collaborations that embody the leader's vision in concrete practice.

Intellectual stimulation involves encouraging followers to question assumptions, explore new perspectives, and engage in creative problem-solving (Bass and Riggio, 2006). It is especially consequential during technological or market disruption, when established routines no longer suffice (Christensen, 1997; Brynjolfsson and McAfee, 2017). The diffusion of artificial intelligence, virtual production, and sustainable practices has made intellectual stimulation a central leadership task in contemporary film production (McKinsey & Company, 2025). Individualized consideration refers to the leader's attentiveness to the developmental needs of each follower. Leaders enacting this dimension function as mentors and coaches, providing tailored feedback and emotional support (Bass and Riggio, 2006; Kram, 1985). It is closely linked to psychological safety, in which followers feel free to voice concerns and admit uncertainty without fear (Edmondson, 1999).

2.3 Explicit and Tacit Knowledge on the Film set

The distinction between explicit and tacit knowledge was developed most influentially by Nonaka (1994; Nonaka et al., 2000), who proposed the SECI model to describe how knowledge is created and converted across these two forms. Explicit knowledge is codifiable, transferable through documents and procedures, and independent of the person who possesses it. Tacit knowledge is embodied, context-dependent, and acquired through experience and participation in practice (Polanyi, 1966; Brown and Duguid, 2001).Film production relies heavily on tacit knowledge in creative activities, craftsmanship, and non-verbal communication. A cinematographer senses the rhythm of a shot, an actor conveys what is not in the script, a director negotiates atmosphere through gestures. This embodied competence is acquired through apprenticeship-like engagement and situated participation, not classroom instruction (Lave and Wenger, 1991; Alony et al., 2007). At the same time, production generates substantial explicit knowledge — budgets, schedules, contracts, technical specifications — that must be coordinated across specialized departments under tight temporal constraints (Bechky, 2006). This distinction is especially significant in project-based teams with network structures, characteristic of the film industry. Tacit knowledge becomes a distinguishing factor among professionals, determining effectiveness in non-standard situations and facilitating coordination under creative ambiguity (Manning, 2017).

3. Methodology

The study employs a qualitative research design, selected to capture the situated meanings and practices through which leaders in the Polish film industry enact transformational leadership and orchestrate knowledge sharing. Participants were selected through purposive sampling using the membership directory of the Krajowa Izba Producentów Audiowizualnych (KIPA), the principal professional association representing audiovisual producers in Poland, as the sampling frame. This approach ensured that all participants were active, professionally recognized producers operating within the established institutional structure of the Polish film industry. Table 1 presents an overview of the eleven participants, with pseudonymous codes (P01–P11) used throughout the paper to preserve confidentiality.

Table 1: Overview of interview participants

Code	Professional role	Industry domain	Professional focus
P01	Line Producer	Poland	Author cinema, academic research
P02	Producer	Poland	Independent film, AI-enabled production
P03	Producer	Poland	Author cinema, international workshops
P04	Producer	Poland	International co-productions
P05	Producer	Poland	Cinema-art, festival films
P06	Producer	Poland	Co-productions, virtual production, AI
P07	Line Producer	Poland	International co-productions
P08	Line Producer	Poland	Sustainable production
P09	Executive Producer	Poland	International co-productions
P10	Producer	Poland	Author cinema, international development
P11	Producer	Poland	Post-production, industry advocacy

Source: Own elaboration.

Data collection comprised eleven semi-structured in-depth interviews conducted between July 2024 and May 2025. All participants had a minimum of ten years of professional experience in domestic and international projects. Interviews lasted 45–90 minutes, were recorded with informed consent, and transcribed verbatim. The interview protocol (Table 2) addressed trust-building, reputation, mentoring, technological change, and uncertainty.

Table 2: Interview protocol

No.	Interview question
1	How do you build trust-based relationships with collaborators in the early development phase of a film project?
2	How is professional reputation built, maintained, and lost in the Polish film industry?
3	How did you learn your profession — who were your mentors, what role did formal education play?
4	How do you support the development of younger crew members or junior collaborators?
5	How are technological changes (AI, virtual production, post-production tools) affecting your work and the way knowledge is shared?
6	What practices help you sustain a long-cycle film project under conditions of uncertainty?
7	What are the most common breakdowns of trust or collaboration you have experienced, and what did you learn from them?

Source: Own elaboration.

Data analysis followed the three-stage grounded coding procedure (Charmaz, 2014; Strauss and Corbin, 1998). Open coding generated 221 first-order gerund-based codes, preserving in vivo expressions where possible. Axial coding consolidated them into 18 second-order categories aligned with the four dimensions of transformational leadership and with knowledge sharing processes. Selective coding integrated the categories within the Strauss–Corbin paradigm model linking causal conditions, contexts, strategies, and consequences. Trustworthiness was supported through verbatim quotation, negative case analysis including pseudo-transformational leadership behaviours, and reflexive memo-writing throughout the coding process.

4. Results

This section presents the empirical findings organized around the three research questions. The analysis links the 18 second-order categories generated through axial coding (presented in Table 3 below) with the four dimensions of transformational leadership and with knowledge sharing processes. The presentation here is descriptive and stays close to the participants' own accounts; the theoretical interpretation of these findings is developed in the subsequent Discussion section.

4.1 Overview of Axial Coding Categories

Table 3 presents the complete mapping of axial coding output. Eighteen second-order categories are organized within the four dimensions of transformational leadership (II, IM, IS, IC) and within knowledge sharing (KS), each linked to one of the three research questions, with the number of first-order codes (N) and the set of participants in whose accounts the category emerged. The categories cumulatively encompass 203 first-order codes from the corpus of 221, while the remaining 18 codes appear across multiple categories, reflecting the multidimensional character of the underlying phenomena.

Table 3: Axial coding categories — second-order categories across Four I's and KS

Cat.	Dim.	Second-order category	RQ	N	Participants
II-1	II	Role modelling and ethical exemplarity	RQ1	9	P04, P08–P11
II-2	II	Reputational capital and informal sanctioning	RQ1	9	P02, P04, P07, P11
II-3	II	Pseudo-transformational leadership / trust violations	RQ1	14	P02, P04, P06–P07, P09, P11
II-4	II	Collective agency and industry-level institutional work	RQ3	8	P01, P03, P05–P06, P11
IM-1	IM	Vision-based partner selection in project ecosystems	RQ1	17	P03–P06, P09–P10
IM-2	IM	Purpose-driven leadership and identity-based motivation	RQ1	12	P01–P02, P04–P05, P08, P11
IM-3	IM	Resilience and ambiguity tolerance under uncertainty	RQ3	11	P02–P03, P05, P07, P09–P11

Cat.	Dim.	Second-order category	RQ	N	Participants
IS-1	IS	Technology-driven shifts and disruptive innovation	RQ3	13	P02–P03, P06, P08, P11
IS-2	IS	Creative autonomy and cognitive alignment	RQ1	15	P02–P04, P07, P09
IS-3	IS	Boundary spanning and cross-system knowledge translation	RQ3	12	P06–P07, P09, P11
IS-4	IS	Managerial multi-competence and entrepreneurial expertise	RQ2	16	P03–P04, P06, P09–P11
IC-1	IC	Dyadic mentoring and master–apprentice transfer	RQ2	13	P01–P04, P06–P07, P10
IC-2	IC	Leader presence and psychological safety	RQ1	13	P05–P07, P10–P11
IC-3	IC	Distributed mentoring and developmental network theory	RQ2	10	P01, P03, P05–P06, P10
IC-4	IC	Structural exclusion and barriers to professional entry	RQ2	12	P01–P02, P05–P08, P10
KS-1	KS	Tacit knowledge transfer through situated learning	RQ2	7	P01, P03, P10
KS-2	KS	Knowledge codification and formal training mechanisms	RQ2	4	P01, P08–P09, P11
KS-3	KS	Network-based knowledge exchange and social capital	RQ2	8	P01–P02, P04–P05, P07
		TOTAL (18 categories across Four I's + KS)		203	11 (P01–P11)

Source: Own elaboration based on grounded analysis of 11 in-depth interviews (P01–P11). N denotes the number of first-order codes consolidated into each category. Dim.: II — Idealized Influence; IM — Inspirational Motivation; IS — Intellectual Stimulation; IC — Individualized Consideration; KS — Knowledge Sharing.

4.2 Trust-based Relationships as the Foundation of Transformational Leadership

The findings indicate that in the Polish film industry, transformational leadership is enacted primarily through the construction and maintenance of trust-based relationships across long-cycle projects. Four mechanisms emerged as central in the participants' accounts: role modelling through ethical exemplarity, reputational sanctioning, vision-based partner selection, and leader presence.

Role modelling is enacted through costly personal choices that demonstrate ethical commitment. Producers defer their own compensation until a project becomes profitable, take personal financial responsibility for errors in their team, and dissolve the symbolic distance between leadership and crew:

> *"In the first instance I pay people — I cashed in my own savings, I borrowed privately from my parents in order to have money for them to survive" (P11). "It is a relationship. And in a relationship, you must feel safe — it is respect, awareness, transparency" (P10).*

Reputational mechanisms function as an informal sanctioning system in the absence of effective formal accountability. Participants described a dense network of mutual warnings, reference checks involving three to four contacts, and a shared informal list of debtors and unreliable partners. Vision-based partner selection emerged as the dominant mechanism in the early development phase. Rather than choosing collaborators on the basis of past acquaintance or commercial success, producers select partners through resonance with the artistic vision of the script:

> *"I select partners through the text, not through the fact that they are excellent" (P10). "What matters most is whether we want to make the same film" (P03).*

Negative cases, however, reveal the fragility of these mechanisms. Six participants described severe trust violations — a co-producer in the United States releasing the film without rights, a Kazakh partner premiering the project at a festival without informing the Polish co-producer, a German lead producer pressuring the team into unfavourable terms, and post-production debts exceeding 900 days. These cases occurred in project ecosystems characterized by asymmetries of finance, jurisdiction, and language, and reveal the structural conditions under which leadership-based trust becomes vulnerable to capture.

4.3 Mentoring and Knowledge-sharing Mechanisms in the Absence of Formal Pathways

Participants consistently reported that formal education does not prepare them for the realities of the profession. One producer expressed this with striking directness:

> *"I would like to say it was the Film School in Łódź, but that is not true. The Film School taught me nothing about being a producer" (P10).*

In the absence of effective formal pathways, professional knowledge is transmitted through three interlocking mechanisms: dyadic master–apprentice mentoring, distributed developmental networks, and tacit knowledge transfer through situated learning. Classical mentoring relationships were named imaginatively and gratefully — a director-producer who took in a young assistant, a master producer whose decisions could be observed at close range, an institutional gatekeeper who agreed to speak with a newcomer:

> *"Observing her and assisting in her work, I acquired a certain kind of competence and realized this was the space I wanted to inhabit" (P10). "You learn what questions to ask, not the knowledge itself, because each film takes about five years" (P10).*

When dyadic mentoring is unavailable, participants substitute distributed developmental networks: international training programmes such as EAVE, ACE, and Inside Pictures; the producers' guild; and informal peer learning across festivals. This substitution is partial and reveals a structural problem: the system reproduces existing inequalities. Several participants reported difficulty entering the profession without family connections, geographic proximity to Warsaw, or class capital. Others described the persistence of a "caste" mentality inherited from the socialist-era film units, which paradoxically continues to restrict access to mentoring opportunities.

4.4 Adaptive Responses to Technological Disruption and Project-based Uncertainty

The third dimension of the findings concerns how transformational leadership adapts to two simultaneous pressures: the technological disruption of artificial intelligence and virtual production, and the chronic uncertainty inherent in project-based creative work. Participants described concrete experiments with AI-enabled production — deep-fake reconstructions of veteran artists, virtual production using LED screens, AI-assisted research replacing assistant director functions, and sustainable production protocols implemented with Netflix:

> *"We scanned masks, scanned facial expressions, we fed the model" (P02). "Instead of paying a second AD fifty thousand złoty, I can pay one hundred fifty dollars for an AI licence that gives me six variants in thirty seconds" (P06).*

Participants engaged primarily in post-production work, however, framed the same technologies through a markedly different lens — as a threat to professional employment and to the integrity of established craft knowledge:

> *"AI will eliminate us from work. It is the first technology that will not give us as many jobs in compensation" (P11).*

Project-based uncertainty represents a parallel adaptive challenge. Participants spoke of the recurring fear that "the phone will stop ringing" (P07), of the lottery-like character of cash-rebate allocations, and of the chronic difficulty of sustaining a long-term vision when each project takes five to seven years to complete. Collective agency at the industry level — producer guild advocacy, the institutional work that secured five million złoty annually for post-production funding, the standardization of intimacy coordination and sustainable production practices — emerged as a second-order response to these conditions.

5. Discussion

The findings presented above can be interpreted along three interrelated theoretical lines, each addressing one of the research questions and engaging with current debates in transformational leadership and knowledge sharing research.

5.1 Trust-based Relationships and the Relational Enactment of the Four I's

The first line of interpretation concerns the relational mechanisms through which transformational leadership operates. The findings show that role modelling, reputational sanctioning, vision-based partner selection, and leader presence constitute what Bass and Riggio (2006) describe as idealized influence and inspirational motivation, but in the project-based context they acquire specific operational forms not fully captured in the original framework. Costly personal choices — deferred compensation, personal financial responsibility, dissolution of symbolic hierarchy — align with the literature on ethical leadership (Brown and Treviño, 2006)

and with Bass and Steidlmeier's (1999) emphasis on authenticity as the boundary between transformational and pseudo-transformational leadership.

Recent empirical work continues to specify how transformational leadership translates into knowledge sharing through relational mediators: perceived organizational support (Chen, Chang and Tian, 2024), organizational commitment (Amin and Sudarmiatin, 2024), psychological safety (Khattak et al., 2025), and team communities of practice (Matsuo, 2025). The Polish film industry case adds a distinctive insight: in environments lacking formal accountability, relational trust acquires a sanctioning function as well as an enabling one, operating through dense reputational networks. This dual character of trust-based relationships is largely absent from dominant survey-based studies and represents a contribution of qualitative interpretive research to the field. The negative cases identified — trust violations in international co-productions, asymmetries of finance and jurisdiction — further illustrate the dark-side dynamics of pseudo-transformational leadership (Tourish, 2013) in project ecosystems where charismatic leaders hold disproportionate informal authority.

5.2 Mentoring and Knowledge Sharing as a Substitution for Absent Formal Pathways

The second line of interpretation concerns how knowledge is transmitted in the absence of effective formal pathways. The three mechanisms identified — dyadic master–apprentice mentoring, distributed developmental networks, and tacit knowledge transfer through situated learning — correspond closely with the situated learning framework (Lave and Wenger, 1991), the tacit knowledge transfer dynamics described by Nonaka (1994) and Alony et al. (2007), and the developmental network perspective developed by Higgins and Kram (2001). Recent work by Bai (2025) further demonstrates that the effect of transformational leadership on career growth is mediated by self-efficacy and psychological capital developed through informal channels, which aligns with the participants' accounts of learning "what questions to ask" rather than transferring codified knowledge.

The Polish case, however, also illuminates a paradox: when individualized consideration is restricted to dyadic mentorship, it can paradoxically reproduce the structural exclusion that creative industries scholarship has long identified (Eikhof and Warhurst, 2013). The persistence of a "caste" mentality inherited from the socialist-era film units, the difficulty of entering the profession without family connections or class capital, and the geographic concentration of opportunities in Warsaw all suggest that the effectiveness of transformational leadership in fostering knowledge sharing depends not only on individual leader behaviours but also on the existence of distributed institutional infrastructures — international training programmes, professional guilds, and peer learning networks — that can substitute for absent formal pathways.

5.3 Adaptive Resilience Under Disruption and Project-based Uncertainty

The third line of interpretation concerns how transformational leadership adapts to technological disruption and chronic project-based uncertainty. The intellectual stimulation dimension (Bass and Riggio, 2006) acquires renewed significance in the context of artificial intelligence, virtual production, and sustainable practices — confirming Christensen's (1997) classical analysis of disruptive innovation and Brynjolfsson and McAfee's (2017) account of the contemporary digital transformation. Recent industry analyses confirm that generative AI is reshaping film and television workflows unevenly across functional domains, with leadership playing a critical role in adoption and translation (McKinsey & Company, 2026).

The contrast identified in the present study — producers in development and physical production embracing AI as a creative and economic enabler, while producers focused on post-production framing it as a threat to professional employment — illustrates that intellectual stimulation is enacted differently across functional specializations within the producing role. This finding complements the longitudinal analysis of project failure and organizational learning in the U.S. film industry by Singh et al. (2025), which similarly demonstrates that responses to disruption are mediated by operational specialization and accumulated project experience. The structural uncertainty of project-based work, exemplified in participants' concerns about cash-rebate allocations and long project cycles (Bechky, 2006), requires what may be termed adaptive resilience: the capacity to sustain vision and trust across temporal compression, institutional fragility, and discontinuity of teams. The collective agency observed at the industry level — producer guild advocacy, institutional work securing post-production funding, standardization of intimacy and sustainable production practices — illustrates Lawrence and Suddaby's (2006) concept of institutional work translated into the creative industries setting, and represents a second-order leadership response to chronic uncertainty.

6. Conclusions

This study examined how transformational leadership fosters knowledge sharing in the Polish film industry, drawing on eleven in-depth interviews with audiovisual producers selected through the KIPA membership directory and analysing the material through three-stage grounded coding that yielded 221 first-order codes and 18 second-order categories.

The study makes three theoretical contributions. First, it extends the Four I's model (Bass and Riggio, 2006) by demonstrating that in project-based creative work the four dimensions are jointly enacted through relational rather than purely behavioural mechanisms — a perspective that complements but is not reducible to variance-based mediation models (Chen, Chang and Tian, 2024; Matsuo, 2025). Second, it integrates the developmental network perspective (Higgins and Kram, 2001) with critical creative industries scholarship (Eikhof and Warhurst, 2013), showing that individualized consideration in contexts without formal training infrastructure carries both enabling and exclusionary effects — a duality not adequately recognized in mainstream TFL research. Third, it reframes intellectual stimulation as a functionally differentiated dimension under disruption, opening a research agenda on how transformational behaviours vary across specializations within a single occupational role.

The study has several limitations. The sample of eleven interviews, while theoretically saturated, was drawn entirely from the KIPA membership and therefore underrepresents independent producers operating outside the formal institutional structure. The findings are situated in the Polish context and may not generalize directly to film industries operating under different funding regimes or labour regulations. Future research could compare the Polish case with other Central European film industries or with mature creative ecosystems such as the United Kingdom, France, or Germany, while longitudinal designs could trace how leadership practices evolve across the five-to-seven-year cycle of an individual film project.

For practitioners, the findings suggest that producers can strengthen team cohesion and knowledge transfer by investing in trust-building practices during early development, formalizing mentoring through industry guilds and developmental networks rather than relying solely on dyadic apprenticeship, and creating internal protocols for evaluating disruptive technologies that involve both creative and technical specializations. For policy-makers, the findings underscore the value of supporting distributed developmental infrastructures — international training programmes such as EAVE, ACE, and Inside Pictures, professional associations, and sector-specific funding mechanisms, particularly for post-production work that remains structurally underfunded.

Ethics declaration: All participants provided informed consent prior to the interviews. Pseudonymous codes (P01–P11) were assigned to protect confidentiality.

AI declaration: I didn't use an AI tool in the development of the paper.

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Masters Research Papers

From Adoption to Knowledge Utilisation: Understanding the Role of Value, Usage, and Social Perception in Generative AI

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Abstract: Generative AI (GAI) has fundamentally transformed how individuals acquire, generate, and apply knowledge in digital environments. While information systems research has extensively explained why individuals adopt new technologies, considerably less attention has been devoted to understanding how initial adoption develops into meaningful knowledge utilisation. Existing post-adoption research has primarily focused on continued system use; however, continued use does not necessarily indicate that AI-generated knowledge has become embedded in users' learning, decision-making, or problem-solving activities. This limitation highlights the need for a broader post-adoption perspective to explain how generative AI supports meaningful knowledge utilisation. To address this gap, this study develops a conceptual framework that extends post-adoption theory by explaining the mechanisms through which adoption intention evolves into knowledge utilisation intention. Drawing upon information systems, knowledge management, post-adoption theory, and social psychology, the proposed framework suggests that utilitarian value and hedonic value jointly influence adoption intention. Rather than assuming that adoption naturally leads to knowledge utilisation, this study argues that users gradually develop post-adoption perceived value through accumulated interaction with generative AI, which subsequently facilitates knowledge utilisation intention. Furthermore, usage frequency and pluralistic ignorance are introduced as behavioural and socio-cognitive boundary conditions that respectively strengthen and weaken this transformation. Together, these mechanisms explain why individuals with similar adoption intentions may demonstrate substantially different levels of knowledge utilisation. By distinguishing knowledge utilisation from continued technology use, repositioning perceived value as a post-adoption evaluative mechanism, and integrating behavioural reinforcement with social perception, the proposed framework offers a more comprehensive explanation of post-adoption behaviour in the context of generative AI. The framework contributes to both information systems and knowledge management research by providing a theoretical foundation for understanding how generative AI becomes meaningfully embedded in users' everyday knowledge practices and offers directions for future empirical research.

Keywords: Generative AI, Knowledge utilisation, Adoption intention, Utilitarian value, Hedonic value, Pluralistic ignorance

1. Introduction

Generative AI (GAI) has rapidly moved from a novel technological development to an everyday tool shaping how individuals search for information, generate content, and engage in knowledge-related activities. Unlike earlier information systems, GAI does not simply provide access to information; it actively participates in processes such as summarisation, explanation, and idea generation. As a result, it is increasingly positioned not just as a tool, but as a collaborator in knowledge work. Given this shift, it is not surprising that a growing body of research has examined users' willingness to adopt generative AI. Much of this work draws on established frameworks such as the Technology Acceptance Model (TAM), which emphasise adoption intention as a key predictor of usage behaviour (Almusharraf & Bailey, 2025). Within this line of research, user decisions are often explained through value-based considerations. In particular, utilitarian value captures the functional and performance-related benefits of technology use, whereas hedonic value reflects the experiential and affective dimensions of interaction (Gu et al., 2010; Hanzaee & Rezaeyeh, 2013; Kim & Han, 2011; Chun et al., 2012). In the context of GAI, both dimensions appear especially relevant, as these tools are simultaneously task-oriented and experience-driven.

However, focusing on adoption alone leaves an important question insufficiently addressed. While it is now relatively well understood why individuals choose to adopt generative AI, it is far less clear whether adoption actually leads to meaningful use in knowledge practices. In everyday settings, users may try GAI tools out of curiosity or convenience, yet this does not necessarily imply that these tools become integrated into their ongoing ways of thinking, learning, or problem-solving. In other words, there is a noticeable gap between adopting a tool and using it in ways that meaningfully support knowledge utilisation. This gap becomes more evident when knowledge utilisation is considered as a broader and more complex process. Rather than a single act of use, knowledge utilisation involves the application, integration, and transformation of knowledge in ways that extend beyond initial access (Zheng & Pee, 2024). From this perspective, adoption represents only an early

stage, and further mechanisms are required to explain how individuals move from initial intention to sustained and meaningful engagement.

To better understand this transition, this study adopts a value-based and socio-cognitive perspective. First, utilitarian value and hedonic value are conceptualised as two primary drivers of adoption intention. However, instead of assuming a direct and automatic link between intention and utilisation, this study argues that individuals engage in an additional layer of evaluation. Perceived value, understood as an overall assessment of benefits relative to costs (Zeithaml, 1988; Lu & Wang, 2020), is therefore introduced as a key mechanism that helps explain whether adoption develops into deeper forms of use. At the same time, this transformation process is unlikely to occur in isolation. It is shaped not only by individual evaluations, but also by behavioural patterns and social perceptions. On the one hand, usage frequency may strengthen the internalisation of benefits, as repeated interaction allows individuals to become more familiar with the capabilities of GAI and incorporate them into their routines (Almusharraf & Bailey, 2025; Lu & Wang, 2020). On the other hand, social perception may also play a constraining role. In particular, pluralistic ignorance—where individuals misperceive others' attitudes—may lead users to hold back from fully utilising GAI, even when they personally perceive it as valuable. Against this background, the present study develops a conceptual framework that seeks to explain how adoption intention may evolve into knowledge utilisation intention in the context of generative AI.

Rather than empirically testing predefined hypotheses, this study adopts a proposition-based approach and outlines a theoretical structure that can guide future empirical work. In doing so, it contributes to the knowledge management literature by moving beyond adoption-focused explanations and highlighting the conditions under which generative AI becomes meaningfully embedded in knowledge practices. Based on the above discussion, this study addresses the following research questions: **RQ1.** How do utilitarian value and hedonic value shape individuals' adoption intention toward generative AI? **RQ2.** How does perceived value influence the transition from adoption intention to knowledge utilisation intention? **RQ3.** How does usage frequency affect the relationship between adoption intention and knowledge utilisation? **RQ4.** How does pluralistic ignorance constrain the transformation from adoption intention to knowledge utilisation?

2. Literature Review

2.1 From Adoption to Knowledge Utilisation: A Conceptual gap

Since the emergence of the Technology Acceptance Model (Davis, 1989), information systems research has predominantly focused on explaining technology adoption. Subsequent post-adoption studies shifted attention towards continuance intention, emphasising why users sustain technology use after initial adoption (Bhattacherjee, 2001). Although this stream has substantially advanced understanding of post-adoption behaviour, its primary concern remains continued system use rather than the extent to which technologies become embedded in users' knowledge practices. This limitation becomes particularly salient in the context of generative AI. Unlike conventional information systems, generative AI functions not merely as a productivity tool but as an active cognitive partner capable of generating, synthesising, and transforming knowledge. Consequently, continued use alone provides only a partial explanation of users' post-adoption behaviour. Users may repeatedly interact with generative AI without incorporating its outputs into learning, decision-making, or knowledge creation. Understanding this distinction therefore requires moving beyond continuance intention towards the concept of knowledge utilisation.

2.2 Utilitarian and Hedonic Value as Drivers of Adoption

A substantial body of literature suggests that user behaviour is shaped by value perceptions. In particular, utilitarian value and hedonic value represent two distinct but complementary dimensions. Utilitarian value is associated with functional and task-oriented benefits, such as efficiency, productivity, and goal achievement (Gu et al., 2010; Hanzaee & Rezaeyeh, 2013; Kim & Han, 2011). In the context of GAI, this includes capabilities such as text generation, grammar correction, and information synthesis, which directly enhance task performance (Almusharraf & Bailey, 2025). In contrast, hedonic value reflects experiential and affective aspects, including enjoyment, curiosity, and emotional engagement (Chun et al., 2012; Hanzaee & Rezaeyeh, 2013; Kim & Han, 2011). GAI systems, through their interactive and conversational nature, can provide a sense of engagement that extends beyond purely functional use. Importantly, these two value dimensions often coexist in multipurpose systems, and both contribute to shaping users' adoption intention (Gu et al., 2010; Chun et al., 2012). Rather than operating independently, they jointly influence how users perceive the attractiveness and relevance of a technology.

Proposition 1. Utilitarian value positively influences adoption intention.

Proposition 2. Hedonic value positively influences adoption intention.

2.3 Adoption Intention as a Necessary but Insufficient Condition

Adoption intention has long been regarded as the most immediate predictor of technology use in established behavioural theories such as TAM, TPB, and UTAUT (Davis, 1989; Ajzen, 1991; Venkatesh et al., 2003). However, this assumption becomes less sufficient in the context of generative AI. Although users may readily adopt AI tools, adoption alone does not necessarily indicate that these technologies become embedded in everyday knowledge practices. Rather, adoption intention should be viewed as an entry point that enables subsequent interaction with GAI. Accordingly, adoption intention represents a necessary but insufficient condition for knowledge utilisation. Through repeated interaction, users accumulate experience and gradually evaluate whether generative AI genuinely contributes to learning, problem solving, and knowledge application. This post-adoption evaluation provides the theoretical foundation for the role of perceived value discussed in the following section.

Proposition 3. Adoption intention positively influences perceived value.

2.4 Perceived Value as a Conversion Mechanism

Perceived value has traditionally been conceptualised as an overall evaluation of the benefits and sacrifices associated with using a product or service (Zeithaml, 1988). Within value-based adoption models, perceived value is commonly treated as an antecedent of behavioural intention because users evaluate expected benefits before deciding whether to adopt a technology (Kim & Han, 2011; Lu & Wang, 2020). However, this assumption primarily reflects a pre-adoption decision-making process. In the context of generative AI, adoption often occurs rapidly due to curiosity, accessibility, or organisational encouragement. Consequently, adoption does not necessarily indicate that users have fully evaluated the technology's contribution to their knowledge practices. Instead, this study argues that value evaluation continues after initial adoption. As users repeatedly interact with generative AI, they gradually assess whether its outputs genuinely enhance learning, decision-making, problem solving, and knowledge creation. Perceived value therefore represents a post-adoption evaluative judgement rather than merely a pre-adoption expectation. From this perspective, adoption intention provides opportunities for meaningful interaction, whereas perceived value reflects users' accumulated evaluation of those interactions. Such post-adoption evaluation determines whether initial adoption develops into sustained knowledge utilisation.

Proposition 4. Perceived value positively influences knowledge utilisation intention.

2.5 Knowledge Utilisation: Beyond Use Toward Integration

Knowledge utilisation represents a post-adoption knowledge outcome that extends beyond continued system use. Rather than reflecting technology use itself, it refers to the extent to which individuals integrate and apply AI-generated knowledge within their ongoing knowledge practices (Alavi & Leidner, 2001; Grant, 1996; Nonaka & Takeuchi, 1995). In the context of generative AI, users do not merely retrieve information but actively interact with AI-generated explanations, ideas, and solutions. Meaningful utilisation therefore requires users to critically evaluate and apply these outputs to support learning, decision-making, and problem solving. Accordingly, knowledge utilisation should be understood as the process through which AI-generated knowledge becomes embedded in users' knowledge practices rather than simply representing continued technology use. Based on this perspective, the present study conceptualises knowledge utilisation intention as individuals' willingness to integrate generative AI into their ongoing knowledge activities. This conceptualisation extends post-adoption research by distinguishing meaningful knowledge utilisation from continued system use (Almusharraf & Bailey, 2025; Zheng & Pee, 2024).

2.6 Usage Frequency as Behavioural Reinforcement

Usage frequency reflects the extent to which individuals repeatedly interact with generative AI over time. Prior post-adoption research suggests that repeated technology use reinforces familiarity, reduces uncertainty, and gradually develops habitual behaviours (Limayem et al., 2007). Rather than simply indicating how often a system is used, frequent interaction enables users to better understand the capabilities of generative AI and incorporate AI-assisted practices into their everyday work and learning activities. In the context of generative AI, repeated interaction provides opportunities for users to refine prompting strategies, evaluate AI-generated outputs, and recognise their value in different knowledge-related tasks. As these experiences accumulate, users become more likely to translate their initial adoption intention into meaningful knowledge utilisation. Accordingly, usage

frequency is expected to strengthen the relationship between adoption intention and knowledge utilisation intention.

Proposition 5. Usage frequency positively moderates the relationship between adoption intention and knowledge utilisation intention.

2.7 Pluralistic Ignorance as a Socio-cognitive Constraint

Pluralistic ignorance refers to a situation in which individuals privately hold favourable attitudes while mistakenly believing that others hold less favourable views, leading them to suppress behaviours that would otherwise be personally acceptable (Allport, 1924; Miller & McFarland, 1987; Prentice & Miller, 1993). As a result, individuals often conform to perceived social norms rather than their own beliefs. In the context of generative AI, users may recognise the benefits of AI-assisted knowledge work but hesitate to integrate AI into their learning or professional practices because they believe that others may regard extensive AI use as inappropriate or unacceptable. Such misperceived social expectations may not prevent initial adoption but can discourage users from fully incorporating AI into their knowledge-related activities. Accordingly, pluralistic ignorance is expected to weaken the relationship between adoption intention and knowledge utilisation intention by reducing users' willingness to openly integrate generative AI into their everyday knowledge practices. This perspective extends previous studies on pluralistic ignorance in knowledge-sharing contexts to the emerging context of generative AI (Chumg et al., 2024; Chumg et al., 2025).

Proposition 6. Pluralistic ignorance negatively moderates the relationship between adoption intention and knowledge utilisation intention.

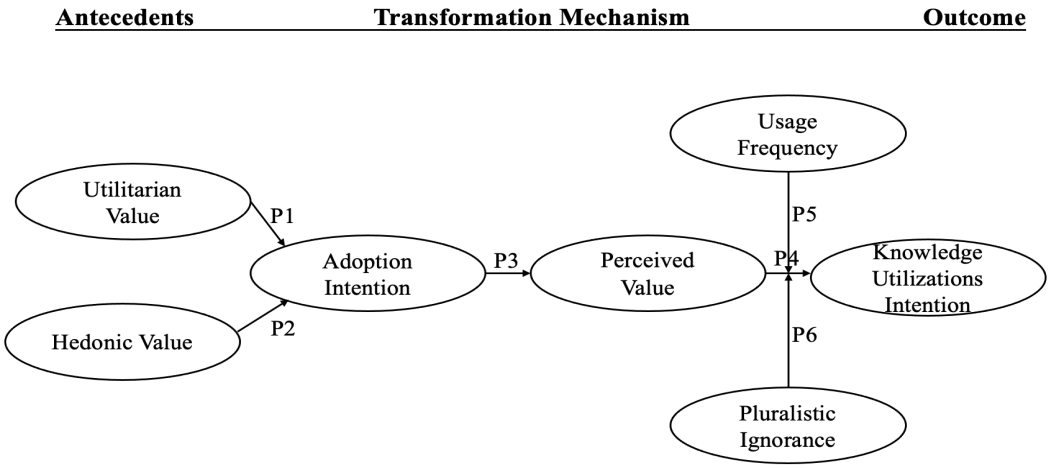


Figure 1: Research Model

3. Conceptual Framework Development

This study adopts a conceptual research approach to develop a theoretically grounded framework explaining how generative AI adoption evolves into knowledge utilisation. Following established approaches to conceptual research (Jaakkola, 2020), the proposed framework was developed through the critical integration and reinterpretation of literature from information systems, knowledge management, post-adoption theory, and social psychology. Rather than generating new empirical evidence, the objective is to synthesise existing theoretical perspectives and identify the mechanisms through which adoption intention develops into meaningful knowledge utilisation.

The proposed framework suggests that utilitarian value and hedonic value shape adoption intention, whereas post-adoption perceived value functions as the key evaluative mechanism linking adoption intention to knowledge utilisation intention. Furthermore, usage frequency and pluralistic ignorance are incorporated as behavioural and socio-cognitive boundary conditions that respectively strengthen and weaken this transition. Together, these relationships provide a more comprehensive explanation of why technology adoption does not necessarily result in meaningful knowledge utilisation. The proposed framework offers a theoretical foundation

for future empirical research across different generative AI contexts and may be examined using quantitative, qualitative, or mixed-method approaches.

4. Discussion and Contributions

4.1 Theoretical Contributions

This study makes three theoretical contributions. First, it extends post-adoption research by arguing that continued technology use does not necessarily result in meaningful knowledge utilisation. Instead, knowledge utilisation is conceptualised as a distinct post-adoption outcome that reflects how generative AI becomes embedded in users' knowledge practices. Second, this study reconceptualises perceived value as a post-adoption evaluative mechanism rather than a pre-adoption determinant of technology adoption. This perspective provides a theoretical explanation of how adoption intention gradually develops into knowledge utilisation through users' accumulated interaction experiences with generative AI. Third, this study integrates behavioural and socio-cognitive perspectives by incorporating usage frequency and pluralistic ignorance into a unified post-adoption framework. This integration explains why individuals with similar adoption intentions may differ substantially in their willingness to incorporate generative AI into everyday knowledge practices.

4.2 Practical Implications

From a practical perspective, organisations and educational institutions should recognise that encouraging initial adoption of generative AI is only the first step. Greater attention should be devoted to helping users integrate AI into meaningful knowledge activities while fostering an environment in which AI-assisted knowledge work is viewed as acceptable and valuable. Such efforts may facilitate deeper knowledge utilisation rather than merely increasing technology use.

4.3 Limitations and Future Research

As a conceptual study, this research does not provide empirical evidence to validate the proposed framework. Future research may examine the proposed relationships across different organisational, educational, and professional contexts using quantitative, qualitative, or mixed-method approaches. Further studies may also explore additional post-adoption mechanisms that influence how generative AI becomes embedded in users' knowledge practices. In conclusion, this study shifts the focus of generative AI research from technology adoption to knowledge utilisation by extending post-adoption theory. By integrating value evaluation, behavioural reinforcement, and social perception, the proposed framework provides a new perspective for understanding how generative AI becomes meaningfully embedded in users' knowledge practices and offers a foundation for future empirical research.

Ethics Declaration: This paper is conceptual in nature and does not involve human participants, personal data, or animal subjects.

AI Declaration: No generative AI was used in the preparation of this manuscript.

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How Does Knowledge Sharing Within Communities of Practice Drive Innovation?

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Abstract: The link between Communities of Practice (CoP) and innovation is a topic that needs to be explored in more detail in organisations and how knowledge sharing within CoPs drives innovation. Knowledge is recognised as a critical resource in organisations that creates competitive advantage. Knowledge sharing practices and behaviours strengthen organisational capability to innovate, however, knowledge sharing does not come naturally to most individuals. A systematic literature review of 24 peer-reviewed articles published between 2015 and 2025 identified three thematic areas that explore relationship between knowledge sharing in CoPs and innovation. The three key themes are 1) tacit knowledge sharing and its link to innovation, 2) knowledge sharing barriers and facilitators and 3) the role of CoPs as a knowledge sharing platform that drives innovation. The findings highlight that tacit knowledge is deeply embedded in individual experience and intuition. It plays a critical role in driving innovation through processes such as learning by doing, interaction and reflection. Motivational factors, such as reward systems, have also been identified in the literature as factors that can either facilitate or hinder knowledge sharing behaviours. The review also identified organisational climate and leadership behaviours as facilitators and/or barriers. Furthermore, CoPs emerge as valuable, low-cost platforms for informal learning and tacit knowledge sharing, strengthening relationships and supporting innovation. However, a gap remains in the literature regarding how tacit knowledge within CoPs drives innovation as few empirical studies have explored this area. This study contributes to the Knowledge Management field by consolidating current insights and emphasising the need for deeper investigation into how CoPs can be leveraged as a knowledge sharing platform that drives innovation.

Keywords: Tacit knowledge sharing, Knowledge sharing and innovation, Knowledge sharing in communities of practice, Communities of practice and innovation, PRISMA

1. Introduction

Tacit knowledge sharing is recognised to play a vital contributor to organisational competitive advantage. CoPs have emerged as a key element of an organisation's knowledge strategy, enabling the social process through which tacit knowledge is shared (Nonaka and Konno 1998). Despite this recognition of importance there remains a lack of research that identifies the factors that contribute to successful knowledge sharing in CoPs and how they contribute to driving innovation (Pohjola 2015; Aljuwaiber 2016; Ji et al, 2017). It is this identified gap that forms the basis and rationale for this study. This study will add to the existing body of knowledge and literature on knowledge sharing processes in CoPs and their link to innovation.

2. Systematic Review Methodology

This literature review utilizes a Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) approach to systematically examine the role of tacit knowledge sharing within Communities of Practice (CoPs) and its contribution to organisational innovation. Drawing on peer-reviewed studies published between 2015 and 2025, this analysis explores current research on tacit knowledge sharing, knowledge sharing facilitators and barriers, and CoPs as a knowledge sharing platform that drives innovation. The review establishes that CoPs provide a valuable social and low-cost structure for fostering informal learning, strengthening relationships, and facilitating tacit knowledge sharing, however, a significant gap persists in literature regarding the factors that enhance tacit knowledge shared within COPs that drives innovation. Consequently, this systematic review aims to consolidate existing findings and highlight areas for future research in this domain.

2.1 Search Process

This systematic literature review (SLR) adopts the PRISMA framework (Prisma 2025) to identify and analyse literature regarding tacit knowledge sharing processes in CoPs as a knowledge sharing platform for innovation. The search and selection of records were conducted solely by the researcher, guided by the PRISMA checklist to ensure transparency and rigour. The researcher identified relevant databases for journal articles related to tacit knowledge sharing, communities of practice and innovation. This search was conducted over a period of 4 days. From September 8 – September 11, 2025, articles were found based on the inclusion and exclusion

criteria identified in section 2.4 of this paper. The primary databases consulted were Scopus and ProQuest. Scopus was selected for its comprehensive coverage of scientific literature, such as scholarly journal articles, conference proceedings, books. ProQuest wash chosen for its wide range of scholarly journals worldwide. Both databases offer advanced and extensive search capabilities, including the selection of specific journals and/or specific domain areas. In addition, both offer export functionality which enabled the researcher to find relevant content faster based on article title and abstract section. For these reasons, Google Scholar was excluded from the search process.

The search strategy employed the following keywords Boolean operators: "Tacit knowledge" AND "innovation", "Knowledge sharing" AND "employee", "Knowledge enablers" AND "Leadership", "Communities of practice" AND "Innovation". The search strings used are broad in scope, yet specific to create a focus around the scope of this research project.

2.2 Selection Process

Peer-reviewed articles were selected to adhere to quality standards. The search was guided by a journal quality list, as well as journal websites such as Emerald, Sage, Taylor and Francis, and Elsevier. Article selection focussed on journals that contained the following keywords in their titles in the ProQuest database: Knowledge management, Innovation management, Technology management. However, any article relevant to the research project that was found in a journal other than the selected list, the researcher included the article. The Scopus database does not have a filter selection for journals, therefore the researcher had to rely on the selection of subject areas instead. The following subject areas were selected: Business, Management and Accounting; Computer Science; Engineering.

The PRISMA flow diagram was used to guide the refinement of the article selection. The first stage, involved identifying and manually removing duplicate articles, using Excel filtering function. The second stage involved screening of article titles for relevance based on keywords such as knowledge sharing, employee knowledge sharing, communities of practice and innovation. The final stage involved reviewing titles and abstracts to further refine the selection. This process resulted in a final sample of twenty-four articles for the systematic literature review. Figure 1 depicts the PRISMA flow diagram and Table 1 lists the journals in which the selected articles were published.

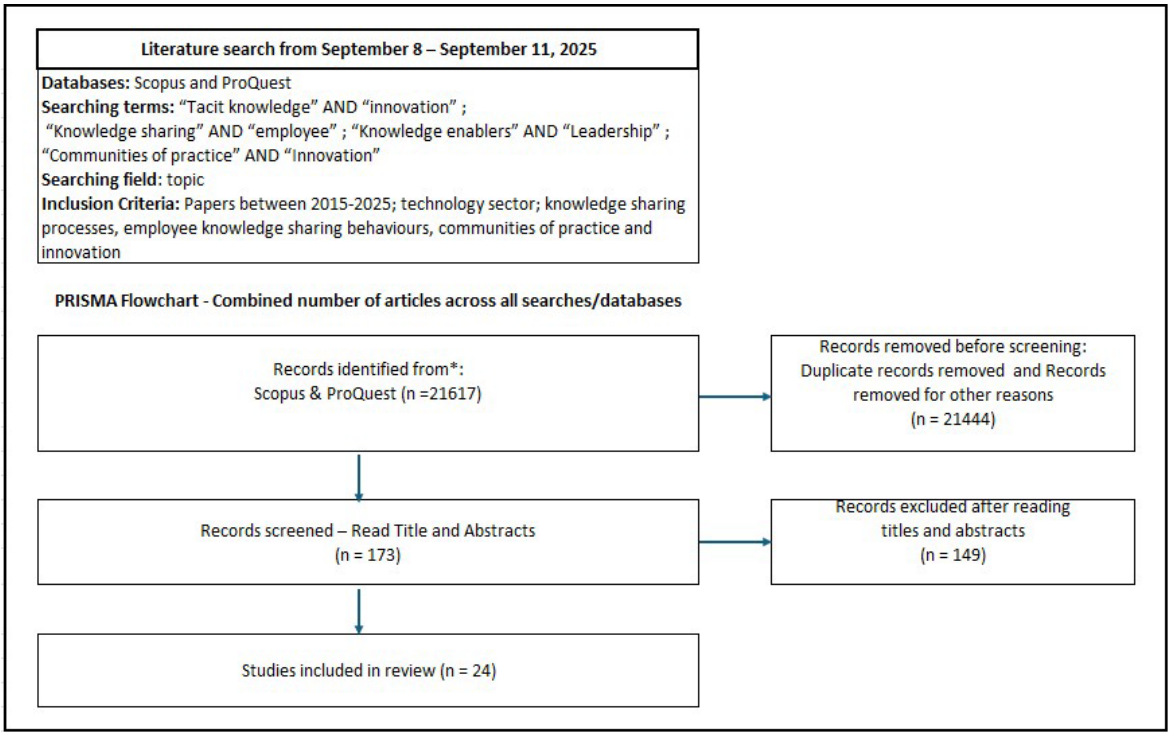


Figure 1: PRISMA Flow diagram

Table 1: List of Journals – Article search results

Journal / Conference Proceedings	Number of Articles
European Journal of Innovation Management	2
International Journal of Knowledge Management	1
Journal of Knowledge Management	4
Personnel Review	1
Electronic Journal of Knowledge Management (EJKM)	1
Technological Forecasting and Social Change	1
VINE Journal of Information and Knowledge Management Systems	2
International Journal of Information Management	1
Journal of Business Research	1
ICICKM Conference Proceedings	1
Eurasian Journal of Management and Social Sciences	1
HICSS Conference Proceedings	1
Technology Analysis and Strategic Management	1
Journal of Innovation Management	1
Problems and Perspectives in Management	1
Project Management Journal	1
Systems	1
Knowledge Management Research and Practice	1
Information and Organisation	1

The literature review incorporated the seminal works by Polanyi, Drucker, Nonaka, Argyris and Schon and Wenger whose pioneering theories on tacit knowledge and communities of practice form the foundational for the research domain.

2.3 Inclusion and Exclusion Criteria

To capture the most recent research on the topic of knowledge sharing processes in communities of practice the review included literature published between 2015-2025. The primary domain focus was the technology sector however, in some cases, articles covered more than one study and spanned multiple sectors were included if the content and findings were relevant to knowledge sharing processes, employee knowledge sharing behaviours, communities of practice and innovation. Articles associated with leadership as an enabler of knowledge sharing was also included. All research methodologies: qualitative, quantitative and mixed methods were considered.

The exclusion criteria encompassed articles and papers published prior to 2015, non peer reviewed and outdated books and articles that were not relevant to the broader technology sector. Papers and articles that were not accessible through the institution login and those not published in English were also omitted.

2.4 Data Collection and Analysis

A bibliometric analysis was conducted to map the annual publication trends between 2015-2025. The distribution of articles identified per year is illustrated in Figure 2 below.

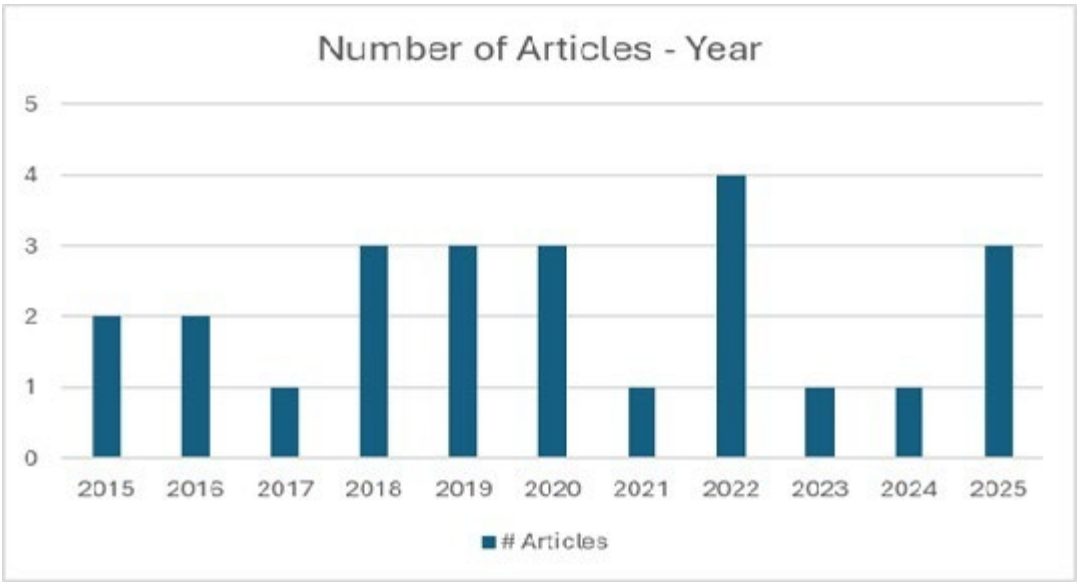


Figure 2: Articles found per year

The selected articles were subsequently organized according to major themes found in the content. This classification of the articles helped structured articles that were published per theme and identify under explored areas. Figure 3 illustrates the distribution of the themes.

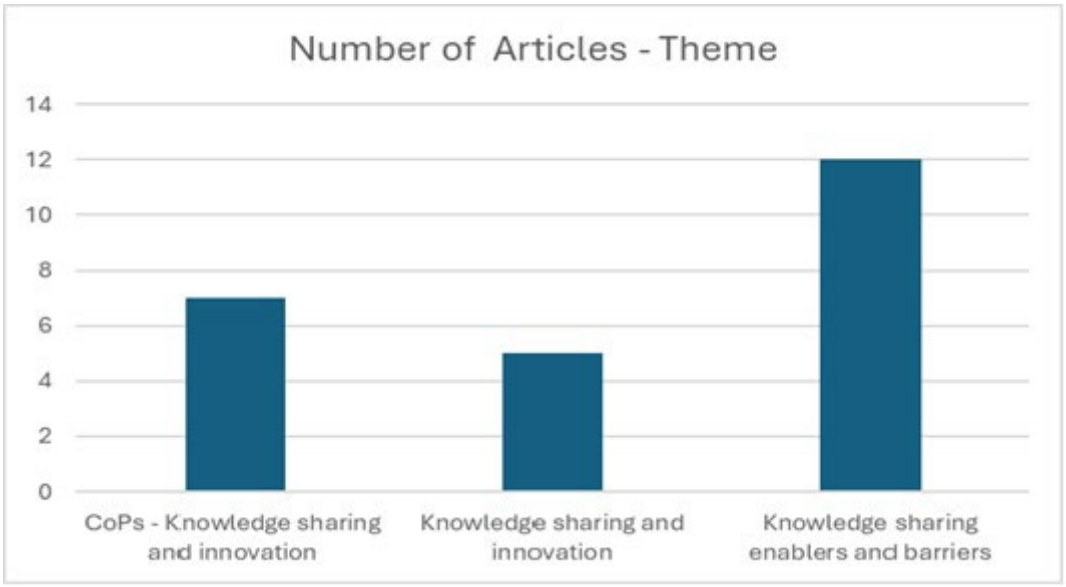


Figure 3: Article count per theme

Based on the search results, several conclusions can be drawn. First, although the topic of knowledge sharing has been broadly researched in the context of enablers and barriers, limited research has been conducted in the context of knowledge sharing and innovation. Second, within the last ten years, few studies have specifically investigated the link between knowledge sharing processes within COP and their link to innovation. The selected articles for this literature review ranged in terms of study design from qualitative, quantitative and mixed methods. Table 2 below presents a breakdown by study method.

Table 2: Study Method in articles - breakdown

Study Method	% Breakdown
Quantitative	54.20%
Qualitative	33.3%
Mixed Methods	12.50%

It is evident from the table that quantitative analysis is the prominent methodology surpassing both qualitative and mixed methods approaches. To analyse the content of each journal article a data extraction method was applied, breaking down each study into its constituent parts (Saunders, 2023). A Thematic Analysis Grid (Anderson et al., 2015) was created to structure notes, key themes, and points made by the article authors.

Figure 4 illustrates an example of how data was extracted using Thematic Analysis Grid framework. Articles and authors are listed in rows, and key themes are noted in columns. This facilitated a comparative analysis of themes across the literature, ensuring the identification of the most relevant and significant concepts. No quantitative meta-analysis was conducted; therefore, no effect measures (e.g. odds ratios, mean differences) were applied.

Author	Problem	Tacit Knowledge Types/Definitions	Tacit Knowledge Transfer and Knowledge Creation and Sharing	Types of tacit knowledge that inhibits innovations
Stokvik, H., D.J Adriaenssen/J-A Johannessen 2016	**We don't know how tacit knowledge, organizational learning and innovation are linked.** Research question: What is the relation between tacit knowledge, organizational learning and innovation? Methodology: Conceptual generalizing. Purpose: To create a link between tacit knowledge, organizational learning and innovation. The authors develop a theory, i.e., a system of propositions related to how do different types of tacit knowledge and organizational learning influence innovation Organizational learning and innovation are dependent on access to knowledge (King, 2009, pp. 1-13; Grillitsch & Rekers, 2015). This means knowledge that is external to the business, as well as the	The research of the authors shows that tacit knowledge may be said to **have three faces: one conservative that limits the continuous improvement process, a second that guards an organization against imitation, and a third that promotes innovation** the development o f tacit knowledge may be said to always consist of three elements: knowing, wanting to know and the practical context; **It is by becoming intimate with phenomena or problems – "dwelling in them"** (Polanyi, 2009, p. ; In other words, it is intimacy and extensive experience of a phenomenon in its context that constitute the approach to tacit knowledge and thereby also a foundation for learning. It is precisely this sensitivity, attained through intimacy by application and execution, that leads to the development and transferral of tacit knowledge. Tacit knowledge exists, says Molander (1993, p. 40), in "the action and the judgements that are carried out in relation to the action". The word 'and' is crucially important here: the action and the judgements. It is not only the action or the judgements by which tacit knowledge may be understood, but also the reflection that is made before, during and after the action. This links tacit knowledge to the learning process.	Accordingly, the basis for Polanyi's concept of tacit knowledge is that we know more than we are able to communicate to others in the form of information. Examples of adequate methods may be mechanisms that release and combine explicit and tacit knowledge. When tacit knowledge is to be transferred from one person to another, this cannot be done completely by means of either language or images (Cannon, 2002). **The transmission of tacit knowledge** to an apprentice is an active creative process; it is not one of passive transmission from master to apprentice (Polanyi, 2009, p. 6). The process of apprenticeship is dependent in part on the apprentice themselves gradually finding out knowledge that the master is unable to transmit, but which becomes apparent through the situation/context at any particular time (Cannon, 2002). This active process means that the tacit knowledge possessed by the apprentice becomes different to that of the master. The apprentice integrates this tacit knowledge into their existing knowledge-base, and makes it their own. Tacit knowledge will comprise a proportion of the knowledge-base in most occupations	there are two types of tacit knowledge: rules of thumb and holistic causal understanding, both of which can slow down innovation (Johannessen & Olsen, 2011). This is because these types are closely linked to the rules, procedures and analysis; they are, thus, bound by the grip of history and experience, and operate as mechanisms that slow down the field of change

Figure 4: Thematic Analysis Grid

2.5 Quality Assessment

The researcher employed the PRISMA process to ensure that all components and methods for this literature review are transparent and fully described. PRISMA flow diagrams outline the results for each search related to a specific theme/topic in line with the research objectives.

3. Literature Review Findings

This systematic literature review examines the processes and behaviours underlying tacit knowledge sharing, concentrating on its role in driving innovation outcomes through CoPs. Knowledge sharing is acknowledged as one of the most critical and widely studied processes in the field of knowledge management, attracting the attention of both researchers and practitioners (Drucker 1992). This interest stems from a shift in organisational strategy, whereby knowledge is recognised as a critical resource, rather than conventional tangible assets (Drucker 1992).

While knowledge sharing is recognised to be vital in developing competitive advantage within organisations managers often find it to be the most difficult practice to promote because knowledge sharing does not come naturally to most individuals (Wang and Hou 2015). However, innovation fundamentally depends on knowledge sharing, which enables the design of services, products, business models, skills and information. One of the hallmarks of innovation is value creation, which is made possible through effective sharing of knowledge and organisations that encourage knowledge sharing also strengthen their innovation capabilities (Salehi and Alanbari 2024). Research shows that knowledge is of no value until it is shared and used (Kaushal and Nyoni, 2025). In addition, research suggests that knowledge sharing behaviours significantly impact employee performance and employees who share knowledge with their colleagues are more likely to generate innovative ideas (Wang 2025).

The literature review is divided into three themes based on the data extraction method detailed previously. Theme 1. The role of tacit knowledge in driving innovation; Theme 2. Knowledge sharing facilitators and barriers and Theme 3. Communities of practice as a knowledge sharing platform for innovation.

3.1 The Role of Tacit Knowledge in Innovation

There is a common theme in the reviewed literature regarding the role of tacit knowledge sharing and innovation. While knowledge is recognised as a critical organisational resource, however, it is specifically through sharing, with others, that tacit knowledge becomes a source of a competitive advantage. For organisations to sustain innovative and competitiveness they must capture and leverage their knowledge assets. This often entails innovating through the pursuit of new knowledge or discovering novel applications for their existing knowledge (Kucharska and Erickson 2023; Perez-Luno et al, 2018; Stokvik et al, 2016). Scholarly authors have explored how tacit knowledge sharing influences innovation from different perspectives. Stokvik et al (2016), focussed on understanding how tacit knowledge development, organisational learning and innovation are linked. They proposed a typology, linking organisation learning and its influence on innovation to tacit knowledge. Perez-Luno et al (2018), focussed on the nature of knowledge that is tacit vs explicit and the process of knowledge exchange and combination. Empirical research conducted by Kucharska and Erickson (2023) showed how tacit knowledge is developed and examined through both "learning by doing" and "learning by interaction", which in turn leads to the willingness of an individual to share their knowledge and as a result of this tacit knowledge sharing it may lead to product/service innovation. "Learning by doing" was identified as one of the tacit knowledge acquisition methods that comes from employee experiences such as observation, simulation or experimentation. Another method called 'learning by interaction' relies on shared learning experiences such as thinking aloud, opinion giving, storytelling, brainstorming. Stovik et al. (2016), argue that tacit knowledge is developed through extensive experience and intimacy working with problems and this act forms the foundation for learning. The authors outline three processes connected to tacit knowledge that enable learning. Process 1: Action, which is linked to the execution of activities, integration, and transfer of tacit knowledge. Process 2: Reflection is essential if learning is to be achieved and Process 3: Interaction is viewed from a perspective of interacting with a problem first, and then interacting with the individuals who possess the knowledge of the problem (Argyris and Schon 1978)

According to Stokvik et al., (2016) action, reflection, and interaction are key processes in developing, sharing, and integrating tacit knowledge. These processes require relationships built on trust and mutual support. Stokvik et al., (2016) highlight that when people feel safe and encouraged, they are more confident in their interactions, which strengthens the flow of knowledge and makes these processes even more effective (Stokvik et al., 2016). Tacit knowledge is also viewed from three aspects according to Kucharska and Erickson (2018). There are three aspects of tacitness: a hidden practical layer, a reflective tacit layer, and a demonstrated tacit layer. These layers range from being easier to explain and closer to explicit knowledge to being virtually impossible to explain. This suggests that knowledge exists on a continuum, with explicit knowledge at one end and tacit knowledge at the other. Tacit knowledge is more difficult to articulate because it sits on a more 'intangible continuum'. It is unstructured, based on personal experience, and more easily shared person-to-person rather than through centralised organisational systems. As knowledge becomes more structured and defined (explicit), it is more easily shared through centralised systems; therefore, it is on the opposite continuum of tacit knowledge. This aligns with the perspective of Nonaka and von Krogh (2009). Terhorst et al (2018) expanded tacit knowledge concepts, stating that knowledge sharing cannot be mandated but happens voluntarily or through free will. Because sharing tacit knowledge is largely 'an act of volition', autonomous motivation could be a reliable predictor of tacit knowledge sharing (Polanyi, 1966). Furthermore, the scholars recognised that tacit knowledge is not transferable as such but is interpreted within a specific context through face-to-face interactions (Nonaka 1994). The development of personal tacit knowledge in organisations can raise productivity to a higher level compared to competitors because tacit knowledge cannot be purchased; it has to be developed inside an organisation. Knowledge creation through sharing is considered an effective and efficient form of achieving successful innovations (Stokvik et al, 2016; Perez-Luno et al, 2018). Similarly, Perez-Luno et al (2018) highlight the importance of knowledge exchange and combination. The scholars explain that companies can only create new knowledge—and use it to innovate and stay ahead of competitors - when employees are able to share and combine what they know.

3.2 Knowledge Sharing – Facilitators and Barriers

Many scholars have explored knowledge sharing in the context of motivations and behaviours. For example, Wang and Hou (2015) examined the influence of various types of motivations – autonomy-oriented and control-oriented motivations–on employees' knowledge sharing behaviours, referencing self-determination theory (SDT). SDT proposes that human behaviours may be encouraged not only by externally induced incentives, called controlled motivation, but also by internally evoked incentives, known as autonomous motivation. Controlled motivation leads to performing behaviours that explicitly contribute to self-care needs

and benefits under pressure or necessity to achieve a desirable outcome. In contrast, individuals feel autonomously motivated when they perceive self-determination in selecting their objectives freely based on self-interests, curiosity, or care (Wang and Hou 2015). The external/controlled motivating factors include reward systems, formal or informal evaluations from others, and status within significant groups, and the

internal/autonomous motivating factors include self-interest, enjoyment, and selfless care for other parties (Wang and Hou, 2015). Mahmood and Toker (2022) posit that people generally have a need to interact with other people, which is known as social motivation. The authors found that people are driven by a need for rewards and reinforcement, which encourages them to emphasise their knowledge-sharing behaviour and knowledge production. Empirical research conducted by Wang and Hou (2015) found that hard and soft rewards influenced knowledge sharing behaviours. Hard rewards are associated with employees obtaining explicit outcomes such as promotions, financial rewards, and reciprocity. Soft rewards are associated with employees' expectations of achieving implicit outcomes, such as personal reputation and relationships with other employees. Interestingly, Wang and Hou (2015) highlighted that soft rewards were more important to individuals than hard rewards. Similarly, Kushal and Nyoni (2025) explored knowledge sharing in various dimensions, such as organisational performance outcomes, trust, collaborative culture, and leadership support. According to the scholars, rewards (e.g. monetary – bonuses or non-monetary - certificates, promotions, and gifts other than money) have been established among several knowledge sharing facilitators. Rewards act as a necessary strategy to recognise employee accomplishments (Kushal and Nyoni, 2025). Monetary and non-monetary rewards make those who have used their intellectual property for the benefit of the organisation feel recognised and honoured for their contributions. However, it was also established that despite the provision of rewards to employees, it is not automatic that those rewards facilitate knowledge sharing behaviour at all times (Kushal and Nyoni 2025). Furthermore, Malik (2022) examined emotional intelligence and tacit knowledge sharing that could promote innovative behaviour at work. Malik (2022) recognised knowledge sharing as a voluntary and prosocial behaviour that people use to share their knowledge with others. In addition, Malik (2022) showed how two dimensions of emotional intelligence, pride and empathy, positively impacted employees' eagerness and willingness to share knowledge.

Knowledge sharing must also be discussed in the context of barriers. It is important to acknowledge that organisations often find it difficult to facilitate effective knowledge sharing practices among employees. Some scholarly thinkers indicated that this is due to human factors, institutional complexities, and the sticky nature of knowledge itself (Wang and Hou 2015). According to Liu and Liu (2008), the sticky nature of knowledge makes it difficult to share because it is embedded in individuals' brains; therefore, it can be slow, costly, and uncertain. Achieving effective knowledge sharing practices relies on an individual's willingness to invest time and effort into the process. Salehi and Alanbari (2024) posit that companies must increase their knowledge through knowledge sharing practices to enhance their competitive advantage and drive efficient innovation.

Research also acknowledges that barriers to knowledge sharing must be identified. Organisational rigidity and insufficient resources may act as barriers to organisational performance. Goh et al (2020) argued that organisational factors play a significant role in initiating or discouraging knowledge sharing behaviour. Institutional structures have been considered as key barriers to knowledge sharing.

3.3 Communities of Practice – Knowledge Sharing and Innovation

Knowledge has become the key to success in the global economy. People can share knowledge through a variety of online sharing and discussion tools. A CoP is a popular tool for knowledge sharing with the ability to share tacit knowledge (Liu and Chen 2018). The term community of practice was first coined by Lave and Wenger (1991, p.98) as 'an activity system about which participants share understandings concerning what they are doing and what that means in their lives and for their community'. Despite the proliferation of CoPs in many organisations, many fail because of members' low willingness to share knowledge (Lie and Chen 2018). Ji et al (2017), argue that CoPs are an efficient and low cost route to promote innovation performance, however, few papers talk about the mechanism and the relationship between CoP and innovation performance. There are also insufficient empirical studies that have examined the role of CoPs in community activities, such as fostering the innovation process (Aljuwaiber 2016).

In the rapidly changing and competitive global market environment, organisations must promote innovation and improve their creative capacity to gain a competitive advantage, which requires them to absorb and integrate various knowledge and skills (Ji et al, 2017). In CoPs, members share their experiences, skills, and explanations. This type of knowledge sharing is not always covered by a traditional organisation's hierarchy. When an organisation requires constant innovation, this system can compensate for the drawbacks of

traditional organisational learning (Ji et al, 2017). According to Aljuwaiber (2016), CoPs have three dimensions. Dimension one: mutual engagement, which refers to the extent to which members interact with one another and form their own relationships and culture. Dimension two: joint enterprise refers to the common purpose that binds people together and builds relationships that enable them to work on a specific interest. Dimension three: shared repertoire which refers to the continual development of the community, through which members produce sources over time through participation (these resources include, for example, procedures, techniques, forms, stories, tools and concepts). Pohjola (2015) argues that the sharing of tacit knowledge requires close involvement and cooperation, network relationships, face-to-face contacts, shared understanding and trust. Tacit knowledge also requires informal learning processes, such as storytelling, conversation, and coaching, which CoPs provide.

Research indicates that the function of a CoP is twofold: (1) CoPs promote knowledge sharing and (2) CoPs improve the performance of individuals or organisations. It helps to promote performance at the individual, group, and organizational levels by reducing the learning curve, avoiding overlapping investments in new products and services, improving employees' working experience, and accumulating professional talent for the organisation (Ji et al, 2017). To reap the full benefits of CoPs, they need to be properly understood, deployed, and supported. CoPs cannot be conceived and supported in the same way as other organisational initiatives because they lack formal structures, standardised protocols, and performance measurements. Organisations must create conducive environments for employees to voluntarily participate and include other members of the community in their pursuit of knowledge sharing and organisational learning (Venkatraman and Venkatraman 2018).

4. In Conclusion

The findings of this systematic literature review demonstrate that while tacit knowledge sharing is widely acknowledged as a critical driver of organisational innovation, the mechanisms through which CoPs enable this practice remains insufficiently explored. The reviewed studies consistently highlight that tacit knowledge is gained through experience and social interaction. CoPs are recognised in the literature as one of the low-cost tools where knowledge sharing occurs. Yet, despite this recognition, empirical research rarely examines how knowledge sharing within CoPs most effectively translates knowledge sharing into innovation outcomes. Three key gaps emerge as most important. First, the actual practices of knowledge sharing within CoPs such as storytelling, conversation or coaching are not well examined in the context of being linked to innovation. Second, there is lack of theoretical as well as empirically validated studies that clearly demonstrate the link between knowledge sharing within CoPs and innovation, leaving organisations without clarity on the value of CoPs and how they contribute to innovation capabilities. Third, while knowledge sharing can be considered common practice among individuals, motivational and organisational factors in the context of CoP dynamics remain poorly understood. Future research should focus on empirical studies that capture knowledge sharing frameworks, flows and processes through which the link between CoP and innovation can be established and innovative outcomes for organisations can be clearly measured. This will advance both theory and practice.

Acknowledgement

I wish to thank my supervisor Geraldine Hamill for providing invaluable support throughout my Master's project journey.

Ethics Declaration: No ethical clearance was required for this paper.

AI Declaration: No AI tools were used as part of the PRISMA and systematic literature review process

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An Information Systems-Supported Strategy for Managing Tacit Knowledge in Organisations

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Abstract: Tacit knowledge represents one of the most strategically significant yet poorly managed resources in knowledge-intensive organisations. Existing research has documented the limits of codification-oriented approaches and the persistence of tacit knowledge problems, but the field lacks an integrated, practice-oriented strategy that connects detection, description, and safeguarding of tacit knowledge into one operational framework supported by information systems. This paper addresses that gap. Drawing on eight semi-structured interviews with senior professionals in knowledge-intensive consulting roles, analysed through qualitative content analysis with abductive logic, the study identifies recurring problems across three core functions: detecting where critical expertise resides; describing tacit and experience-based knowledge in forms that others can understand and reuse; and safeguarding such knowledge when projects end or personnel change. The findings show that organisations do not primarily fail because of missing documentation. The central challenges concern the limited visibility of expertise, the difficulty of making experience-based knowledge communicable without losing its practical meaning, and the fragility of knowledge retention when it is tied to individuals rather than stable organisational structures. Information systems and artificial intelligence can support all three functions, but only when they are aligned with actual work practices and backed by clear governance and ownership. Based on these findings, and grounded in the Knowledge-Based View, Organisational Learning Theory, Sociotechnical Systems Theory, and a Practice-Based Perspective, the study develops a lightweight, information systems-supported knowledge management strategy organised around three conceptual building blocks: Knowledge Hubs, Knowledge Capsules, and workflow-based safeguarding mechanisms, all supported by an enabling digital, governance and motivation layer. The strategy does not aim for complete codification of tacit knowledge but rather for practical and structured support for its detection, description, and safeguarding in everyday organisational work. The paper contributes both an empirically grounded analytical framework and an operationalisable strategy for knowledge-intensive organisations.

Keywords: Tacit knowledge, Knowledge management strategy, Information systems, Detection, Safeguarding, Knowledge hubs

1. Introduction

In knowledge-intensive organisations, competitive advantage depends less on physical assets than on the expertise, judgement, and contextual understanding of employees (Grant, 1996; Davenport and Prusak, 1998). Yet organisations frequently struggle to manage the knowledge that matters most: the tacit, experience-embedded kind that resides in individuals, accumulates through practice, and resists full articulation in documents or systems (Polanyi, 1966; Nonaka and Takeuchi, 1995).

The consequences are well-recognised: critical expertise becomes concentrated in a small number of individuals, knowledge is lost when projects end or people leave, and accumulated insights are rebuilt from scratch each time. These are not marginal inefficiencies. They represent a structural vulnerability that compounds over time, particularly in consulting and professional services contexts where delivery quality depends directly on non-codifiable professional judgement.

Research on knowledge management has documented these problems extensively. What remains less developed is an integrated, practice-oriented strategy that connects the detection, description, and safeguarding of tacit knowledge into one operational framework supported by information systems (IS). This paper addresses that gap.

The study is guided by the following research question: How can organisations address tacit knowledge problems by designing a structured knowledge management strategy, supported by information systems, for the detection, description, and safeguarding of knowledge? To answer this question, the paper draws on eight semi-structured interviews with senior professionals in knowledge-intensive consulting roles, analysed through qualitative content analysis. The findings are translated into a lightweight IS-supported knowledge management strategy built around Knowledge Hubs, Knowledge Capsules, and workflow-based safeguarding, all enabled by a supporting digital, governance, and motivation layer.

The paper makes two contributions. First, it structures tacit knowledge problems around three analytically coherent functions - detection, description, and safeguarding - and shows empirically how each manifests in practice. Second, it translates these findings into a four-component IS-supported strategy comprising Knowledge Hubs, Knowledge Capsules, workflow-based safeguarding routines, and an enabling digital, governance, and motivation layer. Together, these constitute an operationalisable response to a persistent and structurally underaddressed organisational challenge.

2. Background and Theoretical Framework

2.1 Tacit Knowledge and the Limits of Codification

Tacit knowledge, as originally theorised by Polanyi (1966), is knowledge that cannot be fully articulated in formal language. Building on this foundation, Nonaka and Takeuchi (1995) proposed the SECI model - a cycle of socialisation, externalisation, combination, and internalisation - as the central mechanism of organisational knowledge creation, and established the tacit–explicit distinction as the cornerstone of the knowledge management field. In organisational contexts, tacit knowledge manifests as professional judgement, pattern recognition, contextual interpretation, and the practical ability to act appropriately in novel situations (Blackler, 1995; Tsoukas, 2003). It is learned through experience and embedded in practice rather than stored as discrete content.

A central distinction in knowledge management is between codification-oriented approaches, which aim to capture knowledge in reusable artefacts, and personalisation-oriented approaches, which focus on connecting people (Hansen, Nohria and Tierney, 1999). Research has consistently shown that tacit knowledge resists complete codification (Brown and Duguid, 2001; Orlikowski, 2002). Even when knowledge transfer occurs, it frequently encounters what Szulanski (1996) termed internal stickiness: the friction arising from motivational, relational, and absorptive barriers that make replication of best practice difficult even within the same organisation. The implication is that organisations require support mechanisms that go beyond documentation.

2.2 Theoretical Perspectives

This study is guided by four complementary theoretical perspectives. The Knowledge-Based View (Grant, 1996; Spender, 1996) treats knowledge as a strategically important organisational asset and highlights the risks of knowledge concentrated among a small number of individuals and remains difficult for others to identify or access. Organisational Learning Theory (Argyris and Schön, 1978; Crossan, Lane and White, 1999) explains how experience-based learning accumulates and why it remains fragile unless institutionalised through routines and reflection. Sociotechnical Systems Theory (Bostrom and Heinen, 1977) emphasises that organisational outcomes result from the interaction between social practices and information systems, not from technology alone. The Practice-Based Perspective (Orlikowski, 2002; Brown and Duguid, 2001) situates knowledge in action and warns against the assumption that documented knowledge automatically becomes useful.

Together, these perspectives support an analytical focus on detection - making expertise visible; description - representing experience-based knowledge in usable forms; and safeguarding - preserving critical knowledge over time. While individual facets of tacit knowledge management are well-theorised, an integrated IS-supported strategy linking all three functions in a single operational approach remains underdeveloped in the literature.

3. Research Design and Methodology

The study adopts a qualitative, exploratory approach suited to the experience-based and context-dependent nature of tacit knowledge. The empirical research strategy is an exploratory survey, interpreted not as a standardised questionnaire but as a design for identifying recurring patterns across multiple organisational contexts (Johannesson and Perjons, 2021). This approach was selected because the aim was to identify cross-organisational patterns in tacit knowledge problems rather than to examine one organisation in depth.

Data were collected through eight semi-structured interviews conducted in February 2026 via Zoom with experienced professionals knowledge-intensive consulting roles, ranging from consultants to senior leadership roles. Participants were recruited through professional networks on the basis of seniority and sustained experience with knowledge-intensive project work. All interviews were audio-recorded with informed consent, transcribed using Whisper (OpenAI), and anonymised prior to analysis. Interview duration ranged from 40 to 60 minutes. The interview guide was organised around five thematic areas: locating critical expertise; sharing

experience-based knowledge; knowledge loss across project transitions; the role of information systems and AI; and organisational conditions for knowledge sharing.

The transcripts were analysed using qualitative content analysis with abductive logic (Mayring and Brunner, 2010; Timmermans and Tavory, 2012). Abductive logic guided an iterative movement between the empirical material and existing theoretical frameworks: patterns identified in the data were compared with and refined by theory, while theory was in turn re-examined in light of what the data revealed. This approach avoids both pure induction and pure deduction. Meaning units were identified in the transcripts, condensed into codes, grouped into categories, and organised into five higher-order themes: (1) Visibility of critical knowledge and expertise; (2) Externalisation and practical transfer of experiential knowledge; (3) Safeguarding knowledge across projects and personnel change; (4) Organisational conditions for knowledge sharing and learning; and (5) Information systems and AI as knowledge management infrastructure. These themes were subsequently interpreted through the three core analytical functions of detection, description, and safeguarding, which structure the findings reported below.

4. Empirical Findings

4.1 Visibility of Critical Knowledge and Expertise

Across all eight interviews, participants described the limited visibility of critical expertise as a fundamental organisational challenge. Relevant know-how was present within the organisation but not sufficiently transparent beyond the individuals who held it. Employees regularly relied on informal contacts, prior experience, and personal networks to identify who knew what - consistent with transactive memory theory, which holds that in the absence of formal structures, individuals rely on shared meta-knowledge about who possesses what expertise (Wegner, 1987). Formal structures such as organisational charts or role descriptions were widely described as inadequate guides to actual expertise.

Critical knowledge was consistently concentrated in a small number of people, particularly in specialised domains or thinly staffed areas. This concentration only became fully visible when disruptions occurred. The consequences were captured by one participant:

> *"No one remembers because it was never properly prepared."*

From a Knowledge-Based View perspective, this reflects a structural risk, since organisational performance depends on the coordination of specialised knowledge that formal structures fail to surface (Grant, 1996).

4.2 Externalisation and Practical Transfer of Experiential Knowledge

All eight participants described tacit knowledge as inherently difficult to articulate in reusable form. Rather than following fixed procedures, their work required contextual judgement, pattern recognition, and situational adaptation - consistent with the limits of externalisation identified in the SECI model (Nonaka and Takeuchi, 1995) and with Szulanski's (1996) observation that the tacitness of the source is itself a primary source of knowledge transfer stickiness.

The interviews consistently pointed to practice-based transfer as the most effective learning mechanism. As one participant put it plainly:

> *"The rest is learning by doing."*

When describing what could be shared, participants consistently preferred examples, heuristics, models, and demonstrations over abstract explanations. Documentation was seen as useful but limited when it lacked context, was outdated, or was fragmented across repositories.

4.3 Safeguarding Knowledge across Projects and Personnel Change

Project closure routines were repeatedly described as inadequate, inconsistent, or largely absent. Walsh and Ungson (1991) describe this as a failure of organisational memory: the inability to retain, retrieve, and apply experience accumulated through prior action. Seven out of eight participants reported that the departure or absence of a single individual had created visible disruptions. As one participant stated:

> *"When that person leaves, the knowledge leaves with them."*

Existing safeguarding measures - archived materials, shared repositories, onboarding documents - were described as present but inconsistent in quality and heavily dependent on local initiative. The problem was not

that nothing was preserved, but that preserved knowledge was often hard to find, outdated, or disconnected from the work contexts in which it would be needed.

4.4 Information Systems and AI as Knowledge Management Infrastructure

Digital tools were described as necessary but insufficient. Repositories, SharePoint environments, and Teams folders were widespread, yet participants frequently bypassed formal systems in favour of informal workarounds. As Alavi and Leidner (2001) argue, information systems support knowledge management only when they are aligned with the knowledge processes they are intended to support. The core barrier was not missing technology but fragmentation, poor curation, and insufficient alignment with actual work practices (Bostrom and Heinen, 1977).

AI-supported tools were viewed with cautious optimism. One participant reflected:

> *"Perhaps AI will help us more in the future."*

Organisational conditions - particularly time pressure, weak incentives, and unclear ownership of knowledge maintenance - were identified as pervasive and cross-cutting barriers that undermined detection, description, and safeguarding alike. The findings from the interviews are summarised in Table 1

Table 1: Summary of key findings by analytical function

Analytical function	Core finding
Detection	Expertise is invisible through formal structures; detection depends on informal networks and transactive memory.
Description	Critical knowledge is experience-based and resistant to codification; context-rich forms are most effective.
Safeguarding	Organisational memory is fragile; project closure and turnover routinely trigger knowledge loss.
IS and AI support	Systems are necessary but insufficient; fragmentation and misalignment undermine usefulness.
Organisational conditions	Time pressure, weak ownership, and limited incentives impair all three analytical functions.

5. The Proposed IS-Supported Knowledge Management Strategy

5.1 From Findings to Design Requirements

The empirical findings reveal that tacit knowledge problems cannot be resolved through better documentation alone. They require structured support for making expertise visible (detection), representing knowledge in forms that preserve practical meaning (description), and embedding knowledge in stable structures that outlast individual tenures and project cycles (safeguarding). Table 2 maps each analytical function to its corresponding design requirement.

Table 2: From empirical findings to design requirements

Analytical function	Core finding	Design requirement
Detection	Expertise invisible beyond personal networks	Structured, navigable expertise visibility across domains
Description	Tacit knowledge resists codification; context-rich forms preferred	Short, context-embedded knowledge artefacts with heuristics
Safeguarding	Knowledge lost at project closure and departure	Preservation embedded in predictable workflow transitions

Analytical function	Core finding	Design requirement
Cross-cutting	Fragmentation, weak incentives, unclear ownership	Governance layer, digital support, and participation incentives

5.2 Strategy Components

Figure 1 presents the proposed IS-supported knowledge management strategy as an integrated framework. The strategy is built around three operational components - Knowledge Hubs, Knowledge Capsules, and workflow-based safeguarding - each directly addressing one of the three core analytical functions, and all supported by a shared enabling layer.

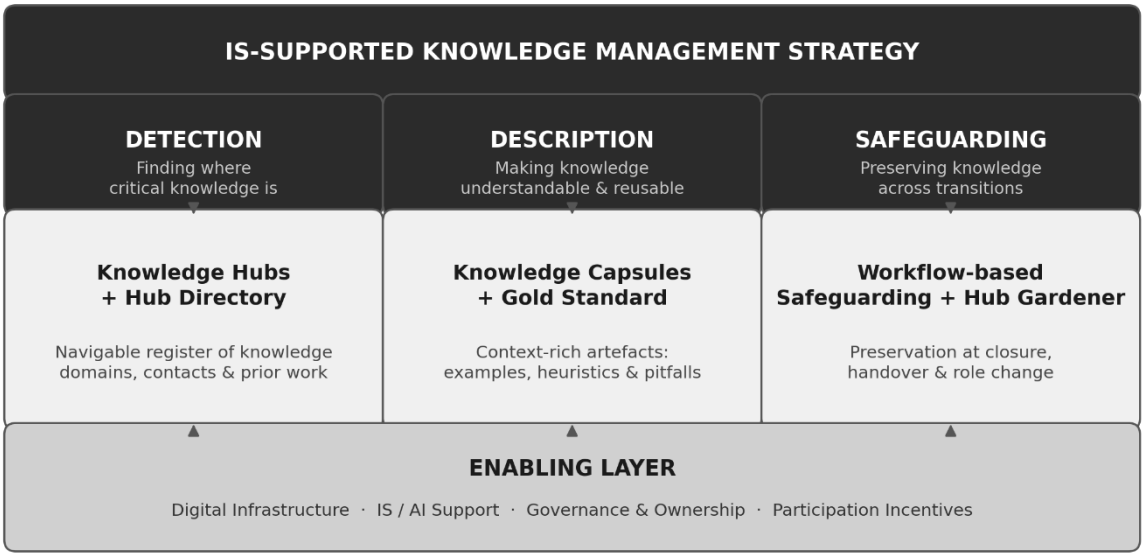


Figure 1: The proposed IS-supported knowledge management strategy

Knowledge Hubs are persistent, topic-based knowledge domains maintained within existing organisational systems. Each Hub covers an area of strategic relevance - for example, a specific service line, recurring project type, or high-dependency domain. Conceptually, the Knowledge Hub draws on the logic of communities of practice (Wenger, 1998): it creates a shared domain around which expertise and practice can be made visible and navigable. The Hub Directory offers a navigable overview across all active Hubs, reducing dependence on personal familiarity and informal networks. Each Hub is maintained by a designated Hub Gardener - a person responsible for keeping the domain current, removing outdated content, and linking new knowledge at key transition points.

Knowledge Capsules are short, structured knowledge objects designed to make experience-based knowledge communicable without reducing it to decontextualised documentation. Each Capsule follows a fixed template covering: the problem or situation context; the approach applied; key heuristics or rules of thumb; typical pitfalls; links to relevant artefacts or prior examples; and the person or role that can provide further clarification. A Gold Standard Capsule in each Hub serves as a reference example for new contributors.

Workflow-based safeguarding embeds knowledge preservation in the moments when knowledge is most at risk of being lost: project closure, handover, onboarding, role change, and departure. At these transition points, relevant Hubs and Capsules are reviewed, updated, and supplemented - making safeguarding a continuous organisational routine rather than a periodic initiative.

The enabling layer supports all three components through lightweight digital infrastructure - searchable Hub pages, AI-assisted retrieval and summarisation, structured Capsule templates - combined with clear governance through the Hub Gardener role and visible recognition of knowledge contributions.

Table 3: Strategy components and correspondence to design requirements

Component	Addresses
Knowledge Hubs + Hub Directory	Detection: making expertise and prior work visible across the organisation.
Knowledge Capsules + Gold Standard	Description: representing experience-based knowledge in usable, context-rich forms.
Workflow-based safeguarding + Hub Gardener	Safeguarding: preserving knowledge at moments of likely loss; maintaining usability over time.
Enabling digital, governance and motivation layer	Cross-cutting: digital infrastructure, AI support, role clarity, incentives, alignment with work routines.

5.3 Theoretical Position of the Strategy

The strategy integrates codification and personalisation logics rather than treating them as alternatives (Hansen, Nohria and Tierney, 1999). Knowledge Hubs reflect personalisation logic: their aim is not to codify exhaustively but to make expertise navigable. Knowledge Capsules represent selective codification: context-rich artefacts that capture enough practical meaning to support reuse, while acknowledging the limits of full formalisation (Tsoukas, 2003). Workflow-based safeguarding reflects the Organisational Learning perspective that knowledge becomes durable when embedded in routines and practices (Crossan, Lane and White, 1999). The enabling layer embodies a sociotechnical understanding in which digital infrastructure, governance, and participation must be aligned (Bostrom and Heinen, 1977).

6. Discussion

The findings and the proposed strategy converge on a key insight: the central challenge in managing tacit knowledge is not that knowledge is absent, but that it is insufficiently visible, communicable, and durable in organisational terms. This reframes the problem away from documentation gaps toward structural and sociotechnical conditions that shape whether critical knowledge can be found, shared, and retained across transitions.

From the perspective of the Knowledge-Based View, the strategy responds to the risk that specialised, unevenly distributed knowledge creates: by making knowledge domains and key expertise more navigable, it reduces the vulnerability associated with knowledge concentration (Grant, 1996). From an Organisational Learning perspective, workflow-based safeguarding operationalises the institutionalisation of experience in a way that does not depend on exceptional individual initiative (Argyris and Schön, 1978; Crossan, Lane and White, 1999). The Practice-Based Perspective justifies the design of Capsules as context-rich rather than comprehensive artefacts (Orlikowski, 2002). The Sociotechnical perspective underpins the enabling layer: technology alone does not resolve tacit knowledge problems; governance, ownership, and practical fit are equally necessary (Bostrom and Heinen, 1977).

The role of AI in this strategy is deliberately bounded. AI-assisted search, retrieval, and summarisation can strengthen detection and support initial Capsule drafting. However, the interpretation of experience-based knowledge, the curation of Hubs, and the judgement required to determine what is worth preserving remain human responsibilities. This is consistent with the empirical finding that participants viewed AI as a promising but not yet mature support tool.

The strategy has practical implications beyond consulting contexts. Knowledge-intensive work - characterised by distributed expertise, project-based delivery, and time pressure - is increasingly prevalent across sectors including professional services, public administration, research, and technology. The three-function framework and the strategy components are sufficiently generic to be adapted across these settings, provided that governance mechanisms are calibrated to the specific organisational conditions encountered.

7. Conclusions and Future Research

This paper has argued that tacit knowledge management in organisations requires more than better documentation. It requires structured support for detecting where critical expertise resides, describing it in forms that preserve practical meaning, and safeguarding it across the transitions that characterise knowledge-

intensive work. The proposed IS-supported strategy - built around Knowledge Hubs, Knowledge Capsules, and workflow-based safeguarding - is grounded in eight qualitative interviews and in four complementary theoretical perspectives. It offers a lightweight, operationalisable response to a persistent organisational challenge.

The study has limitations. The empirical basis is a focused qualitative sample from consulting-oriented contexts. The strategy has not yet been implemented and tested. The findings cannot be generalised statistically, though they support analytical transferability to similar knowledge-intensive settings.

Future research could test the strategy in organisational practice and examine its effects on knowledge continuity, onboarding effectiveness, and reuse over time. A particularly promising direction concerns the role of AI in supporting expert location, contextual retrieval, and reconstruction of fragmented project knowledge. Further work could also investigate how the relative importance of detection, description, and safeguarding varies across different organisational types and scales.

Acknowledgements

The authors would like to thank all interview participants for their time and candour. This paper is derived from a Master's thesis submitted to the Department of Computer and Systems Sciences, Stockholm University, in May 2026.

Ethics Declaration: This study involved semi-structured interviews with professionals in knowledge-intensive roles. Informed consent was obtained verbally prior to each interview, and participants were informed of their rights, including the right to withdraw at any time without consequence. All recordings and transcripts were anonymised and stored with restricted access on the researcher's local device. No personally identifying information appears in this paper. Ethical clearance was not formally required under the guidelines of Stockholm University for this type of qualitative research, but all procedures followed the core principles of voluntary participation, confidentiality, and responsible data handling. Data will be deleted following assessment.

AI Declaration: AI-based tools were used in a supporting capacity during the preparation of this paper. Interview transcription was performed using Whisper (OpenAI). Language refinement and structural consistency checks during the thesis writing phase were supported by ChatGPT (OpenAI), DeepL, and Microsoft Copilot. The adaptation of thesis content into this conference paper, including the development of arguments, interpretation of empirical findings, and design of the proposed strategy, was carried out by the first author. All AI-generated suggestions were reviewed and revised against the empirical material and the manually developed analytical structure. Claude (Anthropic) was used as an AI tool to assist in the formatting and drafting of this conference paper version, under the first author's direction and oversight.

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Adapting InCaS as an Acceleration Architecture for Emerging Organisations: A Work-in-Progress Report

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Abstract: This paper reports on an ongoing research project investigating the adaptation and digital operationalisation of the InCaS (Intellectual Capital Statement) method as an acceleration architecture for emerging, knowledge-based organisations. The research is being conducted within the Impacta Júnior programme, a structured acceleration initiative promoted by Concentro and funded by the Coalizão pelo Impacto, involving ten university-based junior enterprises as the empirical field. The paper presents the theoretical grounding, the methodological design, and the full InCaS application process as implemented in this context, together with preliminary insights drawn from the first application cycle. The adapted process encompasses nine sequential stages, beginning with organisational pre-arrangement and business modelling, followed by intellectual capital factor identification, Quality-Quantity-Systematics (QQS) evaluation, and impact analysis. These stages feed into intervention potential mapping, indicator definition through Key Performance Indicators (KPIs), and structured strategic action planning, culminating in a pitch-based Demo Day as the final output. A purpose-built digital platform was developed to support this process at scale, enabling anonymised multi-stakeholder participation, automated composite scoring, and real-time visualisation of results. Twenty-four management factors were derived from organisational listening sessions and mapped across the three intellectual capital dimensions, using simplified terminology adapted to low-maturity organisational contexts. Early observations indicate that the adapted method fosters structured organisational self-reflection, makes latent knowledge gaps more visible, and encourages collective deliberation processes, even in organisations with limited prior exposure to formal management practices. Recurring challenges were observed in areas such as KPI definition, prioritisation of strategic factors, and the consolidation of shared organisational understanding. Full empirical analysis, including systematic pre-post comparisons of organisational maturity and longitudinal assessment of development trajectories, remains underway. The study contributes a documented and replicable model for adapting the InCaS method to acceleration environments, demonstrates the feasibility of its digital operationalisation, and offers initial evidence of its applicability for practitioners, programme designers, and policymakers working with knowledge-intensive and resource-constrained organisations.

Keywords: Intellectual capital, InCaS, Business acceleration, Intangible assets, Organisational development, Knowledge management

1. Introduction

The growing strategic significance of intangible assets in knowledge-based economies has generated sustained scholarly interest in frameworks capable of making intellectual capital (IC) visible, measurable, and actionable at the organisational level. While macro-level evidence for the positive relationship between IC intensity and economic growth is well established (Gashe, Sime and Mada, 2024), the translation of this evidence into operational tools for organisations with limited management maturity remains a persistent challenge. Small and emerging organisations, particularly those embedded in university ecosystems, frequently possess substantial knowledge potential that remains structurally unrecognised and therefore strategically underutilised.

The Brazilian policy context sharpens this concern. The Nova Industria Brasil (NIB) Action Plan 2024-2026 treats intangible assets as structural vectors of national competitiveness (Brasil, 2024, p. 11), whilst instruments such as FINEP have expanded towards scientific infrastructure and enterprise capacity-building (FINEP, 2024), creating institutional demand for methodological tools capable of supporting IC management in resource-constrained organisations.

Against this backdrop, this paper reports on an ongoing research project adapting the InCaS method as a structured acceleration architecture within the Impacta Junior programme, targeting ten university-based junior enterprises in Brazil. Originally developed by the European Commission for application in SMEs across five countries (Mertins, Wang and Will, 2009), InCaS offers a rigorous yet flexible process for identifying, evaluating, and communicating IC across Human, Structural and Relational Capital dimensions. Its documented applicability in diverse national contexts, including prior Brazilian pilots (Sequeira et al., 2013), makes it a theoretically grounded candidate for methodological adaptation.

The central research question is: how can the InCaS method be adapted and digitally operationalised as a viable acceleration architecture for emerging organisations with low management maturity, and what preliminary evidence can be drawn from an initial empirical application? Three contributions are advanced: a systematic and replicable methodological adaptation of InCaS to a low-maturity acceleration context, including a 24-factor

management model grounded in organisational listening; a purpose-built digital platform that operationalises IC assessment at scale; and actionable design principles for programme developers and policymakers integrating structured IC management into enterprise development instruments.

The paper details the adapted process, the digital infrastructure developed to support it, and preliminary observations from the initial application cycle.

2. Theoretical Background

2.1 Intellectual Capital

Edvinsson and Sullivan (1996) define intellectual capital as knowledge that can be converted into value, a framing that extends well beyond legally protected intellectual property to encompass tacit capabilities, formalised knowledge systems, and relational assets. This conception evolved into the tripartite structure now widely adopted: Human Capital (HC), Structural Capital (SC), and Relational Capital (RC), endorsed by the Danish Ministry of Science (2003), the Fraunhofer Institute (2004), and the European Commission (2008).

A critical evolution in IC scholarship has been the shift from classificatory to process-oriented perspectives. Demartini and Paoloni (2013) argue that IC should be understood through its functionality in organisational processes rather than as a static inventory of resources. Kujansivu and Lonnqvist (2007) that IC management is most effective when embedded within, rather than appended to, the processes through which knowledge is created, shared, applied, and institutionalised. This functional orientation directly shapes the methodological choices documented in this paper, particularly the reframing of IC dimensions as organisational process axes.

Mouritsen and Larsen (2005) offer a further conceptual anchor, arguing that IC measurement cannot be presented as sufficient for value creation in isolation. Measurement must serve as an input to managerial action, supporting interventions in the actual processes through which knowledge is developed and applied. This distinction between IC reporting and IC management is central to the design logic of the adapted InCaS approach presented here.

2.2 The InCaS Method

Understanding what intellectual capital is, and how it can be structured and managed, is the necessary starting point for the methodological contribution this paper advances.

The InCaS method emerged from a European Commission-funded initiative involving more than 120 SMEs across Germany, Spain, France, Poland, and Slovenia (Mertins, Wang and Will, 2009), drawing on the German Wissensbilanz framework and Danish IC reporting guidelines (Mouritsen et al., 2003). The synthesis offers a process individualisable for internal management whilst remaining standardised enough to support external benchmarking (European Commission, 2008).

The method structures IC analysis across three capital dimensions. Human Capital covers what individual employees contribute to value-generating processes, encompassing technical competences, tacit knowledge, motivation, and learning capacity. Structural Capital refers to the organisational residue of knowledge: processes, information systems, culture, routines, and intellectual property that persist independent of individual tenure. Relational Capital captures the organisation's external relationships, including clients, suppliers, strategic partners, and research institutions. The method's process logic moves from business modelling through factor identification, assessment, impact analysis, and indicator definition, culminating in an Intellectual Capital Statement as the formal output.

In Brazil, the first pilot applications were conducted by Sequeira et al. (2013) in ten SMEs in the oil and gas sector. That experience demonstrated that the method's conceptual integrity can survive significant procedural adaptation, establishing a precedent for context-sensitive appropriation that has informed subsequent applications in innovation institutes and technology-based firms (Mota, 2014; Motta and Gomes, 2014; Prim, 2022). The present study extends this lineage to a new context: university-based junior enterprises undergoing structured acceleration.

3. Research Design

This study is positioned within the design science research (DSR) tradition (Hevner et al., 2004), which treats the development and evaluation of purposeful artefacts as its primary mode of knowledge contribution. The research produces and evaluates two utility-driven outputs: an adapted methodological framework and a supporting digital platform, assessed in terms of their fitness for purpose in a low-maturity acceleration context.

The unit of analysis is the individual junior enterprise as an organisational participant in a structured acceleration programme. Ten organisations constitute the empirical field, drawn from the second cycle of the Impacta Junior programme promoted by Concentro and funded by Coalizao pelo Impacto. The two-cycle structure was a deliberate methodological choice, enabling an observational phase in the first cycle and a controlled application phase in the second.

Data collection draws on multiple sources: field observation during the first cycle for qualitative profiling; secondary data from Concentro (session transcripts, performance reports, satisfaction assessments) for model calibration; and primary data from the application phase through the platform's anonymous voting records, consensus deliberations, KPI selections, and Demo Day scores, currently undergoing comparative pre-post and cross-case analysis.

The research unfolded across eight stages: bibliographic review; first-cycle field observation; platform development; usability testing; InCaS application; data analysis (ongoing); preparation of a Technical Conclusive Report; and academic dissemination. This paper reports primarily on Stages 1 through 5, with preliminary observations from Stage 6 in Section 5.

3.1 First-Cycle Field Observation

During the first acceleration cycle, the researcher participated in a non-interfering, observational capacity, documenting data from secondary sources made available by the programme organisers. These included session transcripts, testimony compilations, internal performance reports, and satisfaction assessments. The observation phase revealed a consistent pattern of low organisational repertoire across participants: limited familiarity with strategic management concepts, sparse use of formal processes, and low baseline awareness of intellectual capital. These findings directly shaped vocabulary, sequencing, and scaffolding decisions in the subsequent InCaS adaptation.

3.2 Digital Platform Development

A purpose-built platform was developed to operationalise the adapted InCaS method at the scale and pace required by the programme. Its architecture adopted a hybrid approach: a no-code front-end for rapid iteration and a custom-coded back-end for data flexibility and control, with dynamic spreadsheets as the computational substrate for scoring and reporting. Core functionalities included a general organisational dashboard, individual company pages with member management, anonymised multi-stakeholder voting, and automated calculation of QQS scores, impact rankings, and intervention potential matrices. Usability testing with the researcher's own enterprise and a simulated participant enterprise preceded live deployment, with identified improvements logged for future iteration.

4. The Adapted InCaS Application Process

The application followed the structure proposed by the European ICS Guideline (European Commission, 2008) with respect to core stages and analytical logic. Adaptations were introduced in data collection, scoring, output design, and vocabulary, each documented below with its underlying rationale. The process unfolds across nine stages, from initial onboarding through to the final Demo Day presentation.

4.1 Stage 0: Organisational Pre-arrangement

Prior to substantive engagement, selected organisations registered on the programme platform and designated a primary and secondary representative for organisational liaison. The primary representative received administrative access and was tasked with enrolling all company members. Only registered members were eligible to participate in subsequent voting stages. Inclusive enrolment across functional areas and hierarchical levels was actively encouraged, reflecting the InCaS principle that IC analysis gains diagnostic validity from capturing multiple organisational perspectives simultaneously.

4.2 Stage 1: Business Modelling

Each organisation completed a structured organisational profile encompassing four dimensions: (i) business model, describing how the company creates, delivers, and captures value; (ii) solutions portfolio, detailing current services or products; (iii) strategic objectives, covering short- and medium-term goals; and (iv) organisational maturity level, assessed through a self-report instrument designed and administered by Concentro. This instrument comprised three thematic blocks: life stage and strategic situation (degree of value proposition definition and formal planning); managerial and cultural capacity (leadership practices, process formalisation, and cultural characteristics); and absorption and learning capacity (openness to innovation and

organisational learning mechanisms). The resulting maturity profiles served as the analytical baseline against which post-programme development would subsequently be assessed.

4.3 Stage 2: IC Factor Identification

The 24 management factors used in this study were derived from AI-assisted analysis of first-cycle session transcripts conducted by Concentro, which identified 24 recurrent themes in participants' organisational discourse. These themes were condensed into management factor nomenclature and reframed, following Kujansivu and Lonnqvist (2007), as organisational processes distributed across the three IC dimensions. To reduce conceptual friction for participants with limited management experience, the HC-SC-RC taxonomy was relabelled as People, Processes, and Relations. Each dimension was subdivided into two thematic axes, each containing four factors, producing the model detailed in Table 1.

Table 1: Management Factors Derived from Organisational Listening Sessions

Dimension	Axis	Management Factors
People (Human Capital)	Talent	Competency Management; Leadership Development; Talent Attraction and Retention; Succession Planning
People (Human Capital)	Culture	Innovative Environment; Organisational Climate; Internal Engagement; Decision Architecture
Processes (Structural Capital)	Operations	Portfolio Management; Performance Indicator Monitoring; Technological Maturity; Compliance
Processes (Structural Capital)	Knowledge	Intellectual Property; Organisational Learning; Knowledge Transfer; Information Infrastructure
Relations (Relational Capital)	Partnerships	Engagement Strategy; Process Integration; Demand Management; Relationship Protocols
Relations (Relational Capital)	Positioning	Sustainability; Institutional Narrative; Reputation and Image; Results Transparency

An onboarding session introduced all ten organisations and their registered members to the programme, the InCaS framework, and the 24 factors. Following the presentation, participants gathered in virtual breakout rooms to collaboratively select the nine factors most relevant to their organisational reality. The restriction to nine factors was a technical constraint of the platform architecture, designed to maintain analytical uniformity across organisations. Unlike the original European methodology, proportional selection across the three dimensions was not required, given the programme's emphasis on practical organisational strengthening rather than formal IC statement preparation.

4.4 Stage 3: QQS Evaluation

The first individual mentoring session assessed each of the nine selected factors along three criteria: Quality (the calibre of the factor's current state), Quantity (volume or availability of the resource), and Systematics (degree of formalisation and routine management). Each registered member voted independently through the platform using a four-point percentage scale: 0% (not sufficient), 30% (partially sufficient), 60% (predominantly sufficient), and 90% (absolutely sufficient). This replaced the original visual card system (coloured facial expressions) with a numerical scale, chosen for its reduced cognitive load and greater compatibility with the digital interface.

Where significant inter-voter discrepancies emerged, participants responsible for extreme assessments were invited to justify their positions. Structured deliberation followed, with consensus sought on whether initial scores required revision. Argumentation summaries were recorded separately for each QQS criterion, ensuring traceability. The platform then calculated improvement potential as the arithmetic mean of QQS scores per factor, expressing the gap between the mean and 100 as the available developmental space. This figure became the first axis of the subsequent intervention potential analysis.

The consensus-building element of this stage warrants particular note. It was embedded intentionally as a developmental mechanism, not merely a data-reconciliation procedure. By requiring teams to articulate and defend divergent assessments, the process generates precisely the kind of deliberative self-analysis that

Mouritsen and Larsen (2005) argue must accompany IC measurement if it is to serve managerial intervention rather than mere classification.

4.5 Stage 4: Impact Analysis

The second mentoring session addressed the relative strategic importance of each selected factor. Drawing on the simplified version of this stage (European Commission, 2008, pp. 31-32), each registered member ranked the nine factors on a scale of 1 to 9, with 9 denoting the factor of greatest perceived contribution to the organisation's strategic objectives. The platform computed mean weights across all voters and ranked factors in descending order of perceived impact. This ranking constituted the second axis feeding into the intervention potential matrix.

4.6 Stage 5: Intervention Potential Matrix

The third mentoring session synthesised the QQS improvement potential and impact scores into an intervention potential composite for each factor, visualised as a two-dimensional matrix. Factors located in the high-potential, high-impact quadrant were identified as priority intervention points. The session opened a structured dialogue on the coherence of results and any unexpected patterns. Three or four factors with the highest composite scores were then examined in relation to the organisation's business model and strategic objectives, not to revise them, but to clarify how these priority factors interact with existing strategic commitments. This stage functioned simultaneously as an analytical consolidation and an organisational learning exercise.

4.7 Stage 6: Indicator Definition and the Personalised Development Plan

The original InCaS methodology recommends defining indicators for at least 50% of priority factors. Given that systematic performance monitoring was not institutionalised in any participating organisation, this research restricted indicator definition to three or four factors from those identified as highest-priority in the intervention potential analysis. The fourth mentoring session introduced the concept of Key Performance Indicators (KPIs) and their distinction from targets, illustrating their articulation with Objectives and Key Results (OKRs) through worked examples. Methodologically, the study departed from the European specification by decoupling indicator selection from the residual intervention potential scores. Rather than requiring KPIs to correspond directly to the gap between observed and maximum QQS values, indicators were selected according to the criteria of comprehensibility, applicability, and local verifiability. Intervention potential scores guided which factors to prioritise; they did not determine which metrics to adopt. Teams registered their collective decisions in the Personalised Development Plan (PDP), a structured planning instrument formalising the organisational commitment to monitoring priority management factors.

4.8 Stage 7: Strategic Refinement and Action Planning

The fifth mentoring session invited organisations to specify the actions, projects, or initiatives they intended to implement in pursuit of the targets defined for priority factors. Building on the PDP completed in the preceding session, teams formulated proposals with defined objectives, responsibilities, timelines, and expected outcomes. Deliberations centred on feasibility, with reflection prompted on available resources, implementation complexity, and realistic timelines. Beyond producing formal action plans, the session aimed to strengthen what might be understood, following Zahra and George (2002), as the organisations' absorptive capacity: their ability to identify, assimilate, and apply knowledge to operational and strategic purposes. An emergent and significant dimension of this stage was the conversation it opened about coherence between internal processes and external positioning. As teams revisited their priority factors and established indicators, the relationship between organisational capabilities and the value proposition communicated to clients and partners became a recurring subject of reflection. This connection between internal IC development and external strategic identity, whilst unplanned, proved a consistent feature across multiple organisations, suggesting that the InCaS process may generate strategic self-awareness effects that extend beyond the immediate diagnostic objectives.

4.9 Stage 8: Demo Day

The final output of the adapted methodology replaced the traditional InCaS Intellectual Capital Statement with a pitch-format institutional development presentation, delivered at a closing Demo Day event. Organisations completed the PDP as an internal synthesis document and prepared a public presentation of up to seven minutes, covering their programme journey, learnings, and strategic priorities. An evaluation panel of professionals experienced in operations management and business development assessed each presentation on six criteria rated from 1 to 5, as detailed in Table 2.

Table 2: Demo Day Evaluation Criteria

Criterion	Description	Evaluative Focus
1. Context and Problem Clarity	Presentation of initial challenges and rationale for participation	Capacity to contextualise the prior situation, articulate difficulties, and justify programme engagement as a strategic response
2. Strategy and Prioritisation	Coherence in priority definition and results measurement	Clarity in strategic focus, methodological consistency in KPI use, and feasibility of action plans
3. Results and Internal Impact	Alignment with mission and transformation potential	Realism of expectations, adherence to organisational values, and potential impact on the business model
4. Social-Environmental Impact	Articulation between internal practices and external impact	Coherence between institutional discourse and practice; positioning potential as a social and environmental impact business
5. Presentation Quality	Clarity, narrative structure, time management	Command of oral communication, logical organisation, and emphasis on key contributions
6. Feasibility and Execution	Viability of proposed actions and implementation capacity	Factibility of presented strategies and medium-to-long-term sustainability of solutions

The Demo Day served a dual purpose. At the individual level, it provided each organisation with a structured opportunity to externalise and consolidate their developmental narrative. At the programme level, it created a shared moment of cross-organisational learning and mutual accountability. The choice to replace the formal IC Statement with this format reflects a deliberate trade-off: some of the rigour of traditional IC reporting was sacrificed in favour of accessibility, communicability, and fit with the acceleration programme's cultural logic. This trade-off is explicitly framed as an adaptation rather than a simplification, and its implications are examined further in Section 6.

5. Preliminary Insights and Expected Outcomes

Data collection was completed in early 2026, and comprehensive analysis is currently underway. The observations reported below are preliminary, drawn from qualitative review of platform records, mentoring session notes, and Demo Day assessments. They should be read as initial evidence, subject to revision as formal analysis proceeds, rather than as validated findings. Longitudinal follow-up with participating organisations is planned to assess the persistence of effects over time.

5.1 Preliminary Observations from the Application

A first observation concerns the near-universal absence of prior KPI culture. Across all ten organisations, teams consistently conflated KPIs with activities rather than outcomes, requiring repeated re-anchoring. This aligns with entry-level maturity baselines and suggests the indicator definition stage may require more robust scaffolding in future programme designs.

A second observation concerns patterns in factor prioritisation. People-dimension factors, particularly Internal Engagement and Organisational Climate, received disproportionately high priority selections, whilst Structural Capital factors were systematically less chosen. This raises the question of whether selection patterns reflect genuine strategic diagnosis or factor salience, a dimension being examined in the current analysis.

A third observation concerns the effects of consensus-based QQS deliberation. Significant divergence between individual votes prompted substantive internal debates that would not otherwise have occurred. Participants from different functional areas expressed markedly different perceptions of the same factor, and the process of negotiating these differences generated what might be characterised as an organisational learning event: surfacing tacit knowledge and building shared representations. This was observed across multiple organisations and represents one of the most potentially valuable findings of the initial application.

A fourth observation concerns the intervention potential matrix and strategic coherence. Several organisations expressed surprise at the gap between high-impact and well-developed factors, and the visualisation of this gap prompted reflection on misalignments between ambition and capacity. Several teams spontaneously revised

their strategic objectives in light of these insights, suggesting the matrix operates as a strategic provocation as much as a diagnostic tool.

A fifth observation concerns differentiation across organisations. Despite the sample's homogeneity, substantial variation was observed in factor selections, QQS profiles, and intervention rankings, indicating that the adapted process captures genuine organisational differences rather than producing uniform outputs and underscoring its value as a personalisation mechanism.

5.2 Expected Outcomes Pending Full Analysis

The primary expected finding is a measurable increase in management maturity, with organisations at entry-level classifications anticipated to show advancement in strategic clarity, routine institutionalisation, and learning capacity, alongside more systematic recognition and articulation of the intangible assets underpinning their operations. A secondary expected outcome concerns self-positioning as impact organisations. The integration of social-environmental criteria in both the action planning and Demo Day stages, combined with the method's emphasis on coherence between internal processes and external value propositions, may encourage a proportion of participants to reframe their strategic identities around impact-oriented objectives. Whether and to what extent this reframing is observed will be a substantive dimension of the forthcoming analysis.

6. Discussion

Three claims are now sufficiently grounded to be substantively discussed ahead of complete empirical analysis.

The first concerns methodological flexibility. The InCaS framework's tripartite capital model proved robust enough to sustain significant procedural adaptation without losing its analytical coherence. The relabelling of dimensions as People, Processes, and Relations, the substitution of the visual card system with a percentage scale, the replacement of the IC Statement with a PDP and a Demo Day, and the decoupling of KPI selection from residual intervention potential scores all represent departures from the European specification. Yet across all nine stages, the method's core logic, moving from strategic context through IC diagnosis to prioritised action, remained intact. This resilience extends and confirms observations from prior Brazilian applications (Sequeira et al., 2013; Mota, 2014), whilst adding new evidence from a qualitatively different organisational context characterised by lower maturity and a digital-first delivery mode.

The second concerns the digital platform's contribution to IC operationalisation. Traditional IC assessment has been labour-intensive, consultant-dependent, and difficult to scale. The platform addresses each of these constraints: simultaneous multi-organisation application, anonymised participation reducing social desirability bias, automated composite scoring, and real-time transparency for all members collectively expand the addressable population for IC-based acceleration. The platform may function not only as an operational tool but as an institutional infrastructure capable of supporting ongoing IC assessment across programme cycles.

The third, and perhaps the most theoretically significant contribution, concerns the developmental function of the method itself. The preliminary observation that consensus-building in the QQS stage generates organisational learning effects (see Section 5.1) connects to a body of literature on absorptive capacity (Zahra and George, 2002) and on the conditions under which IC information enables rather than merely documents organisational knowledge. Mouritsen and Larsen's (2005) argument that IC measurement must serve as a managerial input, not a reporting output, finds empirical traction in the observation that the structured deliberation required by the adapted InCaS process surfaces tacit disagreements, builds shared organisational language, and generates the kind of collective self-knowledge that precedes purposeful strategic action. The method, in this reading, is not only a diagnostic instrument but a vehicle for organisational learning.

The consistent difficulty in distinguishing indicators from activities suggests that a minimum threshold of prior management vocabulary may be a prerequisite for effective IC management, pointing to a design implication that the ongoing analysis is expected to clarify. Limitations include the small and homogeneous sample, the absence of a control group, and the researcher's dual role as facilitator and investigator, managed through non-interference protocols. These constrain generalisation without undermining the methodological contribution or the theoretical interest of the preliminary observations.

7. Conclusions and Research Status

This paper has presented a work-in-progress account of an ongoing research project adapting the InCaS method as a structured acceleration architecture for emerging knowledge-based organisations. The nine-stage adapted

process has been fully implemented with ten junior enterprises and initial evidence drawn from the application cycle supports three substantive contributions: a replicable methodological adaptation of a rigorously designed IC framework to a low-maturity context; a digital platform demonstrating that IC assessment can be delivered at scale; and preliminary evidence that the method generates organisational learning effects meaningful even in organisations with no prior IC management experience.

Full empirical results and longitudinal follow-up are underway, with the methodological model and platform being prepared for application in other acceleration contexts to generate comparative evidence on portability. The study's implications extend to practitioners, policymakers and IC researchers alike: it provides a replicable process model integrating IC diagnosis with developmental facilitation, evidence that IC-based acceleration is feasible and scalable, and preliminary indication that the method's developmental value may reside as much in the deliberative processes it activates as in its diagnostic outputs.

Ethics Declaration: The research involved human participants through an acceleration programme context. Ethical clearance was obtained through the institutional review processes of the Instituto Tecnologico de Aeronautica (ITA) and in accordance with the norms of the PROFNIT graduate programme. All participant data were treated confidentially and anonymised in reporting.

AI Declaration: AI tools were used at two stages of this research. In the data preparation phase, Concentro employed AI-assisted transcript analysis to identify the 24 recurrent organisational themes that informed the management factor model; those outputs were subsequently reviewed and theoretically grounded by the researcher. In the preparation of this article, AI-assisted writing tools were used for language revision. In both cases, the researcher retained full critical oversight and assumes complete responsibility for the final content.

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Non Academic Papers

Knowledge Management in Nuclear Waste Disposal: Approaches and Challenges in Germany

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Abstract: Knowledge management (KM) in the field of nuclear waste disposal in Germany was largely neglected in all predecessor organisations and existed mostly within a loose framework of a substandard data archiving system. A reliable KM structure was only established since 2019. The KM team has gradually established various KM methods and tools to meet the current and future needs of colleagues. KM work is, and continues to be, marked by multitude challenges such as an ongoing major company reorganisation for the last years. Reduced KM workforce, loosening interest on KM and the longtime awaited, still missing implementation of Artificial Intelligence (AI) are making the work increasingly difficult.

Keywords: Radioactive waste disposal, Germany, Knowledge management tools, External and internal challenges, Upcoming AI support

1. A Short History of Radioactive Waste Disposal in Germany

The final storage of nuclear waste has been an important issue in Germany for over six decades.

The first trials began in the late 1960s at the Asse II mine, which served as a research facility and later became a final repository for around 126,000 drums of low- and medium-level radioactive material.

Further initiatives regarding nuclear waste disposal in Germany took place in the 1970s with the construction of the exploratory mine in Gorleben (no storage of radioactive material).

From the 1970s to the 1990s, around 37,000 cubic metres of low- and intermediate-level radioactive waste were stored at the Morsleben mine.

Currently the Konrad repository is under construction to store existing and future low- and intermediate-level radioactive material. The Morsleben repository is being decommissioned, with the radioactive waste remaining in the mine. The Gorleben exploration mine will be backfilled and subsequently sealed. The radioactive waste from the Asse II mine is to be retrieved and the mine subsequently sealed.

Since 2017, the Federal Company for Radioactive Waste Disposal (BGE) has been involved in the site selection process and is searching for a final repository for the high-level radioactive waste from nuclear power plants currently held in interim storage facilities.

The last nuclear power station in Germany was decommissioned in 2023, meaning that no new high-level radioactive waste is currently being generated.

2. Knowledge Management in the Past

A look at the history of knowledge management in the field of nuclear waste disposal in Germany reveals a mixed picture. Due to the large number of organisations and institutions (predominantly state-run, but also partly private) that have been responsible for nuclear waste management over the last 60 years, there has been neither a uniform nor a shared approach to knowledge management. This is also because there was no understanding of the importance of preserving and passing on knowledge in the past.

The topic of knowledge management was first discussed in the 2000s. Initially, this referred only to the systematic documentation of existing analogue information. However, even so-called inventory lists of stored waste were, at that time, inadequately recorded and, in some cases, vague.

Considerations regarding knowledge management in line with today's understanding of information preservation, accessibility and knowledge transfer were first recorded in commissioned research projects in the 2010s. However, these approaches and ideas were not implemented. Consequently, every institution responsible for final disposal, whether administratively or operationally, pursued its own uncoordinated, individual approach. Even these individual approaches to knowledge management were, for the most part, little more than documentation organised to a greater or lesser extent within the various organisations' existing, non-standardised systems. Isolated attempts to offer optional information formats, such as a specific internal system modelled on Wikipedia, were discontinued due to low usage and a lack of regular updates.

Furthermore, apart from the mere storage of documents, knowledge management was viewed exclusively as an internal tool for specialist training and the professional development of new staff.

A review of the history of knowledge management in the field of nuclear waste disposal in Germany shows that, prior to the establishment of the Federal Company for the Disposal of Radioactive Waste (BGE) in 2017, there were neither coherent and structured nor standardised knowledge management systems in place within the predecessor organisations.

It was only as part of the process of reorganising responsibilities for radioactive waste disposal in Germany and merging the various competent administrative and operational bodies into a single organisation in 2019 that it became possible to introduce a knowledge management system, which, in its initial phase, was based on the guidelines of the International Atomic Energy Agency (IAEA) (IAEA 2011, 2016, 2022a, 2022b) and the relevant standard literature (Nonaka & Takeuchi, 1995).

3. Establishing a Knowledge Management System - The Portfolio

The wide range of knowledge management tools currently offered by BGE is, on the one hand, the result of planned initiatives based on concept papers, but on the other hand, it is also the result of a gradual development driven by the desire to offer potential customers a broader range of services.

3.1 Digital Information Base (DIB)

The DIB fulfils the purpose of a centralised collection of documents containing information on all aspects of final disposal including all searchable scientific and technical works on the topics of the above-mentioned mining sites, as well as on general issues relating to the final disposal of radioactive waste in Germany, drawn from internal and external sources. The database consists primarily of internal reports, series of publications, presentations and dissertations. It is intended to make the entire body of documented knowledge on all aspects of final disposal available within the BGE and to serve as a source of information for answering current and future questions on this subject area. It is continuously expanded and updated. By today it consists over 25.000 documents, wherein at least one third had to be digitized. Many of the documents were retrieved from former hidden and not available sources.

3.2 Intelligent Search Engine (iFinder)

As part of the development and maintenance of the “Digital Information Base”, the BGE decided to use an intelligent search engine to provide users with an optimised search experience tailored to their specific needs. It is designed to deliver more relevant search results based on the user’s context and profile, with the aim of improving the efficiency of knowledge and information retrieval.

Therefore, we use the “iFinder5elastic” tool (iFinder for short), a proprietary software, as an intelligent search engine to index document content and facilitate efficient research. The iFinder combines enterprise search, artificial intelligence such as machine learning, and linguistic methods such as ‘semantic search’, a search method that focuses on the contextual meaning of a search query. The advantages for the users are the visualisation of knowledge content or hidden knowledge (e.g. via facets), the integration of subject-specific knowledge (glossaries, abbreviations, acronyms, dictionaries), the ability to search for ‘similar documents’ as well as the ability to access information and knowledge from various sources to be made accessible. It provides a central platform that allows users to access a wide range of data internal and external connected sources and quickly find relevant information.

3.3 Interactive Knowledge Maps

Knowledge maps visually represent knowledge within organisations and enable the externalisation of internal knowledge.

The aim of our knowledge maps is to provide clarity regarding internal and/or external knowledge assets. Such a transparent and clear representation of knowledge in knowledge maps is intended to ensure that existing knowledge is visible to and can be effectively utilised by all stakeholders. This information may include, for example, details about knowledge holders, existing knowledge, knowledge sources or the development of knowledge. Knowledge maps serve less as a direct repository for embedded knowledge and more as a reference to relevant information, experts, structures, or documents and records.

Our purpose designed knowledge maps are also intended to support the rapid documentation of both explicit (conscious and accessible) and implicit (less conscious and intuitive) knowledge, and to facilitate and accelerate

access to the knowledge required. This promotes knowledge exchange, collaboration and the shared use of resources. Our various knowledge maps range from project specific information to the support of new colleagues offering a knowledge map for the onboarding process and further questions.

3.4 Lessons Learned (LL)

Before the knowledge management department was established, there were no lessons learned at BGE. The introduction of lessons learned was implemented solely on our initiative. The purpose is that the LL serve to continuously improve the BGE as a learning organisation and, with their implicit, positive culture of error, contribute to a sustainable transformation of the organisational culture.

The systematic approach to capturing, documenting and organising lessons learnt within the framework of knowledge management is:

Selective capture of experiential knowledge using tools such as:

1. Expert debriefing or project debriefing
2. Post-project reviews and debriefings
3. Surveys and questionnaires
4. Analysis of project documentation
5. Experience reports or case studies
6. Data analysis
7. Workshops and brainstorming sessions

as well as

Regular evaluation and systematic analysis of lessons learnt

Active communication and dissemination of lessons learnt

Integration of lessons learnt into existing business processes

and finally, the

Promotion of an open culture of error-acceptance

as well as a culture of knowledge-sharing, a willingness to learn and openness to change

Experience shows that, after some initial hesitation, there is considerable interest in this approach. The KM department supports the interested organisational units, organising, accompany and moderate the initial workshops and brainstorming sessions, and support them units within the framework of the systematic approach with the goal that the resulting reports contain a collection of recommendations on best practice and lessons learnt, which are intended to help avoid or minimise past mistakes and risks in the future.

3.5 Knowledge Café (KC)

The Knowledge Café serves to disseminate and transfer knowledge across our organisational units. It is an informal and interactive event where employees from all departments come together in a relaxed setting to share information on various relevant topics. Furthermore, this setting is intended to provide an opportunity for a free and intensive exchange of thoughts and ideas with the participants. The KC is run as flexibly as possible and tailored to specific needs and the organisational culture. It aims to raise awareness of knowledge management and to promote knowledge sharing and collaboration across departmental boundaries.

The KC is a regular event that takes place every 4–6 weeks and is announced in advance on the intranet. To reach as many staff members as possible, the KC is held exclusively online. It lasts around half an hour and takes place before the lunch break. The session is divided into a 15-minute presentation and 15 minutes for questions and answers; it concludes with a preview of future Knowledge Cafés and their topics. Among other things, the KC aims to act as a catalyst to promote the exchange of knowledge.

3.6 Knowledge Circle (KC^2)

The Knowledge Circle is an extended version of the Knowledge Café.

It is meant to be within a closed expert or working group. This group meets regularly to exchange knowledge on a specific topic. The KC^2 is intended to take place in an informal setting, so that committed colleagues can further

develop their area of interest or expertise together. However, it can also be organised more formally, for example as a working group.

The knowledge circle offers members the opportunity to learn from one another, share their experiences and work together to find better solutions in their respective fields. Through the regular exchange of experiences and the discussion of best practices, existing knowledge is shared, new insights are gained and applied across the relevant areas.

3.7 Interviews

Interviews are one of the most important and fundamental components of knowledge management. They serve to capture and make available the personal knowledge of an individual or group (tacit or implicit knowledge). This individual knowledge can be utilised by groups of people and reassessed as and when necessary. The advantage is that it minimises knowledge loss caused by staff leaving the company, whilst also disseminating expert knowledge to individuals or the entire group. At BGE, three different types of interviews are currently being conducted, each focusing on a distinct area:

Expert Debriefing

- Interviews with experts who are still active on highly topical or specific subjects

Offboarding Interviews

- Interviews with colleagues who are due to leave the company shortly and who have been identified as key knowledge holders, without whom a significant information gap would arise if their tacit knowledge were not passed on

Contemporary Witness Interviews

- Interviews with eyewitnesses are conducted with both colleagues and external stakeholders in order to capture their motivations, goals and views.
- Furthermore, the aim is to tap into hidden or implicit knowledge in order to record authentic
- assessments from the perspective of the respective stakeholders at specific points in time.

3.8 Internal DokuWiki

The internal DokuWiki contains various types of information that we believe are currently best shared in this way. The DokuWiki is operated as a simplified version of Wikipedia, with editing privileges reserved exclusively for the administration.

The DokuWikis operated by the KM Department are:

Knowledge Management Methods Catalog

- Here, all methods currently used by the Knowledge Management Department are explained in detail

Uniform Glossary

- An attempt to create the company's first standardized glossary. Currently, only a fraction (approx. 400) of the identified necessary terms (>3,000) have been included.

Modeling Software

- An overview of all software programs for numerical modeling and simulation, including their location within the company, availability, and experiences with the respective software.

3.9 Community of Practice (CoP)

For BGE, a company newly established in 2019 with a new structure and hierarchy spread across various locations, CoPs are an essential component. Isolated CoPs already existed before the KM department offered support, for example as a neutral body that asked various questions to keep the process moving. In other instances, we saw an opportunity to offer our support or were asked to help initiate CoPs. Today, Knowledge Management initiates, supports, accompanies and promotes all types of Communities of Practice at BGE.

3.10 Cooperations

The Knowledge Management team is involved in various national and international collaborations.

We exchange ideas with sister organisations such as the French ANDRA and the Swiss NAGRA.

We participate in European programmes such as EURAD and are invited to act as consultants and guest speakers (Hoefer, Feuker & Wellmann, 2023); (Hoefer, Wanka & Wellmann, 2022).

We present our KM approach at national and international conferences such as the, SafeND (Hoefer, Wanka & Wellmann, 2021), the ICKM (Abbasova et al, 2022) or the IAEA (Hoefer & Wellmann, 2026).

We are involved in the OECD/NEA's IDKM and EGKM programme areas.

Since 2024/2025, we have been a member of the German working and knowledge initiatives

the Radiation Protection Qualification Network and the Nuclear Safety Qualification Network, within which we have established a Community of Practice.

And our latest collaboration began in 2026 with an exchange with Airbus.

We see cooperation and exchange as absolutely essential and as the best opportunity to critically examine our work, share our knowledge and experience, and, above all, learn from and with others.

4. New Tools for a Better Knowledge Management?

We will shortly be introducing two new methods and tools, which we expect will lead to significant improvements that will benefit our colleagues. Firstly, this involves the introduction of an

4.1 Expert Compass (EC)

The "Expert Compass" is designed as an intelligent network of employees for the future.

The EC will function as a database on a digital platform where information about the skills, experience and knowledge of an organisation's employees is stored. It enables employees to find expert contacts for various specialist topics or with specific skills and to seek their advice or support. Data protection guidelines ensure the security and confidentiality of the data.

This EC serves to map the pool of specialist skills within the organisation, thereby facilitating the identification of competent contacts depending on the required field of expertise. This is intended to promote and strengthen communication, networking and knowledge transfer between employees.

This increases transparency regarding existing knowledge and enables networking across sites and organisational units.

It also supports effective skills management within the organisation, enabling the full potential of employees' existing knowledge and skills to be realised.

The aim is to provide the HR department with additional information and for the system to serve as a company-wide yet personalised tool for skills management and HR. We hope this will result in improved efficiency in project and staff planning.

4.2 Artificial Intelligence (AI)

The introduction and use of artificial intelligence (AI) within the company is long overdue. The Knowledge Management Department was the first organisational unit to call for the use of AI. The implementation of a generative AI called 'iAssistent' will build on the aforementioned intelligent enterprise search tool, 'iFinder'. We expect better and more precise context-based answers, as well as results with a significantly shorter response time compared to the current system (iFinder).

We therefore anticipate that the search results will be more efficient for staff and will function as a dialogue-driven staff information system.

Our first step following the implementation of iAssistent will be to run a test system to evaluate the performance of large language models (LLMs). This will be trained using our in-house content. To ensure the reliability of the results, we will have the trained version tested by groups of employees. From experts to beginners, from long-serving employees with diverse project experience to new colleagues with varied professional backgrounds, from older to younger staff. In this way, we aim to ensure the highest possible level of reliability. Following this test phase and the final implementation, we envisage numerous use cases, such as the onboarding process, tools for skills development, and knowledge sharing such as knowledge maps, etc. We see the potential for

communities of practice to be elevated to a new level, as well as the option for a chat with final storage expertise.The possibilities are diverse and will be positive.

Nevertheless, the foundation for AI-generated results is knowledge management, which encompasses the continuous maintenance of data and the evaluation of the results delivered by the AI.

5. Challenges that Affected and Still Affect Knowledge Management

In recent years, there have been a number of challenges and difficult, sometimes ongoing, situations that have undermined the concept and practice of effective knowledge management, in some cases quite significantly.

5.1 Concept

When the KM Department first began its work, only a few of the team members had prior knowledge or a basic understanding of knowledge management. As a result, we all started from virtually scratch, without having a predefined overall concept for knowledge management. Before we began, there was only a concept for the digital capture and analysis of historical documents, which served as the basis for the DIB. Subsequently, the concept for the "Introduction to Knowledge Management in the Learning Organization" was developed later; however, this is a theoretical concept with an extremely limited practical approach to capturing implicit and tacit knowledge. It was not until three years after the department was founded that a concept for capturing explicit knowledge in a digital information database was developed, which provided a practical approach to using a search engine for the dissemination of explicit knowledge.

As shown, there was no overarching guiding principle as a starting point before we began working on knowledge management.

5.2 Survey

A survey based on a questionnaire that took staff needs into account was not introduced until 2022. As a result, the KM team worked for three years with great dedication and a firm belief that they were doing the right thing for their colleagues, without having received any feedback prior to the aforementioned survey.

5.3 Methods

Experience over the years has shown that, whilst some of the methods introduced by the knowledge management department were frequently used initially, they were almost completely forgotten and fell out of use after a year or several years. A good example of this is the Knowledge Circles and 'Lessons Learned' mentioned above. After a while, interest in the Knowledge Circles was so low that they were discontinued. Demand for 'Lessons Learned' is now so low that they hardly exist or are requested anymore.

Both methods and the cause of the lack of demand must be investigated.

5.4 Continuous Reinvention

A key insight from work in the field of knowledge management is the ongoing development and optimisation of existing tools, as well as the introduction of new techniques and methods. The life cycle in knowledge management encompasses the introduction of a method, its dissemination, its acceptance, its use (to a greater or lesser extent), a decline in frequency of use, further development, optimisation or discontinuation, and the introduction of an improved version or a new tool.

5.5 Key Performance Indicators (KPI)

One of the problems in knowledge management is the lack of reliable key performance indicators (KPIs). To a certain extent, it is possible to determine the usage figures for certain tools or the attendance figures for various events. However, when it comes to hard facts in the form of KPIs, as demanded by senior management to justify the existence of KM, these are unfortunately lacking, particularly as access figures or attendance figures vary greatly depending on the topic (35 people versus 200 people).

5.6 Reorganisation

The main problem for practical knowledge management and the very existence of a KM department is the ongoing and repeated restructuring of the company over months and years. Taking a smaller organisational unit as an example, the previously independent KM department is transferred to the HR department, with new additional tasks being added, key components being removed, and the workforce being reduced by a quarter at

the same time. Within just over a year, the KM department within the HR department is moved to another sub-division with different additional tasks, whilst the workforce is reduced by a third in total.

The same situation arises in most departments across the entire company.

The impact and consequences of this type of restructuring are immense and severe for the KM department. All new and newly established departments (most of which officially carry out the same work under a different name) require a considerable amount of time (1–2 years) to develop a consistent structure and identify their needs. During this period, there are few or no demands placed on knowledge management. These measures deliberately push knowledge management to the sidelines.

6. Key Insights and Considerations for Successful Knowledge Management – in Brief

In our experience, what are the key considerations and prerequisites for successful KM?

6.1 Support

First, the unconditional support from senior management. Without this, all attempts to introduce a KM system and ensure its successful implementation. This is also a prerequisite for the next stage.

6.2 Attitude

A positive or at least neutral attitude towards knowledge management, which implies acceptance and therefore does not hinder the dissemination of KM ideas.

6.3 Concept

Development of a concept that is also practicable before work on KM begins. Individual concepts can always be developed subsequently. The consequences of an overly theoretical approach and a basic concept developed too late only become apparent in the medium term, but they are clear.

6.4 Customer Focus

Given these prerequisites, it is absolutely essential to take into account and ascertain colleagues' expectations and wishes regarding KM. They should be regarded as customers to whom a service is being offered. Consequently, all tools and methods introduced subsequently are always linked to the success of persuasion.

6.5 Constant Communication

It is absolutely essential to keep the topic in the conversation or in people's minds. This can be achieved through various initiatives, new projects or so-called KM ambassadors within organisational units.

It is important that KM is viewed as positive, relevant and necessary.

6.6 Parallel Systems

It is equally essential that no independent parallel KM systems are created within the organisation that compete with one another and have a negative impact on each other.

Should a variety of KM approaches exist within the organisation, they should all operate under the same high-quality and mutually agreed regulations. Ideally, there should be a coordinating, overarching knowledge management system in place.

7. Recent Developements

Whilst this paper is being drafted, the BGE's Knowledge Management Department is independently launching a comprehensive review process. The new strategy will need to reflect the impact of the company's current restructuring and ongoing reorientation, including the loss of a third of the department's staff.

One outcome that is already certain is, that there will be a significant reduction in the portfolio including the transfer of nearly fully developed projects, such as the abovementioned Expert Compass, to other departments. This is necessitated by the reduced workforce and the reorientation of content as part of the HR strategy and development department.

The changes to content and staffing intended by the company's management will determine the future direction and future of the knowledge management department.

However, as long as we have a dedicated team and the department remains in place, we will continue our work in the field of knowledge management.

For us, knowledge management is not only an absolute professional necessity, but also a passion that we live and breathe, guided by our philosophy of knowledge management:

Approach – Combination – Dissemination – Reflection … and back to the beginning.

Acknowledgements

I would like to express my sincere thanks to all my current and former colleagues and team members for their contributions, suggestions and support. They are (in alphabetical order):

Ute Bauer, Gerd Breitfelder, Andrea Färber, Panja Feuker, Beate Opitz, Anselm Tiggemann, Sebastian Wanka and Peter Wellmann.

Ethics Statement: I hereby declare that no ethical approval was required for this non-academic work.

AI Statement: I hereby confirm that no AI tools were used in the preparation of this work, apart from the use of the free Deepl web translator to partially optimise sentence structure and phrasing, as well as for spell-checking.

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From Knowledge Retrieval to Execution: Designing Executable Knowledge Systems

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Abstract: Generative AI is changing the role of knowledge in organisations. Traditional knowledge management (KM) systems have primarily supported storage, access and retrieval, assuming that knowledge is interpreted and applied by human users. In AI-enabled environments, however, organisational knowledge increasingly becomes a direct input into execution, shaping generated proposals, analyses, summaries, recommendations and other workflow outputs. This shift exposes a limitation of retrieval-oriented KM: fragmented, outdated or weakly governed knowledge can be amplified through AI-generated outputs, reducing consistency, reliability and trust. This paper introduces executable knowledge systems as a conceptual model for structuring organisational knowledge to support reliable human and AI-assisted execution. The term executable is used in a socio-technical sense. Knowledge does not necessarily become code, but is curated, validated and embedded into workflows so that it can guide outputs, decisions and actions. The paper distinguishes this concept from prior work on executable knowledge graphs and executable knowledge bases, which primarily focus on deterministic execution through rules, scripts or formalised representations. The paper further develops a framework of decay and compounding loops to explain how AI-enabled knowledge systems evolve over time. In decay loops, AI-generated outputs re-enter the knowledge environment without sufficient validation, allowing inconsistency and low-quality knowledge to accumulate. In compounding loops, curated knowledge assets are refined through governed feedback, domain ownership and controlled reuse, enabling improvements in reliability over time. The framework is informed by an exploratory case study within a global professional services organisation, where a curated knowledge environment was introduced to support AI-assisted workflows in the Retail, Consumer Products, Travel and Transportation domain. The evaluation compared outputs generated from a controlled, subject matter expert (SME)-validated knowledge dataset with outputs generated from an unconstrained organisational knowledge base. Findings indicate improved retrieval relevance and output quality when AI systems operate on validated knowledge assets. he paper contributes to KM research by reframing KM as a system design challenge for AI-enabled execution and by positioning governance, validation and feedback control as central mechanisms for reliable organisational knowledge use.

Keywords: Knowledge management, Generative AI, AI Reliability, Knowledge governance, Executable knowledge systems, AI-assisted workflows

1. Introduction

Organisations have invested in knowledge management (KM) for decades with the expectation that captured knowledge can be reused to improve efficiency, consistency and organisational learning. KM is commonly understood as encompassing knowledge creation, storage, retrieval, transfer and application (Alavi and Leidner, 2001). In practice, however, many KM initiatives have emphasised storage and retrieval through repositories, intranets, taxonomies and search tools. This has created a persistent gap between knowledge availability and knowledge application: organisations may possess large volumes of knowledge, yet employees still recreate work, rely on informal networks or struggle to apply existing knowledge in execution contexts.

The adoption of generative AI makes this gap more consequential. Recent KM research argues that generative AI reshapes core knowledge processes and requires new frameworks to manage productivity gains alongside risks to knowledge quality, expertise and organisational control (Storey, 2025). Studies of AI-enabled knowledge work similarly show that effective use of generative AI requires adaptable user control, transparent collaboration mechanisms and the ability to integrate organisational background knowledge with external information (Yun et al, 2025).

AI-enabled systems increasingly generate proposals, analyses, summaries, recommendations and other workflow outputs. Knowledge therefore becomes a direct operational input into execution workflows. When the underlying knowledge is fragmented, outdated or poorly governed, AI systems may amplify inconsistency at scale. This risk is consistent with research on large language model hallucination, which shows that generated outputs can be fluent and plausible while remaining unsupported, contradictory or unverifiable (Huang et al, 2025; Li et al, 2023).

This paper addresses this challenge by introducing executable knowledge systems: governed knowledge environments in which curated knowledge assets are designed to support reliable execution by both humans and AI systems. The term "executable" is used in an organisational and socio-technical sense. It does not imply that all knowledge becomes code; rather, it means that knowledge is structured as an operational input that shapes workflow outputs, decisions and actions.

The paper further clarifies how this concept relates to prior work on executable knowledge graphs and executable knowledge bases. Existing approaches, such as ExeKG, focus on representing knowledge so it can be translated into executable scripts or reusable workflow components for analytics and machine learning (Zheng et al, 2022a; Zheng et al, 2022b). Related work on executable clinical knowledge bases emphasises the formalisation of guideline rules for decision support (Quimbaya et al, 2014). By contrast, the model proposed here addresses generative AI environments in which reliability depends not only on formal representation, but also on governance, validation, ownership and feedback control.

The paper makes three contributions. First, it reframes KM as a system design challenge for AI-enabled execution rather than only a problem of knowledge access. Second, it defines executable knowledge systems and distinguishes them from deterministic executable-knowledge approaches. Third, it introduces decay and compounding loops as a framework for understanding how AI-enabled knowledge systems degrade or improve over time depending on governance.

2. Background and Literature

KM has traditionally been grounded in the premise that organisational knowledge can be captured, stored, shared and applied to improve performance. Foundational KM literature emphasises knowledge creation, transfer and reuse, while also recognising that knowledge creates value only when it is applied in organisational activity (Nonaka and Takeuchi, 1995; Davenport and Prusak, 1998; Alavi and Leidner, 2001). However, many KM systems have operationalised this agenda primarily through repositories, taxonomies, search and document access, contributing to a gap between knowledge availability and usability.

Information quality research helps explain this gap. Lee et al (2002) argue that information quality is multidimensional and must be evaluated in relation to use, including intrinsic, contextual, representational and accessibility dimensions. For AI-enabled work, this distinction is important because accessible knowledge may still be unsuitable for execution if it is outdated, duplicated, poorly contextualised or weakly governed.

Recent research on generative AI and knowledge work reinforces this limitation. Storey (2025) argues that generative AI changes the role of KM by altering how organisational and worker knowledge is accessed, applied and evaluated. Kirchner et al (2025) show that generative AI can support knowledge creation and sharing in software development, but expert review remains necessary to assess reliability, adapt outputs and maintain quality. Taken together, these findings suggest that AI-enabled KM requires mechanisms for validation, governance and contextual use.

The reliability challenge is also visible in research on large language model hallucination. Hallucination refers to outputs that are fluent but unsupported, contradictory or unverifiable. Huang et al (2025) show that hallucination remains a central challenge for LLM reliability, including in retrieval-augmented systems. Li et al (2023) similarly show that LLMs may fabricate unverifiable information and that external knowledge and structured reasoning steps can help reduce hallucination. In organisational contexts, hallucination should therefore be understood not only as a model-level problem, but also as a knowledge-system problem.

Research on retrieval-augmented generation (RAG) and knowledge graphs provides one response to this problem. RAG approaches seek to ground generated outputs in external knowledge sources, while knowledge graph-based approaches add structure and relationships to improve retrieval and reasoning. Zhu et al (2025) propose knowledge graph-guided RAG to preserve fact-level relationships between retrieved chunks and improve response coherence. Liu et al (2025) show in a clinical triage setting that knowledge graph-based RAG outperforms prompt-only and naïve RAG approaches, suggesting that structured domain knowledge can improve reliability in knowledge-intensive workflows.

This paper also builds on, but differs from, existing work on executable knowledge. Zheng et al (2022a) introduce ExeKG as an executable knowledge graph system for user-friendly data analytics, where semantic representations of machine-learning knowledge can be translated into reusable scripts. Zheng et al (2022b) extend this idea to an industrial machine-learning context through a Bosch welding-monitoring case. In

healthcare, Quimbaya et al (2014) present an executable knowledge base for clinical practice guideline rules, illustrating how domain knowledge can be formalised for rule-based decision support.

These approaches are important foundations, but they address a different execution problem from the one examined in this paper. In executable knowledge graphs and executable clinical knowledge bases, execution is primarily deterministic: structured knowledge is translated into scripts, rules, queries or compliance mechanisms. In AI-enabled KM, execution is probabilistic and generative: systems interpret and recombine organisational knowledge to produce proposals, analyses, summaries and recommendations.

Taken together, these studies clarify both the foundation and the distinction of the present paper. Existing executable knowledge research shows that formalised knowledge can be operationalised through rules, scripts, queries and machine-learning workflow components (Zheng et al, 2022a; Zheng et al, 2022b; Quimbaya et al, 2014). The concept of executable knowledge systems proposed here extends this work to AI-enabled organisational settings, where decay and compounding loops describe how such systems evolve: without validation, generated outputs can degrade the knowledge environment; with governed feedback, they can improve curated knowledge assets.

3. Conceptual Framework

3.1 From Retrieval to Execution

The emergence of generative AI changes the role of knowledge in organisational work. In traditional KM environments, knowledge is retrieved, interpreted by humans and applied through manual execution. In AI-enabled environments, AI systems increasingly retrieve, interpret and recombine knowledge to generate outputs directly within workflows. Knowledge therefore becomes not only a resource for human interpretation, but an operational input into execution.

This paper defines executable knowledge systems as governed knowledge environments in which curated knowledge assets are structured to support reliable execution by humans and AI systems. The term executable is used in a socio-technical sense. It does not mean that all knowledge becomes code. Rather, it means that knowledge is organised so that it can shape workflow outputs, decisions and actions.

In executable knowledge systems, the unit of value shifts from static documents and repositories toward reusable knowledge assets embedded within workflows. These may include structured best practices, validated approaches to recurring problems, standardised decision frameworks and reusable workflow patterns. Such assets act as governed inputs that shape how AI systems generate outputs and support decision-making across contexts.

As knowledge becomes embedded in AI-enabled workflows, organisational control also shifts upstream. Rather than relying primarily on post-hoc review of generated outputs, organisations must govern the knowledge inputs that shape execution. This shift is summarised in Table 1.

Table 1: From retrieval-oriented KM to executable knowledge systems

Dimension	Traditional Knowledge Management	Executable Knowledge Systems
Primary goal	Improve access to knowledge	Enable reliable execution of work
Core paradigm	Retrieve, read and interpret	Generate, apply and refine
Unit of value	Documents and repositories	Governed knowledge assets and workflows
Quality control	Post-hoc review of outputs	Governance of knowledge inputs
Feedback model	Outputs re-enter knowledge base with limited validation	Only validated outputs update governed knowledge assets
Main failure mode	Fragmentation and low reuse	Inconsistency at scale
Success pattern	Improved access and discoverability	Improving reliability through governed reuse
Role of KM	Curate and organize content	Design and govern execution workflows
Measurement	Usage, access, reuse	Cycle time, consistency, output quality

3.2 Decay and Compounding Loops

The shift from retrieval to execution turns KM systems into feedback systems. In AI-enabled environments, knowledge is repeatedly used to generate outputs that may influence future knowledge assets and workflows. This creates two possible trajectories: decay loops and compounding loops.

A decay loop occurs when AI-generated outputs are reintroduced into the knowledge environment without sufficient validation or governance. In this situation, generated outputs become inputs for future execution regardless of quality. Over time, inconsistencies, duplications and inaccuracies become harder to distinguish from validated knowledge. The system may still produce outputs quickly, but reliability and trust decline.

A compounding loop occurs when knowledge is curated and governed before use in execution, and when generated outputs are reviewed before updating knowledge assets. In this model, domain experts remain responsible for validating and maintaining knowledge assets. Their role shifts from ad hoc contribution or repeated output creation toward continuous stewardship, refinement and improvement of reusable knowledge.

Figure 1 illustrates these contrasting dynamics. The decay loop is driven by uncontrolled feedback, while the compounding loop is driven by governed feedback, validation and ownership.

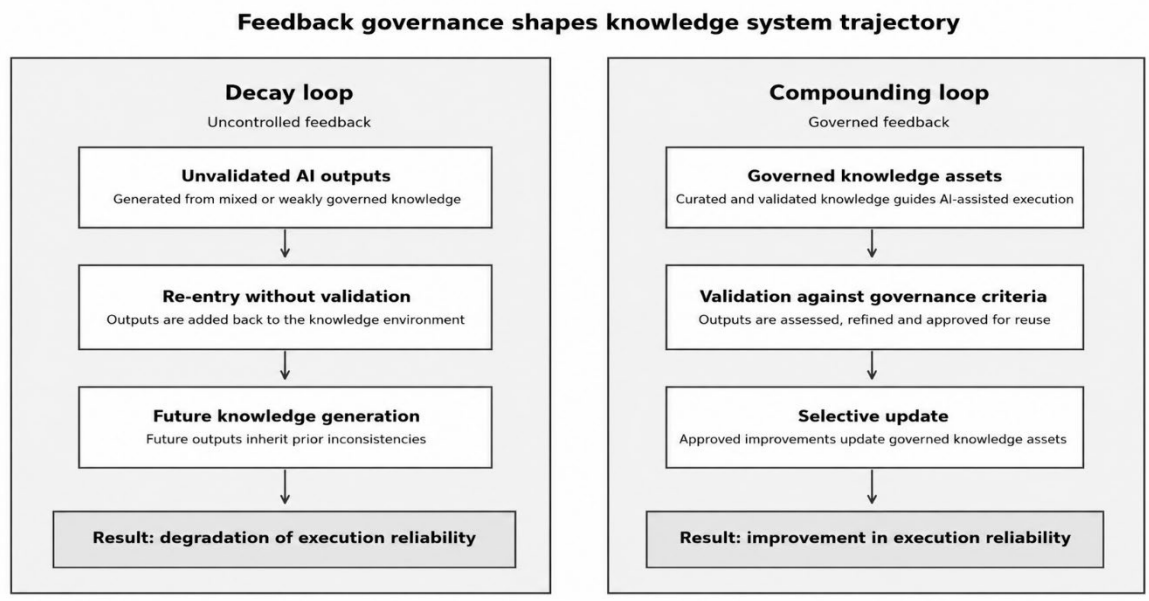


Figure 1: Decay and compounding loops in executable knowledge systems

In decay loops, signal quality declines as validated and unvalidated knowledge become mixed; provenance weakens because sources may remain traceable but lack clear authority; and trust declines as users encounter inconsistent outputs. In compounding loops, consistency improves because execution is guided by standardised inputs; reliability improves because outputs remain grounded in curated knowledge; and reuse accelerates because expert refinements become available for future workflows.

Table 2 summarises the distinction between the two trajectories.

Table 2: Decay and compounding loops

Feedback mechanism	Outputs re-enter the knowledge base without validation	Only validated outputs update governed knowledge assets
Knowledge evolution	Accumulation of inconsistency and duplication	Selective refinement and continuous improvement
Human contribution model	Ad hoc creation and interpretation	Validation, refinement and stewardship

User behavior	Increased reliance on individual judgment	Increased reliance on system-supported
System trajectory	Progressive degradation of knowledge	Progressive improvement in execution

The relationship between executable knowledge systems and decay and compounding loops is therefore direct. Executable knowledge systems are the socio-technical architecture through which knowledge is structured for AI-assisted execution. Decay and compounding loops describe how that architecture evolves under different feedback-governance conditions. Without validation, scale amplifies inconsistency. With governed feedback, scale amplifies validated knowledge, expert refinement and execution reliability. This interpretation is consistent with practitioner-oriented KM research emphasising that future-ready KM requires formal ownership, governance roles and knowledge embedded in the flow of work (APQC, 2025).

4. Case Study and Evaluation Design

4.1 Organizational Context and Intervention

The empirical component of this paper is an exploratory case study conducted within a global professional services organisation employing approximately 10,000 knowledge workers across multiple regions. The organisation delivers complex client engagements that require the reuse of institutional knowledge, including proposals, case studies, delivery patterns and industry insights.

The intervention focused on the Retail, Consumer Products, Travel and Transportation (RCTT) domain. This domain was selected because its work depends heavily on reusable industry knowledge, including retail e-commerce modernisation, marketplaces and omnichannel operations. The RCTT industry team partnered with the AI-First Knowledge Management team to establish a curated source of truth for industry knowledge assets designed for both human and AI-assisted workflows. Confluence was used as the primary platform for structuring and publishing validated knowledge assets.

Prior to the intervention, relevant knowledge was distributed across repositories, collaboration tools and personal storage systems. Although knowledge was abundant, it lacked consistency, validation and clear ownership. Employees were required to identify, interpret and adapt content independently, resulting in duplicated work, variable output quality and reliance on informal networks. These conditions reflected a retrieval-oriented KM model, where access was prioritised but usability within execution workflows was not systematically ensured.

The intervention introduced a controlled knowledge environment designed to improve the consistency, reuse and reliability of knowledge used in proposal development, delivery support and client-facing work. The evaluation focused specifically on RCTT workflows rather than the organisation as a whole.

4.2 Evaluation Design

The evaluation assessed whether constraining AI-assisted workflows to curated and validated knowledge assets improved retrieval relevance and output quality compared with an unconstrained organisational knowledge base. Two knowledge environments were compared:

- Controlled dataset: approximately 450 structured RCTT knowledge pages validated and approved by subject matter experts.
- Unconstrained knowledge base: the broader organisational knowledge environment containing more than one million documents.

Nine representative prompts were defined to simulate common knowledge-intensive tasks, including proposal development, industry analysis and client preparation. Each prompt was paired with an SME-approved reference response representing the expected high-quality answer. The reference responses were defined by an SME with more than 15 years of professional services experience across Retail, Consumer Products, Travel and Transportation.

For retrieval relevance, responses were evaluated using a pass/fail assessment. A response passed when it aligned with the SME reference in content, structure and relevance. Response accuracy was calculated as the proportion of responses aligned with SME-approved references. Resolution rate measured whether a response was generated for each prompt.

For output quality, three artefact types were evaluated: case studies, statements of work (SOWs) and client pitches. Outputs were assessed using a five-point scale across correctness, readiness for use, completeness and overall quality. Because the evaluation was conducted in an applied organisational setting, the design prioritised practical relevance over experimental control. The findings should therefore be interpreted as indicative rather than causal.

4.3 Evaluation Results

The controlled dataset produced substantially higher alignment with SME-approved reference responses than the unconstrained knowledge base. As shown in Table 3, both datasets achieved a 100% resolution rate. However, the controlled dataset achieved 89% accuracy against SME-approved references, compared with 44% for the unconstrained knowledge base.

Table 3: Retrieval relevance evaluation

Dataset	Total Prompts	Passed	Failed	Accuracy Score	Resolution Rate
Controlled dataset	9	8	1	89%	100%
Unconstrained dataset	9	4	5	44%	100%

The difference lies not in the ability to generate a response, but in the relevance and alignment of the response with domain expectations.

Output quality results showed a similar pattern. As shown in Table 4, scores are reported as controlled dataset / unconstrained knowledge base. The controlled dataset outperformed the unconstrained knowledge base across all evaluated artefact types. The largest gap appeared in SOW generation, where the unconstrained knowledge base produced outputs that required substantial correction before use.

Table 4: Output quality evaluation

Artefact type	Correctness	Readiness for use	Completeness	Overall quality
Case study	4 / 3	4 / 3	4 / 2	4 / 2.6
Statement of work	5 / 1	4 / 1	4 / 1	4.3 / 1
Client pitch	4 / 3	3.5 / 3	4 / 3	3.8 / 3

Across the evaluated artefacts, outputs generated from the controlled dataset showed stronger correctness, completeness and readiness for use. The SOW results suggest that tasks requiring precise delivery structure and validated organisational knowledge are particularly sensitive to knowledge governance. Overall, the findings suggest that constraining AI systems to governed knowledge inputs can improve retrieval relevance and output quality in AI-assisted workflows.

5. Operational Implementation and Observations

The controlled dataset evaluated in Section 4 was created through an AI-assisted operational implementation across discovery, prioritisation, classification, validation and publication. The implementation was designed to transform fragmented industry knowledge into a curated and reusable knowledge environment suitable for AI-assisted workflows. This shifted the focus of KM from storing knowledge toward governing how knowledge is identified, refined, validated and operationalised.

AI-assisted discovery processes identified approximately 4,500 RCTT-related resources distributed across team repositories, collaboration platforms and personal storage locations. AI-assisted prioritisation was then used to shortlist more than 1,040 resources for detailed review and curation. These figures are programme-level operational measures used to track the transformation of distributed content into governed knowledge assets.

AI-assisted classification and metadata enrichment organised resources across categories such as industry segments, value chains, offerings and reusable delivery patterns. SMEs then validated and refined the shortlisted assets to resolve inconsistencies, remove duplication and ensure alignment with organisational standards. This human-in-the-loop process was central to governance: AI accelerated discovery and structuring, while SMEs retained responsibility for determining which assets were sufficiently reliable for reuse.

Approximately 450 structured knowledge pages were published into the curated Confluence-based knowledge environment used as the controlled dataset for evaluation. AI-assisted workflows were constrained to operate on these validated assets rather than unrestricted organisational repositories.

The implementation also produced operational efficiency gains. Based on internal programme estimates, the delivery timeline was reduced from approximately 12 weeks to 4 weeks. Several classification and enrichment tasks required more than 90% less manual effort than the prior approach. These measures are indicative rather than experimental, but they suggest that AI-assisted curation can make governed KM more operationally feasible at scale.

The intervention also changed the role of domain experts. By reducing manual effort in discovery and structuring, SMEs were able to shift attention from execution-oriented activities toward validation, refinement and governance of reusable knowledge assets. This pattern is consistent with the compounding loop described in Section 3: expert effort is redirected from repeatedly producing or interpreting outputs toward improving the governed knowledge inputs that support future execution.

6. Discussion

The study suggests that the integration of generative AI into organisational knowledge systems exposes structural limitations in retrieval-oriented KM. When knowledge is primarily accessed and interpreted by humans, repositories, taxonomies and search tools may support reuse. However, when knowledge becomes a direct input into AI-assisted execution, weaknesses in structure, quality and governance can be amplified through generated outputs. The central issue is therefore not only whether knowledge can be found, but whether it is sufficiently governed to support reliable execution.

The evaluation provides indicative evidence for this argument. Across retrieval relevance and output quality assessments, outputs generated from the controlled dataset were more aligned with SME-approved references and more usable than outputs generated from the unconstrained knowledge base. This supports the paper's claim that AI reliability depends not only on model capability, but also on the knowledge environment in which AI systems operate.

The findings also clarify the relationship between executable knowledge systems and decay and compounding loops. Executable knowledge systems provide the socio-technical architecture through which knowledge is structured for AI-assisted execution. Decay and compounding loops describe how that architecture evolves over time. Without validation, generated outputs may re-enter the knowledge environment and amplify inconsistency. With governed feedback, outputs can be reviewed, refined and used to improve the knowledge assets that support future execution.

The case study further suggests that scalable knowledge governance may become more operationally feasible when supported by AI-assisted workflows. AI was useful in discovery, prioritisation, classification and metadata enrichment, while domain experts retained responsibility for validation and approval. Rather than removing human expertise, the intervention shifted expertise upstream, where it shaped the knowledge inputs that guide future workflows.

These findings extend prior executable knowledge work by moving from deterministic execution of formalised rules or scripts toward governed execution in generative AI environments. For practice, the implication is that organisations adopting AI need governance mechanisms that define ownership, validation criteria, feedback pathways and controlled updating of knowledge assets. Without these mechanisms, AI may accelerate production while degrading trust; with them, AI-assisted workflows can support compounding improvements in execution reliability.

7. Limitations

This study has several limitations. First, it is based on a single organisational context within a professional services environment, which may limit generalisability to other industries and organisational settings. The RCTT domain was selected because it depends heavily on reusable knowledge assets, but other domains may have different governance needs, knowledge structures or workflow characteristics.

Second, the empirical evidence is exploratory. The evaluation used nine prompts and relied on SME-approved reference responses and judgement-based quality assessment. This approach is appropriate for an applied organisational case study, but it does not provide the level of control associated with experimental methods. The findings should therefore be interpreted as indicative patterns rather than precise causal estimates.

Third, some operational measures, including reductions in delivery timeline and manual effort, were based on internal programme estimates and local benchmarking practices. These measures provide useful evidence of operational feasibility, but future research should apply more standardised measurement methods across workflows.

Fourth, the implementation remained transitional. Although curated knowledge assets, constrained execution and human validation were introduced, governance and feedback mechanisms were not yet fully standardised across all domains. The long-term sustainability of compounding loops therefore remains to be tested.

Finally, the framework of decay and compounding loops has not yet been validated through longitudinal or system-dynamics-based research. Future studies should examine whether these dynamics can be observed over time using measures such as knowledge asset reuse, validation latency, provenance quality, correction rates, output consistency and user trust.

8. Conclusion

Generative AI changes the role of knowledge in organisations. Traditional KM systems were designed primarily to improve access through storage, search and retrieval. However, when knowledge becomes a direct input into AI-assisted execution, access alone is insufficient. Knowledge must be structured, governed and continuously refined so that it can support reliable outputs and decisions.

This paper introduced executable knowledge systems as governed environments in which curated knowledge assets support reliable human and AI-assisted execution. It distinguished this concept from prior executable knowledge approaches by focusing on generative organisational workflows rather than deterministic execution of formalised rules, scripts or queries. The paper also proposed decay and compounding loops as a framework for explaining how AI-enabled knowledge systems evolve under different feedback-governance conditions.

The exploratory case study suggests that curated and validated knowledge inputs can improve retrieval relevance and output quality compared with unconstrained organisational knowledge sources. It also indicates that AI-assisted curation can make large-scale knowledge governance more operationally feasible when combined with SME validation and ownership.

The central contribution of the paper is to reframe KM as a system design challenge for the AI era. Reliable AI-assisted execution depends not only on model capability, but on the quality, governance and feedback mechanisms of the knowledge systems that support it.

Acknowledgements

The author acknowledges the contributions of the AI-First Knowledge Management team and the Research and Intelligence team at Thoughtworks. The author thanks Jessie Jie Xia and the Office of the CIO for their sponsorship of the knowledge management transformation described in this paper.

Ethics Declaration: This study is based on organisational observations conducted within a professional setting. It did not involve human subjects research requiring formal ethical approval. No personal or sensitive data was collected or analysed, and all information is presented in aggregated and non-identifiable form.

AI Declaration: AI tools were used to support the drafting, structuring and refinement of language in this paper. All AI-generated outputs were critically reviewed, edited and validated by the author. AI was not used to generate original research findings, core concepts or interpretations. The ideas, framework and conclusions presented in this paper are the result of the author's own analysis and professional experience.

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Knowledge as the Energy Flow of the Project Ecosystem

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Abstract: An ecosystem is a community of organisms and their physical environment interacting together. Ecosystem involves both biotic (living) organisms (plants, animals, microbes) and abiotic (non-living) physical surroundings (air, water, soil, sunlight). A project is an ecosystem because it is a dynamic, interdependent community of living parts (stakeholders) and non-living parts (OPA – Organizational Process Assets and EEF – Enterprise Environmental Factors). The parts of an ecosystem are linked together through an energy flow, essential for its survival. Energy flow relies on a source, mostly solar. If energy flow stops, an ecosystem will rapidly and completely collapse. Without a continuous flow of energy to maintain complex structures, biological organization breaks down into simple components. Similarly, knowledge is the energy flow that assures the life of the project ecosystem. Without knowledge project naturally moves toward disorder, entropy and chaos. The local profile of the single stakeholder (history, values, and culture, reputation, distinctive skills, organizational structure, and, last but not least, its interest and power over the project), prevails over the global dimension of the project (common goal, synergies, collective way of working, contamination of ideas, points of view, perspectives). This paper is aimed at discussing how to address the peculiarities of a project ecosystem through the energy flow of knowledge. Project peculiarities are: limited life cycle; interdependent stakeholders; fragile relationships; adaptation and learning; emergent value; agency for change. First of all, each peculiarity is briefly explained in terms of meaning, strengths and weaknesses. Then, the practical use of knowledge is discussed for enhancing strengths and reducing weaknesses. Finally, some advices are provided to project key roles, such as project manager, subject matter experts, agile coach, in order to become more familiar with knowledge as the energy flow of the project ecosystem. The topics of this paper may effectively feed the integration of knowledge management other business disciplines, project management first and foremost.

Keywords: Energy Flow, Project ecosystem, Stakeholders engagement, Knowledge sharing, Complexity theory, Second law of thermodynamics, Serendipity

1. Profile of an Ecosystem

An ecosystem is a community of organisms and their physical environment interacting together. Ecosystem involves both biotic (living) organisms (plants, animals, microbes) and abiotic (non-living) physical surroundings (air, water, soil, sunlight). These two are inseparable but inter-related, forming a dynamic system. Main types of ecosystems are terrestrial ecosystem, forest ecosystem, grassland ecosystem, desert ecosystem, tundra ecosystem, aquatic ecosystem, freshwater ecosystem, marine ecosystem. Ecosystems are fundamental for life. The parts of ecosystem are linked together through an energy flow, essential for survival. Energy flow relies on a source, mostly solar. If energy flow stops, an ecosystem will rapidly and completely collapse, as life is an energy-driven process that cannot be sustained without constant feed. It leads to entropy and chaos. The behavior of an ecosystem can be basically explained referring to the second law of thermodynamics: This law states that *"the entropy of the universe tends to a maximum"* (Clausius, 1867). Particularly: a) heat spontaneously flows from hotter to colder objects ("heat flow"), b) energy conversions through trophic levels aren't completely efficient ("10% rule of energy conversion efficiency"), c) the total disorder of an isolated system always increases over time ("increase of entropy"); d) disorder increases because it is statistically more likely than order ("statistical mechanics"); e) an ecosystem can only unfold in one sequence, where the transition from concentrated energy to dispersed chaos determines that the past and future are never interchangeable ("arrow of time").

2. Project as an Ecosystem

In a broader context, the term "ecosystem" is used to describe complex systems of interacting people, businesses, and technologies. Weick argues that *"organized action under uncertainty is maintained through ongoing interpretation and enactment"* (Weick, 1995). Applied to projects, this quote suggests that project coherence does not persist automatically; it must be continually reproduced through shared sensemaking. Projects, especially complex ones, do not simply "run" once designed; they remain coherent only while participants continuously reconstruct shared meaning about goals, risks, priorities, and actions. Thus, a project may be represented as an ecosystem because it is a dynamic, interdependent community of "living" parts. It's a temporary ecosystem because its functions as a short-lived, collaborative environment, bound by an ad-hoc mission rather than a permanent institutional lifespan. Peculiarities of projects as ecosystems are: a) limited life cycle (project is initiated, planned, and executed within a defined timeframe and then it dissolves one the goal is met); b) interdependent stakeholders (projects bring together a heterogeneous mix of individuals,

departments, organizations that must rely on one another to succeed); c) fragile relationships (because the project structure is temporary, trust and coordination are vital; if one party hoards resources, the entire system can fail, much like a diseased organ in a body); d) adaptation and learning (like natural systems, projects must undergo steep learning curves and adapt rapidly to internal or external changes to carry out the expected result); e) emergent value (a project should generates value that exceeds what was strictly contracted, similar to how biological ecosystems produce emergent traits); f) agency for change (projects are often set up as temporary units to bypass the inertia of permanent organizations, allowing for faster experimentation and innovation). In a project ecosystem, stakeholders can be assimilated to living organisms, while OPAs and EEFs to non-living physical surroundings. Each stakeholder is unique due to its intrinsic characteristics and the environment in which it lives and works. Similarly, the stakeholder's action is conditioned (limited and/or facilitated) by its own endogenous assets and by exogenous environmental factors. The single stakeholder with its profile and its specific environment is the atomic component of the project ecosystem. The more numerous, heterogeneous and geographically distributed the stakeholders are, the more complex the project ecosystem is. Lundin and Söderholm (1995) conceptualize projects as temporary organizations characterized by limited duration, specific tasks, transition, and contextual embeddedness, which makes them inherently less stable than permanent organizational forms. Thus, we can represent the initial state of a project ecosystem as a multitude of unique subjects seeking for emergent relationships within the scope and duration of the project. By analogy with the second law of thermodynamics, a project ecosystem tends toward entropy unless it receives continuous sustaining input. In projects, this sustaining input takes the form of knowledge flow, communication, coordination, and shared sensemaking, which function as the organizing energy that preserves coherence. Without a continuous flow of energy, breaks down into simple components moving toward disorder. The consequence is that project becomes *"mission impossible".*

3. Knowledge as the Energy Flow of the Project Ecosystem

> *"Much of the theory associated with project management is explicitly organized according to taxonomic Bodies Of Knowledge (BOK). Although such BOK are conceptually simple and easily disseminated, their generally static and explicit nature is out of phase with the dynamics of critical, tacit knowledge as it flows through the project organization. We argue for a more descriptive view of project management theory, one that captures the dynamics of knowledge flows, addresses tacit knowledge and provides new insight into interrelationships between the management of project knowledge and the management of project activities in the enterprise". (Snider Nissen, 2003).*

Thus, knowledge should be the energy pervasive flow of the temporary project ecosystem. In ecosystems, energy is what sustains processes and interactions, enabling the system to function and thrive. Similarly, in a project ecosystem, knowledge drives the behavior of each stakeholder and interactions among stakeholders, from decision-making and problem-solving to collaboration and innovation. It flows in various forms, such as shared information, lessons learned, vertical expertise, insights, and communication. This exchange feeds collaboration, aligns stakeholder efforts, enhances collective actions, coherent and effective towards the common goal of the project. Moreover, the quantity and quality of knowledge can amplify or limit the performance of the project ecosystem: knowledge sharing fosters trust and alignment among stakeholders, while bottlenecks in knowledge transfer can create misalignments and conflicts. In short, knowledge not only powers the project, but essentially binds its parts together, enabling stakeholders to work collectively and adaptively, as a cohesive whole. Viewing knowledge as the energy flow of the project ecosystem can radically shift how to consider project dynamics and success. In projects, knowledge is the vital force that sustains coordination, adaptation, learning and collaboration. When knowledge does not flow across the project ecosystem, the project loses its adaptive energy: decisions weaken, silos deepen, learning slows, risks intensify, and the likelihood of delay, rework, and failure increases. *PMI® states that "Managing knowledge involves more than just documenting explicit knowledge for transfer lessons learned at the end of the project for use in future projects. It entails that tacit knowledge, often deeply ingrained in experts' experience and intuition, can be shared within a project by fostering a collaborative and trust-filled environment. This effort involves creating opportunities for knowledge transfer (A/N sharing) through open communication, mentoring relationships, team-building activities. Encouraging face-to-face interactions and hosting regular brainstorming sessions can help make implicit knowledge more accessible" (PMI, 2025).*

4. Knowledge in Limited Life Cycle

A project is temporary adventure based on limited life cycle. "The project life cycle provides the foundational framework for managing the project. The project life cycle should be flexible enough to meet or exceed the

project target objectives in a way that protects and enhances the project's value proposition as much as possible". (PMI, 2025). Project must be initiated, planned, executed and closed within a defined timeframe in terms of final deadline and intermediate milestones. The life cycle consists of a set of phases. Each phase is unique in terms of purpose, contents, management style, way of working, requested behaviors. For example, on the one hand the phase "Feasibility" has this profile: the purpose is to determine whether the project idea is viable, the focus is on understanding the problem or opportunity, exploring alternatives, and deciding whether to proceed; typical contents include business need analysis, high-level scope, cost-benefit review, risk identification, stakeholder analysis, and possible options. The team tries to build enough understanding to support a go/no-go decision; the management style is usually exploratory, analytical, and flexible. Project manager encourages investigation, discussion, and critical thinking rather than strict control of delivery; the way of working is research-oriented and collaborative. The team gathers information, evaluates assumptions, compares options, develops early recommendation. Activities often involve workshops, interviews, studies, and concept reviews; requested behaviors entail that people are expected to be curious, open-minded, realistic, and willing to challenge. Assumptions, strong communication, learning, and stakeholder engagement are important because uncertainty is high. On the other hand, the phase "Construction" has this profile: the purpose is to build the approved project deliverables. The focus shifts from deciding what should be done to making sure the work is completed effectively, on time and on budget; typical contents include detailed execution, resource deployment, procurement, coordination of teams, quality control, schedule tracking, cost control, issue resolution, progress reporting; the management style is more structured, controlled, and performance-driven. The emphasis is on coordination, productivity, compliance, and meeting milestones; the way of working is execution-focused and follows approved plans, designs, and specifications. Team performs defined tasks, monitor progress, manage changes, and resolve operational problems quickly; requested behaviors entail people to be disciplined, accountable, safety-conscious, and delivery-oriented. Team members need good coordination, responsiveness, and commitment to quality and deadlines. According to this scenario the knowledge flow must be tailored on the uniqueness of each project phase. In other words, the energy flow must enlighten and fuel each phase in a different way. For example, on the one hand the knowledge flow for the "Feasibility" phase should be broad, exploratory, and analytical, so the team can evaluate options, test assumptions, and make a sound go/no-go decision; implicit and tacit knowledge usually prevail over explicit knowledge. On the other hand, the knowledge flow for the "Construction" phase should be structured, fast, and operational. Information needs to move continuously among planners, engineers, suppliers, management roles and others stakeholders to coordinate execution, solve issues quickly, control quality, and keep the work aligned with schedule, cost, and scope; explicit knowledge usually prevail over implicit and tacit knowledge. In short, during Feasibility knowledge flow supports understanding and decision-making, while during Construction knowledge flow supports execution and control. Summing up: "The management of projects requires different emphases at different stages in the project life cycle." (Turner, 2009); "Knowledge has to be improved, challenged, and increased constantly, or it vanishes." (Drucker, 1993).

5. Knowledge Among Interdependent Stakeholders

Project is a dynamic and emergent system of interests, less declared and more implied. By their nature, these interests are not necessarily aligned with the project objective. Moreover, interests of a stakeholder are related with the interests of another stakeholder. They can converge, diverge, coexist. The result is a complex network of relationships. According to the Cynefin framework, *"a complex system has the following characteristics: it involves large numbers of interacting elements; the interactions are nonlinear and minor changes can produce disproportionately major consequences; the whole is greater than the sum of its parts, and solutions can't be imposed, rather they arise from the circumstances, this is frequently referred to as emergence; unlike in ordered systems (where the system constrains the agents) or chaotic systems (where there are no constraints), in a complex system the agents and the system constrain one another, especially over time"* (Snowden Boone, 2007). Therefore, a project can be understood as a complex system because it involves many stakeholders whose interactions are interdependent, dynamic, and not fully predictable in advance. Therefore, the project manager should create the conditions where knowledge moves across boundaries and where stakeholders collectively make sense of what is happening. Knowledge as energy flow can support project managers in addressing interdependencies among stakeholders. How? We can refer to the topics of the second law of thermodynamics. For *"heat flow"*: in projects, heat tends to flow from the most pressured stakeholders to the less pressured ones. For example, if a regulator raises compliance concerns, that pressure moves to the sponsor, then to the project manager, then to the delivery teams, and finally to suppliers who must adjust designs or documentation. This helps to explain why unresolved issues do not stay local. Project manager should use knowledge flow to channel

and absorb pressure before it becomes disruptive, converting pressure into actionable understanding so that stakeholder reactions are informed rather than emotional. For *"10% rule of energy conversion efficiency"*: in projects, every stakeholder handoff loses value across trophic levels. A strategic objective from the project sponsor is rarely received with full fidelity by other stakeholders. For example, the sponsor message "to improve customer experience" may become for a supplier "to reduce click count," which is only one fragment of the original intent. Project manager should use knowledge flow to protect the original purpose by creating traceability. For example, the sponsor message "to improve customer experience" should be translated into business requirements, design choices, testing criteria, and adoption measures in a visible chain. Because of this PMI suggests to adopt a holistic view: *"this perspective aligns with the concept of system thinking, which emphasizes the interconnectedness of elements within a project. It provides a framework for viewing interrelationships in their full context and for seeing patterns rather than static snapshots"*. (PMI, 2025). For *"increase of entropy"*: a project stakeholder isolated from the normal flow of communication, feedback, decisions, and shared understanding gradually increases disorder in the project ecosystem. Because of this isolation decisions become guided more by local priorities than by shared project objectives. For example, a department that was consulted at project initiation but not engaged afterward. Over time, it develops its own interpretation of the project purpose, believe its needs are being ignored, and begins resisting implementation decisions. Project manager should use knowledge flow to open the isolated stakeholder, even if supportive, through regular exchanges: governance meetings, stakeholder check-ins, risk reviews, and updated communication tailored to each audience. For *"statistical mechanics"*: in projects disorder is often more probable than order because there are many more ways for coordination to go wrong than to go right. It takes only one missed dependency, one ambiguous approval, or one unshared assumption to create friction, while successful coordination usually requires multiple conditions to align at once. For example, a project for the launch of an innovative product involves marketing, compliance, IT, sales, and customer support. There are countless combinations of partial readiness that produce confusion, but only a relatively narrow set of coordinated states that produce a smooth launch. The project manager should use knowledge flow to design structure against the natural probability of confusion, through stakeholder map, RACI matrix, formal escalation thresholds, and standard reporting formats. For *"arrow of time"*: once stakeholder decisions are made, contracts signed, architecture chosen, or trust damaged, the project ecosystem cannot simply reverse to an earlier condition without additional costs. For example, the sponsor publicly announces a delivery date before technical stakeholders validate feasibility. That announcement changes behavior across the projects: procurement accelerates, teams compress testing, suppliers negotiate around urgency and customers form expectations. Even if the date was unrealistic, the project cannot return to the pre-announcement state. The project manager should use knowledge flow to improve the quality of irreversible decisions. He/she should ensure that when stakeholders make those choices, they do so with enough knowledge about impacts, dependencies, and risks. For example, before committing to a delivery date, the project manager should organize a round table among project sponsor, technical leads, and operations stakeholders for fostering a shared visibility of feasibility constraints and downstream implications.

6. Knowledge Across Fragile Relationships

The temporary dimension of the project influences the relationships among stakeholders. In many cases these relationships can't rely on stable and codified rules, long-term routines, shared history, but must instead be built quickly and put in action under pressure. For this reason, relationships are contingent, precarious, unstable, ephemeral. In short, fragile. The fragility of relationships is undoubtedly a critical factor for the success or failure of a project. It depends on how they are nurtured. Fragility is defined as *"a concave sensitivity to stressors, where an entity has more to lose than to gain from random events. A fragile system is one that is short- volatility, performs worse as disruption increases and breaks under large shocks"* (Taleb, 2012). This means that project relationships, if not protected, are damaged by stressors: an intact better shape before stress versus a broken worse shape after stress. A stressor is *"any form of disorder, volatility, randomness, uncertainty, or external pressure that acts upon a system"* (Ibidem). Stressors are the inhibitors that cause a fragile system to break, degrade and become weaker. Speaking about projects, under the term "stressor" we can group errors, changes, failures, attacks, risks, unforeseen events, malfunctions. How to protect the fragility of project relationships? Knowledge can protect this fragility because it acts as the medium through which relationships can gain consistency, trust, and continuity, preventing them to break. In which ways? The first way is through a shared understanding. Fragile relationships often suffer from ambiguity. Stakeholders may not fully understand each other's roles, expectations, constraints, or motivations. When knowledge flows openly and continuously, uncertainty decreases. Stakeholders begin to see not only what others are doing, but why they are doing it. The

second way is through a swift trust. Project stakeholders usually don't have the advantage of developing trust over long periods. Swift trust can be developed through reliable exchanges of knowledge: clear communication, transparent decisions, visible assumptions, timely escalation of risks, and honest sharing of constraints. Thus, stakeholders perceive relationships as dependable, even if they are new and fragile. The third way is through the visibility of interdependences. During the project execution, stakeholders depend on one another in asymmetrical and changing modes. Fragility increases when one stakeholder's actions unexpectedly disrupt another's work. Continuous knowledge flow makes dependencies more visible. In this way, knowledge flow acts as a "glue" against instability created by fragile interdependences.

7. Knowledge in Adaptation and Learning

At first sight, this peculiarity of the project may appear obvious. New knowledge derives from learning and learning is based on current knowledge. However, this is not such a foregone conclusion. Learning during the project life cycle is not innate and free, but instead requires an ad-hoc strategy, investment and action plan. *"Organizations learn only through individuals who learn. Individual learning does not guarantee organizational learning. But without it no organizational learning occurs".* (Argyris Schön, 2007). The project is an incredible learning opportunity that is too often under and poorly exploited. The consequence is that the project doesn't socialize the experiences gained in the field, doesn't translate them in lessons learned, and accordingly doesn't adapt the way of working and interacting for the remaining part of the project. The file rouge *"inspect, reflect, learn, adapt"* is broken! A key principle of the adaptive (agile) approach for managing projects states that *"at regular intervals, the team reflects on how to become more effective, then tunes and adjusts its behavior accordingly"* (Authors of agile manifesto, 2001). The Disciplined Agile toolkit entails the process "Evolve way of working". The focus of is *"continuous improvement to support and enable teams to choose their way of working and share learnings across the organization"* (Ambler Lines, 2019). If the project fits an agile approach, knowledge flow for learning and adaptation should be based on techniques that are frequent, transparent, collaborative, and iterative. Some typical techniques are: Daily standups that help the team surface blockers, dependencies, and progress in real time, which strengthens short-cycle coordination; Sprint reviews that help the project adapt based on feedback from the field more than initial assumptions; Sprint retrospectives that help the agile team to reflect on what worked, what failed, and what should change in the next iteration; Information radiators that make knowledge visible and strengthens collective awareness; Pair work that helps agile people to learn directly from one another while work is being done, instead of only after work is done. For a waterfall or predictive approach, knowledge flow for learning and adaptation should be based on techniques that are planned, documented, sequential, and controlled across phases. Some typical techniques are: Requirements documentation that captures stakeholder needs helping to preserve a shared understanding early in the project; Design reviews that allow to analyse results before execution moves forward. They create opportunities to validate assumptions, surface errors, and improve solution quality before costly downstream work begins; Phase-gate reviews that organize learning at transition points. At the end of each phase, the project team can assess what has been achieved, what risks remain, and what knowledge must be transferred before the next phase begins; Formal handoffs that protect continuity across specialized teams and sequential work stages; Lessons learned registers that support organizational learning by regularly capturing experiences, recurring problems, and good practices; Change control procedures that ensure that new knowledge about scope, risk, quality, or stakeholder needs is not ignored but incorporated in a structured way; Configuration management that helps to maintain the integrity of project knowledge by controlling versions of requirements, designs, specifications, and deliverables; Status reports that keep knowledge flowing across managerial and governance levels (portfolio, strategic objectives).

8. Knowledge for Emergent Value

A project justified itself if creates value (positive exceed between achieved benefits and incurred costs). This challenge requires to move across the value chain, particularly along the time-lined sequence *"deliverables – outcomes – benefits".* Deliverables are useless if not translated into outcomes and benefits are not achievable without outcomes. An example: a project has built *"a car with seat belts compliant with specific safety standards".* This deliverable is useless if the outcome *"car drivers fasten their seat belts regularly"* is not in place. Only if this outcome is in place the benefit *"fewer deaths and injuries while traveling by car"* is achieved. Outcome is the bridge between deliverable and benefit, too often badly and poorly addressed. The value of the project may be planned upfront but also emerges in progress. The project is an ecosystem whose dynamics are better discovered, understood and addressed through a combination of structured management and a serendipity-oriented mindset that remains open to emergent signals, unexpected connections, and unplanned

opportunities. Serendipity is *"the faculty of making happy and unexpected discoveries by accident"* (Walpole, 1977). A serendipity approach can be useful for sensing and leveraging unexpected patterns, weak signals, informal insights, accidental discoveries, beneficial unplanned connections. For example, in an R&D project, a supplier raises a concern that seems marginal to the initial scope. Instead of ignoring it, the project manager explores it and discovers a broader interoperability issue that could later affect regulators, users, and future partners. What appeared as an unexpected side comment becomes a powerful system insight. This example points out that serendipity is not random luck alone, it is more like disciplined receptivity. This way, serendipity can foster outcomes that are not fully predictable from the plan alone. The project manager should create the conditions in which unexpected but useful knowledge can surface and then acts on it. Knowledge flow may be a powerful enabler of the emergent side of project value. It connects the production of deliverables with their effective use in practice, allowing intended outcomes to materialize and consequent benefits to be realized. Through continuous sharing, interpretation, and application of knowledge, the project moves beyond output delivery toward sustained value creation. For example, at the outcomes level, knowledge flow becomes the key that enables deliverables to be understood, adopted, uses used, embedded in practice. Outcomes are not generated automatically by handing over deliverables. They emerge when users, sponsors, operators, and affected stakeholders understand what a deliverable is for, how it changes work, and how it should be integrated into existing processes. In this sense, knowledge flow converts a delivered artifact (things) into a new operational state (people).

9. Knowledge as Agency for Change

Project, by its nature is an agency for change. Deliverable must be translated into outcomes. Outcomes occur when people alter behavior, routines, decisions, and interactions in response to the deliverable. Thus, project outcomes (new organizational state) may be in place only through change management. The goal is to move from to current state (as-is) to the future state (to-be). The wider is the gap, the bigger is the change management effort. We can argue that change management addresses the transition from deliverables (things) to outcomes (people). Change management is a *"comprehensive, cyclic and structured approach for transitioning individuals, groups and organizations from a current state to a future state with intended business benefits"* (PMI, 2013). Change management runs parallel to project management, right from the start of the project, regardless the project approach selected: waterfall, agile or hybrid. Change management entails different approaches. The main types are: "Fully prepared to act", "Continuously sustain action", "Deliberately build capacity", "Quickly organize to act". The choice of the approach that best fits with the change to address depends on the combination of two factors: urgency to change and readiness for change. With no doubt, the project manager is accountable to set-up and coordinate the change management plan, including in the project team specialized roles such as change ambassadors, change catalysts, change leads. In which way knowledge as energy flow of the project ecosystem can make the difference in change management? Mainly in four connected ways. First, it gives stakeholders sensemaking capacity, helping them interpret the purpose of the change and their role within it. Second, it provides relational connectivity, linking people who must coordinate to implement the new reality. Third, it enables adaptive learning, allowing the organization to respond to resistance, misunderstanding, and unintended effects as they emerge. Fourth, it supports reinforcement, so the new ways of working become normalized rather than temporary compliance behaviors. Summing up, knowledge flow is what keeps the project ecosystem responsive and coherent across the full transition from delivery to adoption to sustainment.

10. Conclusions

Project is an ecosystem which behavior can be basically explained referring to the second law of thermodynamics. Heat flow, 10% rule of energy conversion efficiency, Increase of entropy, Statistical mechanics, Arrow of time can be applied to discover and understand the complexities of the project ecosystem. Knowledge is the pervasive energy flow of the temporary project ecosystem. Knowledge flow is essential to address the peculiarities of the project: limited life cycle, interdependent stakeholders, fragile relationships, adaptation and learning, emergent value, agent for change. Project managers, and more in general project key roles, should improve their awareness in using knowledge from an ecosystem point of view. With no doubt, this is a big challenge that must be embraced and that can lead to improved project performance in terms of benefits and value. Otherwise, the project ecosystem is left at the mercy of entropy and chaos.

Ethics and AI Declarations: For this paper, an ethics declaration is not required, AI Infinity chatbot by PMI® was used for finding key concepts and definitions, adapting them within the text for the purpose of the paper.

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Integrating Organizational Knowledge Sources into a Knowledge Management Portal

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Abstract: This paper presents a practical (non-academic) case study of organisational knowledge-resource sharing through the corporate knowledge management portal at Mobarakeh Steel Company in Isfahan, Iran. It explains how a structured portal was designed and implemented to integrate dispersed knowledge assets, improve access to organisational experience, and support learning across operational and managerial domains. In many industrial organisations, valuable knowledge is created through operations, maintenance and repair, projects, audits, training, and continuous improvement activities; however, retrieval and reuse are often difficult because knowledge artefacts are distributed across multiple units and information systems. The experience reported in this paper shows how the portal was developed as a pragmatic response to this dispersion challenge. The portal was designed to provide a single point of access to a portfolio of knowledge resources, while explicitly considering organisational structure, content ownership, and access-control policies. The initiative was informed by established knowledge management concepts as well as practical frameworks for assessing and developing knowledge management capabilities (Alavi and Leidner, 2001; Bhatt, 2001; Davenport and Prusak, 1998; APQC, 2025). The paper also describes how the organisational context influenced the portal's evolution. Prior experience in technology transfer, the implementation of management systems, the development of quality procedures and document control, training and empowerment mechanisms, and organisational excellence initiatives provided the foundation for more structured management of knowledge resources. Therefore, the portal emerged not as a standalone digital tool, but as part of a broader organisational effort to capture, reuse, and share knowledge. In this process, institutional standards and approaches, including ISO-based practices, contributed to structuring and consolidating the initiative (ISO, 2019).

Keywords: Knowledge management, Knowledge portal, Organisational knowledge sharing, Case study, Industrial organisation, Mobarakeh Steel Company

1. Introduction

Industrial organisations continuously generate valuable knowledge through daily operations, maintenance activities, improvement projects, audits, training programmes, and problem-solving routines. However, this knowledge often remains fragmented across departments, personal files, local databases, and heterogeneous enterprise systems. As a result, employees spend significant time searching for relevant experiences and documents, lessons learned are not consistently reused, and organisational learning becomes dependent on individuals rather than embedded organisational practices.

Mobarakeh Steel Company, as one of Iran's largest industrial companies, faced similar challenges regarding dispersed knowledge resources and inconsistent access pathways. In response, the company developed and implemented a corporate Knowledge Management (KM) Portal to provide a structured, organisation-wide mechanism for capturing, organising, and sharing knowledge resources. The portal aimed to (i) create a single point of access to knowledge assets, (ii) improve findability and reuse of organisational experience, and (iii) support learning for both operational and managerial decision-making.

"This paper reports a practical case study of that experience and describes how organisational context, governance considerations (e.g., content ownership and access control), and institutional frameworks shaped the portal's design and evolution. The work is informed by established KM perspectives (Alavi and Leidner, 2001; Bhatt, 2001; Davenport and Prusak, 1998) and capability-oriented approaches (APQC, 2025), while also acknowledging the role of ISO-based practices in structuring the overall initiative (ISO, 2019).

Methodologically, this study adopts a practical case-study approach grounded in the authors' direct involvement in the development and evolution of the portal. The analysis draws on internal project documentation, portal design records, content-ownership discussions, governance notes, and implementation artefacts. Where relevant, these materials were complemented by informal consultations with organisational stakeholders involved in content provision, review, and portal use. This approach is intended not to test a hypothesis, but to

document how organisational knowledge sources were identified, structured, and integrated into the portal over time.

2. Organisational Context and Background

The company's knowledge management journey did not begin with the portal. Rather, the roots of this journey can be traced to earlier organisational developments in which knowledge transfer, documentation, and process discipline played a key role. In the early stages of industrial growth and technology acquisition, technical and operational knowledge entered the organisation through external collaboration and technology transfer. Over time, these experiences contributed to greater organisational attention to technical learning, maintenance knowledge, and mechanisms for preserving and transferring experience.

Subsequently, the implementation of management systems such as ISO 9001, ISO 10015, and ISO 30401 strengthened formal approaches related to documentation, process stability, and knowledge retention. Mechanisms such as the suggestions system, document control, training, and managerial reporting procedures provided a context in which knowledge gradually came to be regarded as an organisational asset rather than remaining solely at the individual level (ISO, 2019).

At the same time, the development of information systems and managerial tools made organisational processes and data more visible. Systems related to management information and executive reporting indirectly reinforced the infrastructure required for presenting organisational knowledge and experience. In addition, excellence frameworks and organisational assessments created incentives for identifying, documenting, and showcasing successful experiences. Taken together, these factors contributed to the organisation's gradual movement from dispersed information resources towards more coherent knowledge management.

At the strategic level, attention to broader strategic directions, capability development, and the strengthening of organisational learning also created the necessary readiness for implementing portal-based solutions (Mobarakeh Steel Company, 2026). From an operational perspective, the portal emerged as a mechanism for connecting knowledge assets that already existed across different parts of the organisation, but for which integrated and user-centred access had not previously been available.

Accordingly, the main problem addressed by the project can be explained at three levels:

2.1 Dispersion of Knowledge Resources

The organisation's knowledge resources had been developed in the form of multiple systems and infrastructures. Each resource had its own structure, access path, and level of maturity. This dispersion prevented organisational knowledge from being viewed in an integrated manner.

2.2 Multiple Authentication Requirements and Difficult Access

The existence of separate authentication procedures across different resources meant that user access to information and knowledge became a time-consuming and multi-step process. This was a particularly serious limitation for operational staff, who typically have less time and patience to interact with complex systems.

2.3 Lack of Clear Evidence of the Effectiveness of Knowledge Sharing

Despite the existence of the portal and various knowledge resources, it was difficult to demonstrate that knowledge was actually being used across the organisation or that it was contributing to performance improvement. For this reason, one of the project's main objectives was to create a platform capable of making the use of knowledge and its impact as visible as possible.

On this basis, the need for a structured redesign emerged—a redesign that would focus both on the integration of resources and on respecting the organisation's operational constraints.

3. Conceptual Foundations and Influential Frameworks

Although this paper is practice-oriented, the experience of developing the portal can be explained within well-established knowledge management concepts. One common perspective views knowledge management as a set of processes for creating, storing, sharing, and applying knowledge in line with organisational objectives. Within this approach, technology is an enabler; however, its effectiveness will be limited without organisational processes, governance, and user participation (Alavi and Leidner, 2001).

From another perspective, knowledge management relates to an organisation's ability to connect people, processes, and systems in a coherent way so that knowledge can flow and create value. In this context, both explicit knowledge (embedded in documents and systems) and tacit knowledge (embodied in experts' experience and judgement) are important—particularly in industrial environments, where lessons learned and experience often emerge at the boundary between formal documentation and practical problem-solving (Bhatt, 2001; Davenport and Prusak, 1998).

Alongside these theoretical foundations, practical reference frameworks such as APQC have directly influenced the development of knowledge management capability in this project. APQC models and tools offer a process-oriented lens for capability assessment, helping organisations strengthen core components like governance, content management, accessibility, learning mechanisms, and reuse in a structured manner (APQC, 2025). In the case of our portal, APQC served as the main reference for organising portal functions around governance, content lifecycle, and knowledge reuse—leading to specific design choices such as structuring resources by ownership and type, defining review and approval responsibilities, and making retrieval pathways more transparent for end users. Similarly, ISO-based practices reinforced documentation discipline, competence development, and controlled access, all of which shaped the portal's rules for publishing, updating, and maintaining knowledge resources.

Furthermore, a standards-oriented environment and the organisation's experience in implementing ISO-based approaches across different domains have supported the discipline required for documentation, competence development, and the management of knowledge resources (ISO, 2019). Overall, the portal can be seen as a point of convergence between real business needs, reference frameworks, standards, and the organisation's operational logic.

4. Development of the Knowledge Management Portal

The knowledge management portal was designed with the aim of creating a central access point for the organisation's knowledge resources, which were dispersed across different units and functions. One of the main challenges in implementing the portal was that these knowledge assets had not been produced within a single architecture; rather, they existed in different formats and systems, with different ownership arrangements and uneven levels of maturity and quality. Therefore, in addition to displaying content, the portal needed to help create coherence and logical connections among heterogeneous resources.

To address this need, a modular design approach was adopted. This approach makes it possible to connect different knowledge domains and applications within an overall framework, while preserving the specific functions of each domain and its governance arrangements. Modularity also helps align the portal with the needs of different user groups, organisational levels, and operational contexts. Rather than imposing a single integrated repository, the portal plays the role of an "integrated gateway" that brings together access paths to multiple knowledge resources at one point.

The implementation of the portal required close interaction with the owners of knowledge resources, facilitators, and relevant stakeholders. In practice, this involved holding working sessions, clarifying the nature of the content, reviewing access boundaries, and determining how different types of knowledge should be presented and linked. Such interactions are essential, because the success of the portal is realised only when the system reflects the realities of organisational work and accommodates the responsibilities and constraints associated with content production and maintenance.

Access policies were also a key consideration. In industrial organisations, not all information can be made available to all users. The portal therefore needed to support the application of access levels and the separation of responsibilities, while at the same time strengthening the overall objective of knowledge sharing as far as possible. Achieving a balance between "openness" and "control" is one of the enduring challenges of organisational knowledge systems.

The home page of the knowledge management portal plays an important role in the user experience. As the main gateway, it must guide users towards relevant content, simplify navigation, and increase the visibility of knowledge assets. From this perspective, the home page is not merely a technical interface; rather, it represents a practical expression of the organisation's philosophy of knowledge sharing and a means of day-to-day access to organisational memory.

5. Knowledge Resources and Portal Functions

A central objective of the knowledge management portal was to improve the accessibility, integration, and practical use of organisational knowledge resources. Prior to the development of the portal, knowledge existed across multiple repositories including departmental files, internal reports, technical documents, lessons learned records, and other knowledge artefacts distributed across organisational units. Although these resources contained valuable operational and managerial knowledge, their dispersion across different systems and locations significantly limited their discoverability and reuse. The portal was therefore designed as a unified access point through which diverse knowledge resources could be integrated, structured, and made more easily accessible to employees. The main categories of organisational knowledge resources currently integrated into the portal are presented in Table 1.

Table 1: Organisational Knowledge Resources Integrated into the Knowledge Management Portal

Knowledge resource	Approximate number	Software infrastructure	Audience within the organisation
Operational workflows and instructions	12000	In-house office automation software based on .NET infrastructure	Entire organisation (approximately 12,000 employees)
Lessons learned	130000	In-house "Transformation Cartable" software based on Oracle BPMS infrastructure	Entire organisation (approximately 12,000 employees)
Suggestions	6940052	In-house "Transformation Cartable" software based on Oracle BPMS infrastructure	Entire organisation (approximately 12,000 employees)
Improvement and transformation projects	17556	In-house "Transformation Cartable" software based on Oracle BPMS infrastructure	Entire organisation (approximately 12,000 employees)
Research projects conducted in collaboration with university centres	500	No specific software infrastructure	Entire organisation (approximately 12,000 employees)
Experts' knowledge booklets and knowledge packages	200	No specific software infrastructure	Entire organisation (approximately 12,000 employees)
Meetings and findings of specialist groups	143	No specific software infrastructure	Entire organisation (approximately 12,000 employees)
Minutes and reports of failure-analysis meetings	11111	In-house EIS software based on Oracle Forms infrastructure	All personnel in the company's maintenance areas (approximately 5,000 employees)
Organisational books, standards, and international resources related to the steel industry	200	No specific software infrastructure	Entire organisation (approximately 12,000 employees)
Employees' professional and knowledge profiles, including their educational and professional records	12000	No specific software infrastructure	Entire organisation (approximately 12,000 employees)

5.1 Improving Knowledge Discoverability

One of the primary functions of the portal is to enhance the discoverability of organisational knowledge. In many organisations, the challenge is not necessarily the absence of knowledge but the difficulty of locating relevant information at the moment it is needed. The portal addresses this challenge by providing a centralised interface through which users can search, browse, and access knowledge resources originating from different organisational sources. The main interface of the portal, which enables users to navigate and retrieve knowledge resources, is illustrated in **Figure 1.**

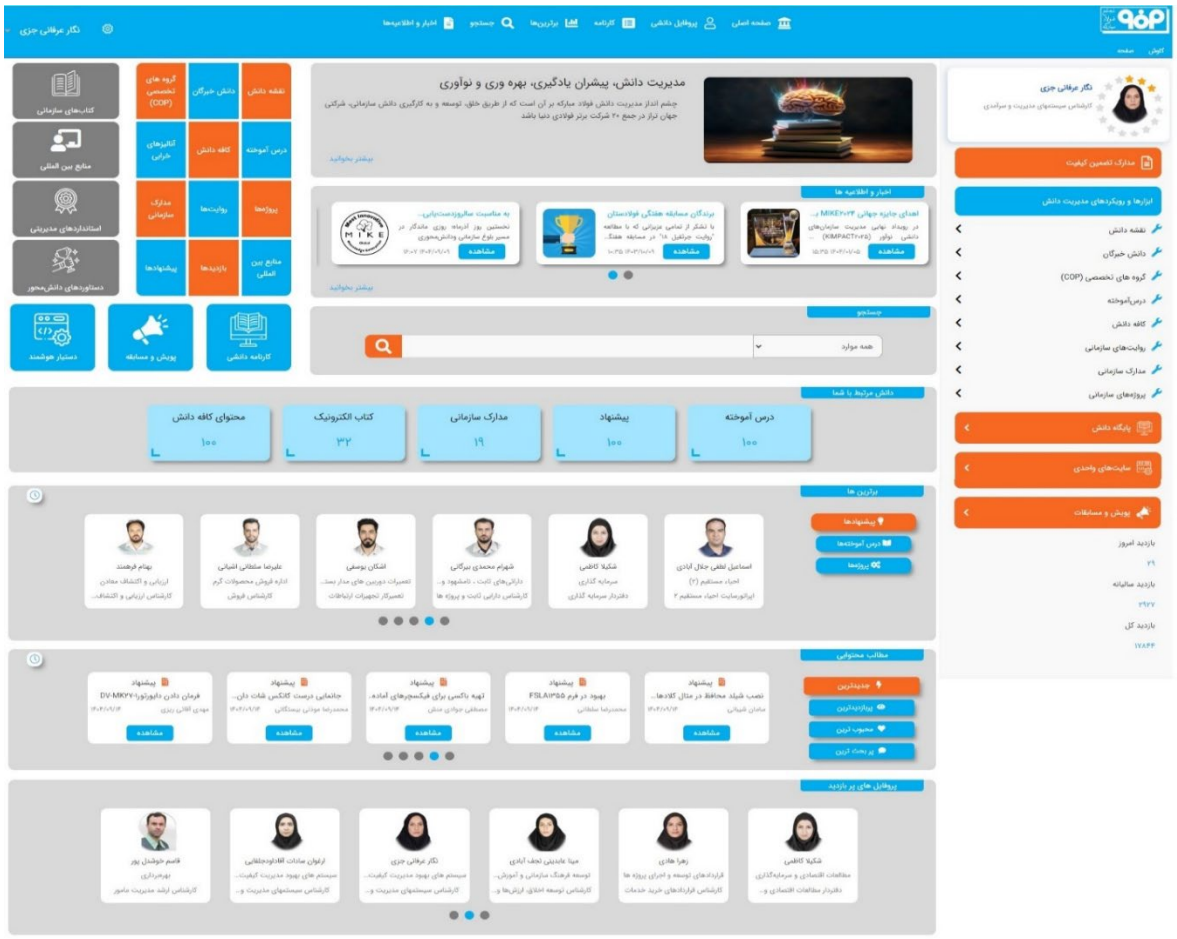


Figure 1: Main Interface of the Knowledge Management Portal

The proposed KMS architecture, (conceptualised in **Figure 1**), serves as the technological cornerstone of the organizational knowledge framework. It seamlessly integrates the three pillars of KM: it empowers **people** by providing personalized knowledge access, streamlines **processes** through structured workflows such as the CRA (Failure Analysis Groups) module, and leverages advanced **technology** to ensure the codification and retrieval of organizational learning. Consequently, this platform transforms fragmented operational data into a cohesive knowledge asset, enabling evidence-based decision-making across the enterprise.

By consolidating dispersed repositories into a single environment, the portal reduces fragmentation and improves the visibility of existing knowledge assets. Initial use of the portal has indicated a noticeable improvement in the retrieval of internal documents and knowledge resources. Users reported that materials previously scattered across different departments are now easier to locate, and that recurring operational problems can be resolved more quickly because earlier solutions and experiences are accessible through the portal. These observations suggest that the portal contributes to both improved knowledge findability and increased opportunities for knowledge reuse within the organisation.

5.2 Monitoring Knowledge Use Through Portal Indicators

In addition to integrating knowledge resources, the portal also enables the monitoring of how knowledge is accessed and used within the organisation. To support this objective, a set of standardised usage indicators has been defined for different types of knowledge resources available in the portal. These indicators include metrics such as views, user feedback, comments, and other forms of user interaction.

The introduction of these indicators makes it possible to observe patterns of knowledge use and engagement across different organisational units. Unlike the previously dispersed repositories, where no consistent evaluation criteria existed, the portal provides a unified analytical perspective that allows knowledge managers to monitor the relative visibility and utilisation of different knowledge resources. Over time, these usage indicators can support the identification of high-value knowledge assets, highlight areas where knowledge resources require improvement, and provide a basis for evidence-based refinement of the knowledge base.

5.3 Linking Lessons Learned with Organisational Procedures

An additional integration mechanism implemented through the portal concerns the systematic linkage between organisational lessons learned and the formal body of procedures and operational guidelines. Historically, lessons learned were collected within the organisation as a means of capturing experiential knowledge derived from operational activities. However, despite the accumulation of a large number of lessons learned, their practical utilisation in the revision of formal procedures and organisational documentation remained limited.

One of the main reasons for this limitation was the absence of a structured connection between the two domains. Lessons learned were managed through a knowledge management process, while the revision of procedures and operational guidelines was conducted by specialised teams within organisational units. Because these processes operated largely independently, there was no systematic mechanism to demonstrate how experiential knowledge could inform the revision of formal documents.

To address this challenge, the knowledge portal introduced a structured linkage between lessons learned and organisational procedures. When submitting a new lesson learned, contributors can identify the specific procedures or operational guidelines that may potentially benefit from the knowledge captured. During subsequent reviews of these documents by the responsible organisational units, the system automatically presents the lessons learned that have been associated with the relevant document. This enables subject-matter experts to examine these insights and, where appropriate, incorporate them into the revision of procedures and operational guidelines.

Through this mechanism, the portal establishes a systematic bridge between informal experiential knowledge and the organisation's formal documentation system. In addition, a dedicated indicator has been defined to monitor the extent to which lessons learned are utilised during the revision of organisational documents. This indicator enables organisational units to track the practical application of captured knowledge and provides evidence of how operational experience contributes to the continuous improvement of organisational practices.

This approach also supports the practical implementation of recognised knowledge management frameworks. In particular, it aligns with the principles of ISO 30401, which emphasise the systematic application of organisational knowledge in operational processes and decision-making. By connecting lessons learned with the revision of formal procedures, the portal helps ensure that experiential knowledge is not only captured but also embedded within organisational practices. Similarly, the mechanism reflects the process-oriented perspective of the APQC knowledge management framework, which highlights the role of organisational learning in the continuous improvement of organisational processes.

6. Implementation Challenges and Lessons Learned

The development of a knowledge management portal in a large industrial company highlights several key lessons. First, the success of the portal depends less on the *presence of technology* and more on the *alignment of users, content, governance, and organisational processes*. A purely technical portal will not create sustained value if it is not connected to users' real work practices.

Second, stakeholder engagement is critical. Knowledge resources are typically produced and maintained by different organisational actors, each with distinct language, priorities, and documentation standards. Coordinating these actors requires facilitation, negotiation, and trust-building. The organisation's experience indicates that continuous interaction with resource owners and facilitators was essential in moving from dispersed content towards an integrated system.

Third, modularity is an advantage. In many organisations, attempts to fully centralise all knowledge into a single repository fail because functional diversity is overlooked. A modular architecture provides a more realistic route to integration: knowledge domains can retain relative autonomy while becoming accessible through a shared gateway.

Fourth, access control is a determining issue. Organisational knowledge sharing is always constrained by practical requirements relating to confidentiality, accountability, and organisational policies. The goal is not to remove all boundaries, but to design a system in which appropriate knowledge can flow effectively without weakening organisational governance. This case suggests that successful approaches require a combination of *targeted openness* and *structured control*.

Fifth, knowledge management maturity is cumulative in nature. This initiative benefited from the organisation's prior investments in quality systems, training structures, documentation practices, information systems, and

organisational assessments. For this reason, the portal should be seen as the outcome of a trajectory of organisational development, rather than its starting point. This lesson is important for other organisations: effective knowledge portals are typically built on existing managerial infrastructures.

7. Conclusion

This paper presented a practical case study of sharing organisational knowledge resources through the corporate knowledge management portal of Mobarakeh Steel Company. The initiative demonstrates how an organisation can overcome dispersed knowledge by moving towards an integrated, user-centred environment. A key lesson is that KM maturity develops cumulatively; the portal's success was not an isolated technological achievement, but the result of sustained investment in documentation, training, and governance.

The portal serves as a manifestation of this progressive development, informed by frameworks such as APQC and ISO 30401. It underscores that sustainable KM depends on the alignment of processes, governance, and organisational learning. For similar industrial entities, this experience offers a blueprint for moving beyond fragmented initiatives, proving that modular design and process alignment are critical enablers for embedding knowledge sharing into everyday infrastructure.

Ultimately, this study provides a significant contribution by demonstrating how traditional KM frameworks can be operationalised within a large-scale industrial context. By integrating diverse resources into a unified KMS architecture, this research highlights the transition from reactive problem-solving to proactive knowledge codification. This approach offers a scalable, replicable model for heavy industries to mitigate operational risks by embedding tacit knowledge management directly into daily workflows, thereby enhancing organisational resilience in complex environments.

Ethics Declaration: No ethical clearance or ethics approval was required for the research reported in this paper.

AI Declaration: Artificial intelligence tools were used solely for language translation and to improve the clarity and academic tone of the manuscript. The authors did not use AI tools to generate research content, analyze data, or develop the core arguments of the paper. All research, findings, and conclusions presented herein are the result of the authors' own work.

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Mobarakeh Steel Company (n.d.) Knowledge Management System (KMS) home page. Internal knowledge management source.

MSC (2026) Business Intelligence (BI) Portal. Internal corporate source

Work in Progress Papers

Knowledge Management as a Determinant of Social Well-being: A Cognitive-based composite Indicator

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Abstract: Knowledge management is a central element in contemporary processes of transformation across organizations, territories, and societies. Understanding its relationship with residents' quality of life can contribute to progress toward models of sustainable human development. At the organizational level, knowledge management plays a pivotal role in enhancing the work environment by fostering autonomy, motivation, and creativity, as well as by promoting the development of employees' skills and capabilities. These factors are strongly associated with key indicators of work-related and social quality of life. From a social perspective, knowledge management promotes more equitable access to educational, health, and labour opportunities, thereby reducing structural inequalities and strengthening civic participation, with positive effects on social well-being. Moreover, the consolidation of knowledge-based social ecosystems enhances collective resilience to complex challenges such as demographic ageing, climate change, and territorial inequalities, by improving communities' adaptive and responsive capacities. In this study, we develop a methodological approach to measure individuals' levels of knowledge using Likert-scale data obtained from a survey of Spanish citizens, which yielded a total of 4,147 validated responses. Specifically, we propose an individual knowledge indicator constructed using Item Response Theory (IRT) models and defined through three dimensions related to applied cognitive capacities: structural knowledge derived from formal education; digital competencies as an expression of applied knowledge; and access to and use of information as a measure of autonomy and informational capacity. Moreover, we examine the relationship between knowledge management and quality of life, measured from a subjective perspective. The main results highlight the importance of individual knowledge as a determinant of well-being and reveal that the quality of life dimensions most strongly influenced by individual knowledge are the work environment, educational opportunities, and economic situation.

Keywords: Knowledge management, Quality of life, Item response theory, Digital competencies, Cognitive indicators

1. Introduction

In the field of knowledge management (KM), the measurement of individual knowledge constitutes a key methodological challenge, especially when this knowledge is conceived of as a multidimensional construct that incorporates both formal and applied components. Digital competencies assume a central role in this framework, as they represent the most visible operational manifestation of applied knowledge in a society increasingly mediated by technology. These competencies—ranging from the use of basic devices to the autonomous management of complex information—are key to understanding how individuals' access, process, and transform information in contemporary environments. Furthermore, it is important to highlight that KM is not limited to processes of information creation and transfer; it also encompasses elements of human resource management, particularly the training and capacity-building required to develop digital competencies. Consequently, incorporating digital competencies into the definition of individual knowledge not only strengthens the conceptual coherence of the construct, but also aligns with current approaches that treat digital training as an essential factor for personal autonomy, employability, and quality of life.

Our proposed methodology enables the operationalization of the individual knowledge construct within the KM framework, providing a robust, replicable metric. Also, we examine the relationship between KM and quality of life, measured from a subjective perspective. In addition, we identify the quality of life factors that are most strongly influenced by access to knowledge, through elements such as education, skills development, and digital literacy.

Finally, we discuss the implications of the model for public policy design aimed at reducing cognitive inequalities and strengthening individual capabilities, emphasizing that adequate access to information enables more informed, efficient, and evidence-based decision-making.

2. Literature Review

KM and Human Resource Management (HRM) are closely interconnected, as HRM provides the human capabilities, competencies, and training required for knowledge to be effectively created, shared, and applied within an organization. In this sense, training and capacity-building, particularly digital training, constitute a fundamental component of HRM and act as a key mechanism for sustaining KM. Indeed, recent evidence shows that digital competence is strongly associated with learner autonomy, digital self-efficacy, and problem-solving abilities in technology-mediated contexts (Rizza, 2023), as well as with more effective use of digital tools and meaningful learning (Blanc et al., 2025). At a broader level, digital competence is essential not only for learning and digital citizenship but also for participation in ever more complex educational environments.

Regarding quality of life, this multidimensional construct is increasingly being influenced by people's ability to participate fully in digital environments. Recent scientific evidence indicates that digital skills promote social inclusion, personal autonomy and employability, three fundamental pillars of contemporary well-being. Along these lines, various studies focused on higher education confirm that the acquisition of digital skills contributes to greater access to opportunities, more active participation in academic and professional environments, and a better psychological adjustment to modern-day technological challenges (Kosklin et al., 2023). On the contrary, a lack of or deficiency in such skills can adversely affect people's social participation, access to information, and economic opportunities, which can in turn exacerbate inequalities and hamper people's general ability to function in digital environments. Mejías Acosta et al. (2024) show that difficulties in aspects such as information management, digital security or problem-solving pose obstacles to learning and have a negative impact on academic and personal well-being. Likewise, research on digital autonomy in higher education shows that greater mastery of digital skills is related to higher levels of autonomy, a decisive factor for subjective well-being and personal development in ICT-mediated educational contexts.

3. Methodology

The database used to construct the individual knowledge indicator comes from a multidimensional questionnaire administered to the Spanish population between May and September 2025. A total of 4,147 validated responses were obtained anonymously of Spanish citizens over the age of 18. The survey has a margin of error of 1.52% with a 95% confidence level. The questionnaire includes a set of Likert scale variables that assess the quality of life of Spanish citizens from a multidimensional perspective. Furthermore, it incorporates socioeconomic classification variables and variables related to digital competencies, also measured on a Likert scale. These variables (Figure 1), which are key for the construction of the indicator, capture aspects related to structural knowledge; digital competencies; and the access to and use of information.

These digital competencies variables, together with the education level, will be used to construct the proposed indicator. To that end, we draw on Item Response Theory (IRT), specifically employing Samejima's Graded Response Model (GRM) (Samejima, 1970). Unlike classical summative scores, IRT provides sample-independent scaling and separates item discrimination from ordered threshold parameters, ensuring measurement properties aligned with the latent construct.

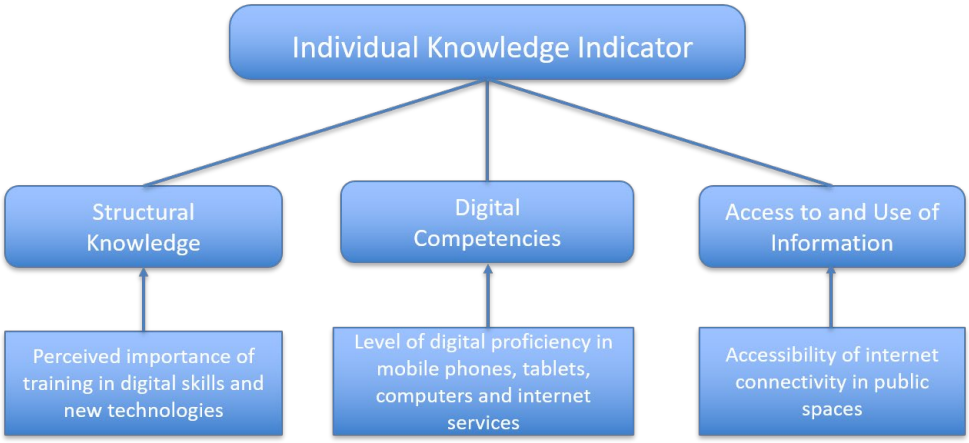


Figure 1: Individual Knowledge Indicator

In the GRM, the probability that the response of person *i* is in category *k* or higher for item *j* is modelled through the cumulative logistic function:

$$P(Y_{ij} \geq k|\theta_i) = \frac{1}{1 + exp[-a_j(\theta_i - b_{jk})]'}$$

where a_j denotes item discrimination, $b_{jk}$the ordered category thresholds, and $\theta_i$the latent trait level. The probability of responding in category *k* is obtained from adjacent cumulative curves:

$$P(Y_{ij} = k|\theta_i) = P(Y_{ij} \geq k|\theta_i) - P(Y_{ij} \geq k + 1|\theta_i)$$

Recent research supports the applicability of IRT to applied knowledge domains. Vuorikari et al. (2025) validate IRT-based instruments for digital competence measurement, while Barroqueiro et al. (2024) apply IRT to human intellectual capital assessment. Accordingly, GRM provides a robust foundation for constructing a multidimensional indicator of individual knowledge. All estimations are performed using the *mirt* package in R (Chalmers, 2012), which by default estimates a unidimensional GRM with freely estimated discrimination and threshold parameters, no guessing or upper asymptote terms, EM optimization, and a standard normal latent trait distribution.

4. Results

The results of the mean individual knowledge indicator standardized show significant differences across sociodemographic variables (Table 1).

Table 1: Indicator mean value for sociodemographic variables

Sociodemographic variable	Category	Mean	Sociodemographic variable	Category	Mean
Marital Status	Single	0.1234	**Annual Income**	<€12,500	-0.1156
	Married	-0.0162		€12,500€-€25,000	-0.1715
	Divorced	-0.0903		€25,001-€42,000	0.1323
	Widowed	-0.7362		> €42,000	0.3654
Gender	Male	0.0613	**Education Level**	No formal education	-1.5675
	Female	-0.0532		Compulsory education	-0.7201
	Non-binary	0.0833		Upper secondary education	-0.2842
Age	Up to 19 years	0.0689		Vocational training	-0.2162
	20-29 years	0.3677		University studies	0.1460
	30-39 years	0.2222		Postgraduate and doctoral studies	0.4922
	40-49 years	0.0543			
	50-59 years	-0.0098			
	60-69 years	-0.2615			
	Over 70 years	-0.5516			

The indicator is also significantly associated, using the Pearson correlation coefficient, with three key quality of life measures: life satisfaction (0.168), final happiness (0.320), and the multidimensional quality of life index (0.271). Among the specific dimensions of quality of life, the most strongly influenced by individual knowledge are the work environment (0.313), educational opportunities (0.289), and economic situation (0.210).

These findings highlight the importance of individual knowledge as a determinant of well-being and reveal systematic cognitive inequalities across population groups. The implications for public policy design are substantial: strengthening information access, promoting educational opportunities across life stages, and reducing sector-based knowledge disparities can support more informed, efficient, and evidence-based

decision-making at the individual level. Enhancing these capabilities contributes to reducing cognitive asymmetries and fostering more equitable conditions for personal development and social participation.

5. Conclusions

This study demonstrates that individual knowledge, captured through a multidimensional IRT based indicator, is a relevant determinant of social well-being. By operationalizing applied cognitive capabilities through structural knowledge, digital competence, and informational autonomy, the analysis shows that higher levels of individual knowledge are consistently associated with improved quality of life outcomes.

The proposed indicator provides a more accurate measurement of the latent capabilities underpinning knowledge creation, transfer, and application in digital environments. In this sense, digital competencies should be understood as a key enabler of knowledge flows and organizational learning. Additionally, the results reveal systematic inequalities across groups, pointing to asymmetries in knowledge use and management. Thus, the study extends KM research by integrating the measurement of individual knowledge in digital contexts and offering a robust tool for its empirical assessment. The results underscore the need for policies that enhance access to information, strengthen digital and educational capacities, and reduce cognitive inequalities, thereby fostering more equitable opportunities for informed decision making and sustainable human development.

Acknowledgement

The authors are grateful Universidad de Castilla-La Mancha under Grant 2025-GRIN-38351 and JCCM through INNOCAM under the project SBPLY/24/180225/000049.

Ethics Declaration: The Social Research Ethics Committee of the Universidad de Castilla-La Mancha (CEIS-30844R) granted ethical approval for the study**.**

AI Declaration: We did not use an AI tool in the development of this paper.

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Assessing Knowledge Provenance Quality for CEO Decision Support: An OWL-DL Ontological Framework

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Abstract: The ontology demonstrates approaches to enhancing the precision of knowledge provenance and outlines the systematic engineering of a knowledge provenance ontology designed to improve its reliability for executive decision-making. Utilizing architectural principles, we propose a formal model that evaluates knowledge provenance quality based on standardized coding systems such as PROV-O. The methodology follows a rapid prototyping lifecycle, employing the "Ontology 101" development process to transform domain expertise into a rigorous OWL-DL framework. By implementing constraints and functional properties, the ontology ensures data integrity and consistency, which are critical for CEOs navigating complex information environments. The results demonstrate that formal ontological reasoning, supported by tools such as Pellet, can effectively filter low-quality knowledge sources, providing a trustworthy basis for strategic corporate oversight.

Keywords: PROV-O, Ontology, Quality, Knowledge engineering

1. Problem

Organizational decision-making at all levels relies on tacit and explicit knowledge, which must be high-quality and verifiable, especially when involving Agentic AI (Wang and Leem, 2026). While universal data quality dimensions include completeness, correctness, consistency, and timeliness (Reda et al., 2023; Secundo et al., 2024; Wang and Leem, 2026), organizational knowledge quality (KQ) requires distinct dimensions, including adaptability, applicability, expandability, truth, innovativeness, and justification (Waheed and Kaur, 2016).

Furthermore, knowledge provenance quality enables informed decision-making by providing transparent evidence of changes. Documenting an item's origin serves as a critical trust indicator (Choi and Cheng, 2025). This process-centered provenance captures the specific actions and production steps taken to generate information (Gil and Miles, 2013; Herschel et al., 2017). This transparency is vital for Explainable AI (Kale et al., 2023) and high-stakes decision-making (Sode, 2026).

The objective of this study is to develop an ontology to represent the characteristics of knowledge provenance quality, addressing the central question: How can we assess the knowledge provenance quality used in business processes?

2. Methodology

The decision to use a heavyweight ontology was made with the aim of building a shareable and reusable knowledge base and representing the “processes and activities for solving a given problem by abstracting the domain context” (Isotani and Bittencourt, 2015).

This study adopted OWL-DL, a W3C standard sublanguage, for ontology modeling because of its maximum conceptual expressiveness, computational completeness, and decidability. Positioned between propositional and first-order logic, OWL-DL provides key capabilities, such as automatic inference, cardinality constraints, and semantic interoperability, which motivated its selection.

The implementation tool selected was Protégé (Musen, 2015), version 5.6.7, because it is a collaborative OWL ontology editor. The development of the ontology followed the seven steps of the “Ontology 101” process (Noy and McGuinness, 2001), described below.

1. Domain and scope: The ontology’s domain is knowledge provenance, and its scope is to determine whether a source is “good” or “bad,” taking into account the following competency questions:

- 1.1 Who has the authority to create knowledge?
- 1.2 Which department within the organisation is responsible for creating knowledge?
- 1.3 When was the knowledge created?
- 1.4 What is the knowledge provenance: human [tacit], machine, or media [explicit]?
- 1.5 What is the quality of the knowledge provenance?

2. Reuse of existing resources: The W3C's PROV-O standard was used to ensure that this ontology is interoperable with international standards (Lebo *et al.,* 2013).
3. List of terms: Table 1.

Table 1: Concepts dictionary (draft)

Concept	PROV-O (W3C)	The Authors
Entity, Activity, Agent, Influence, InstantaneousEvent, Location, Role	https://www.w3.org/TR/prov-o/#cross-reference-index	--
KnowledgeProvenance	--	Knowledge about its production process.
ProvenanceQuality	--	Characteristics that address the essential requirements for understanding its production process.

4. Class hierarchy using a top-down approach: (Figure 1).

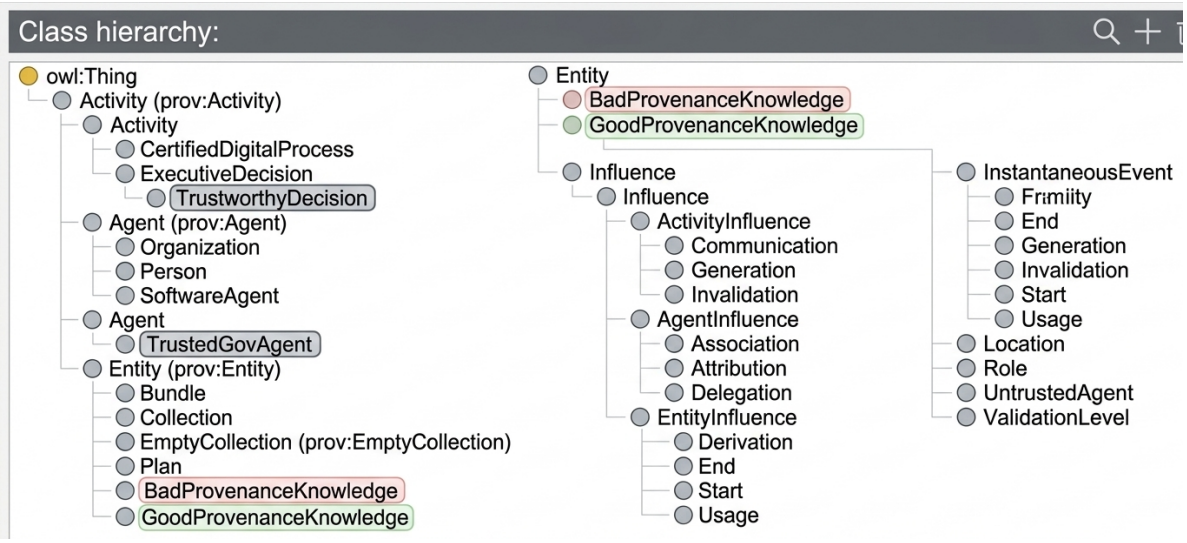


Figure 1: The world of Knowledge Provenance (Protégé).

5. Definition of properties: Object properties were imported from the W3C's PROV-O standard. To satisfy the integrity and consistency requirements, functional properties such as "hasQualityScore" were defined. In OWL, this means an individual can have at most one quality score, preventing contradictory "Good" and "Bad" labels for the same entity.
6. Facets definition: In the decision-making process, a "poor" source of knowledge results from contradictory, missing, or fraudulent information.
7. Instance creation: The process of populating the assertional box (A-Box), moving from an abstract model to the specific real-world model that the ontology represents.

The ontology categorizes knowledge provenance quality as "Good" or "Bad" based on the intersection of three dimensions: (1) it must be generated by a "CertifiedDigitalProcess"; (2) it must be attributed to a "TrustedGovAgent"; and (3) it must not have any links to an "UntrustedAgent." Through formal reasoning, an entity is classified as "Good" only if it satisfies the following Description Logic criteria:

$$GoodProvenanceKnowledge \equiv Entity \sqcap \exists\, wasGeneratedBy.CertifiedProcess \sqcap \forall\, wasAttributedTo.TrustedAgent \sqcap \exists\, hasQuality.\{Timely, Complete, Certified\}$$

To establish a functional binary classification gate within an arbitrary coding exercise, these three criteria were pragmatically identified to directly exploit the structural primitives of the W3C PROV-O standard, specifically by mapping them to its core Activity, Agent, and Entity components. The first criterion, requiring generation by a "CertifiedDigitalProcess," isolates the data's procedural history, enabling the script to algorithmically distinguish audited automated pipelines from unverified manual entries.

The second criterion, attribution to a "TrustedGovAgent," establishes a strict origin checkpoint by verifying structural authority through the standard "prov:wasAttributedTo" object property. The final criterion, requiring the complete absence of links to an "UntrustedAgent," was deliberately introduced to operationalize universal quantification ("owl:allValuesFrom") within an OWL-DL environment. This design choice functions as a strict logical contamination filter; if an entity is linked to an unauthorized source, it triggers an immediate logical failure.

Taken together, these three dimensions form a rigid Boolean intersection within Description Logic (DL). This framework enables an OWL reasoner such as Pellet to automatically and deterministically determine whether incoming data instances belong to the "Good" or "Bad" provenance classes, thereby providing a clean, algorithmic gate for an executive decision-making dashboard without requiring manual oversight or subjective human evaluation.

3. Results

The metrics reported by Protégé are as follows: 42 classes, 6 individuals, 48 object properties, and 6 data properties. The class axioms comprise 32 subclasses, 3 equivalent classes, and 5 disjoint classes.

The main goal of the ontology is to explain how to assess the knowledge provenance quality used in business processes. We present an illustrative use case involving the formulation of public policies aimed at regulating the use of artificial intelligence agents within public servants' workflows. The ontology indicates whether the knowledge possesses the qualities necessary for decision-makers to proceed with or halt a course of action.

This OWL-DL framework provides a real-time, automated trust filter for a CEO leading digital transformation, for example. Instead of manually auditing complex data lineages, the executive relies on the reasoner to automatically flag information quality issues. By dynamically restricting strategic decisions to only consume certified, complete, and timely knowledge, the ontology creates an explicit mathematical safety gate.

This ensures that high-stakes public sector implementations are protected from unverified sources and outdated data, directly mitigating critical strategic governance risks.

4. Discussion and Contribution

Evaluating information is challenging due to contradictory content, making knowledge provenance vital for trust (Moreau and Missier, 2013). While recent studies have explored ontology quality assessment (Wilson *et al.*, 2023) and the tracking and assessment of provenance, knowledge quality remains a persistent real-world challenge (Huynh *et al.*, 2021; Osman, Mohd Noah and Saad, 2022; Zhang, Zhou and Ujcich, 2024; Prudhomme *et al.*, 2025; Arora *et al.*, 2025)

In high-stakes corporate or government scenarios, Knowledge Engineering addresses this challenge by converting raw data into "actionable knowledge" through structured ontologies. These ontologies support explainable Hybrid Intelligence, reducing human cognitive biases (Tiddi *et al.*, 2023; Said *et al.*, 2025). When combined with Trust Recommender Systems—which use social trust networks—this approach ensures that recommendations are transparent, highly credible, and aligned with trusted expert consensus, ultimately aiding executives such as CEOs in confident decision-making (Akdim, 2026). To ensure system integrity, automated reasoners (such as Pellet) evaluate knowledge provenance quality so both human and AI agents work solely with consistent and valid data.

This study introduces an ontological framework designed to assess knowledge provenance quality and mitigate misinformation risks. The main limitation of this study is the lack of real-world application.

5. Conclusion and Future Works

This study is a work in progress within a thesis. Assessing knowledge provenance quality using OWL-DL provides a rigorous and scalable solution, and future studies will refine the framework by implementing it within an eligible Brazilian Federal Executive Branch unit while considering the role of ontology and hybrid-intelligent environments (Pileggi, 2024).

Ethics Declaration: No ethical clearance was required for this research.

AI Declaration: An AI tool was used for summarizing some parts of the paper, and creating figures, with careful decisions made by the authors.

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Testing Evolutionary Psychology as a Foundation for Strategic Brand Building

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Abstract: This Work-in-Progress study conducts a theory-guided exploratory mapping of brand-following motives onto evolutionary motive systems (prestige/status, affiliation/belonging, resource security/trust, and leadership/followership). The purpose is to provide initial, preliminary evidence on whether brand-following motivations show patterns consistent with evolved coordination motives, and to outline implications for strategic knowledge management (KM). Building on the knowledge-based view, the study treats brands as socially distributed knowledge assets that compress reputational information and reduce uncertainty. Evolutionary psychology provides a candidate mechanism for why such symbolic knowledge structures scale and persist. Empirical evidence comes from a survey of marketing students (N = 113; Bachelor n = 37; Master n = 76). Respondents named a brand they actively follow and evaluated motivational drivers of that behavior. Motivations were grouped into four theory-derived clusters: resource security/trust, prestige/status, affiliation/belonging, and leadership/inspiration. Descriptive comparisons across educational levels and brand categories provide preliminary pattern evidence. Results suggest that brand following is not explained by security/trust motives alone: social-symbolic motives (prestige, belonging, and leadership) appear salient alongside trust/security. As a WIP contribution, the paper offers a focused empirical proof-of-concept and a lean theoretical bridge, with deeper KM integration planned after conference feedback.

Keywords: Strategic knowledge management, Competitive advantage, Evolutionary psychology, Branding, Consumer behaviour

1. Introduction

This Work-in-Progress study conducts a theory-guided exploratory mapping of brand-following motives onto evolutionary motive systems (prestige/status, affiliation/belonging, resource security/trust, and leadership/followership). The aim is to provide initial, preliminary evidence on whether reported brand-following motives show patterns consistent with these evolved coordination motives and to outline implications for strategic knowledge management (KM).

Strategic KM research argues that sustained advantage increasingly depends on intangible, socially embedded knowledge assets (Barney, 1991; Grant, 1996; Kogut and Zander, 1992; Nonaka, 1994). Branding research likewise shows that brands operate as shared meaning structures that shape relationships, community, and consumer cognition beyond product attributes (Fournier, 1998; Keller, 1993; Muniz and O'Guinn, 2001; Hirschman, 2010). Yet both streams often describe brand value without explaining why symbolic markers can coordinate beliefs and behavior at scale.

This paper proposes evolutionary psychology (EP) as a candidate explanatory layer: brands may become influential because they align with evolved motives guiding imitation, affiliation, and trust calibration under uncertainty (Cosmides and Tooby, 1997; Griskevicius and Kenrick, 2013). In particular, prestige-biased learning predicts preferential attention to respected and competent targets, a mechanism that may generalize to symbolic targets such as brands (Henrich and Gil-White, 2001), consistent with evolutionary consumer research on status and social motives in consumption (Saad and Gill, 2000; Taheran et al., 2024).

Research question (RQ): What motivational patterns underlie brand-following behavior, and how do these motivations map onto evolutionary motive systems (prestige/status, affiliation/belonging, resource security/trust, and leadership/followership)?

2. Theoretical Background

2.1 Strategic KM and Brand Knowledge as an Intangible Asset

In the knowledge-based view, organizations are repositories and coordinators of knowledge, and competitive advantage arises when knowledge is valuable, difficult to imitate, and socially embedded (Barney, 1991; Grant, 1996; Kogut and Zander, 1992; Nonaka, 1994). From this perspective, brands can be treated as socially distributed knowledge assets: they stabilize expectations, compress reputational information, and help market participants coordinate interpretations and choices under uncertainty (Grant, 1996; Muniz and O'Guinn, 2001;

Fournier, 1998). However, KM and branding research often describe these functions without specifying why humans are so responsive to symbolic reputation markers such as brands (Keller, 1993; Hirschman, 2010).

2.2 Evolutionary Psychology and Consumption Motives

Evolutionary psychology explains behavior as the output of domain-specific motivational systems shaped by recurrent coordination challenges in ancestral environments (Cosmides and Tooby, 1997). In modern consumer settings, these systems can be activated by symbolic cues and expressed through consumption, social preference, and learning from others (Griskevicius and Kenrick, 2013; Saad and Gill, 2000). Prior work in evolutionary consumer research highlights motives that are directly relevant to brand following, including attaining status, forming and maintaining social ties, managing risk and resource security, and engaging with leadership or guidance cues (Griskevicius and Kenrick, 2013; Taheran et al., 2024).

2.3 Prestige-biased Learning, Affiliation, and Leadership Cues

A particularly relevant mechanism is prestige-biased social learning: humans tend to attend to, defer to, and imitate targets perceived as successful, respected, or competent because such learning historically offered adaptive efficiencies (Henrich and Gil-White, 2001). In markets, brands can function as scalable prestige proxies by condensing reputational knowledge into stable symbolic forms (Henrich and Gil-White, 2001; Hirschman, 2010). In parallel, affiliation motives support coalition-like behavior, where shared brand use signals group belonging and identity alignment (Muniz and O'Guinn, 2001; Fournier, 1998). Leadership/followership dynamics provide an additional lens: some brands are experienced as norm-setting, inspirational, or "benchmark" targets that guide preferences and behavior beyond utilitarian evaluation (Hirschman, 2010; Henrich and Gil-White, 2001).

2.4 Bridge Claim for this WIP Paper

Combining these views, this paper conceptualizes brands as knowledge coordination targets that become influential because they align with evolved motives for prestige/status, affiliation/belonging, resource security/trust, and leadership/followership (Cosmides and Tooby, 1997; Griskevicius and Kenrick, 2013; Henrich and Gil-White, 2001). This WIP paper tests whether brand-following motivations show patterns consistent with this mapping, and uses the results to outline a focused implication for strategic KM: brand knowledge may operate as an evolved-friendly, socially distributed coordination asset rather than only as informational content (Grant, 1996; Nonaka, 1994).

3. Research Design and Data

3.1 Data Collection and Sample

Data were collected through a structured questionnaire administered to Bachelor- and Master-level business students during a university lecture. The final sample consisted of 113 respondents (Bachelor n = 37; Master n = 76). Respondents named one brand they actively follow and indicated the brand category. In this study, "brand following" refers broadly to sustained psychological or behavioural engagement with a brand, including regularly consuming brand-related content, purchasing products, monitoring brand activity, or identifying with the brand symbolically.

The student context supports an initial WIP mapping of motivational patterns, while limiting generalizability to broader populations.

3.2 Measures and Motive Clusters

Respondents rated motive statements capturing inspiration/leadership cues, prestige/status signaling, affiliation/belonging, and trust/security (1–7 Likert scale). Items were grouped a priori into four motive clusters aligned with the EP framing used in this paper: resource security/trust, prestige/status, affiliation/belonging, and leadership/inspiration. Cluster scores were computed as respondent-level means of the items assigned to each motive cluster (1–7). Because the study is exploratory and theory-guided, formal reliability validation of the clusters was not conducted at this stage and is planned for future research.

3.3 Analytical Strategy

The analysis is descriptive and theory-guided. The paper summarizes the relative salience of the four motive clusters and compares patterns across educational level (Bachelor vs. Master) and across reported brand categories. The purpose is to provide initial pattern evidence suitable for conference feedback rather than causal

inference or confirmatory hypothesis tests. Comparisons between Bachelor and Master students are descriptive only and should be interpreted as hypothesis-generating rather than statistically conclusive.

4. Findings

4.1 Brand Categories and Motive Clusters

Respondents named brands across categories such as technology, fashion, sports and lifestyle. Tables summarize how the four motive clusters appeared across brand categories and educational levels.

4.2 Key Patterns

- Security/trust motives were consistently high across categories (approx. 5.6-6.1), indicating a strong risk-reduction component in brand following.
- Leadership/inspiration motives were also consistently moderate-to-high (approx. 4.9-5.8), suggesting that brands are often followed as guidance/benchmark targets rather than evaluated purely as utilities.
- Prestige/status motives were moderate-to-high (approx. 4.2-4.9), and belonging motives varied by category (highest in Sports among Masters).
- Descriptively, Master students show slightly higher leadership scores across categories and higher prestige scores in most categories, with Technology as an exception.

These patterns are interpreted as preliminary consistency evidence for the EP mapping: brands may function as coordination targets that concentrate prestige cues, affiliation signals, and security expectations.

Table 1: Brand category × motive cluster scores (Mean [SD]) (Bachelor students)

Category	Leadership M (SD)	Prestige M (SD)	Belonging M (SD)	Security M (SD)	N
Fashion	4.91 (0.96)	4.20 (1.07)	4.72 (1.33)	6.14 (0.62)	13
Lifestyle	4.99 (0.93)	4.23 (0.91)	4.47 (1.79)	5.63 (1.14)	12
Sports	5.29 (0.17)	4.56 (0.26)	4.33 (0.94)	5.63 (0.51)	5
Technology	5.12 (0.38)	4.89 (0.76)	5.10 (1.45)	6.02 (0.56)	7

Note: Values are cluster means (standard deviations) on a 1–7 Likert scale; higher values indicate stronger endorsement of the motive cluster.

Table 2: Brand category × motive cluster scores (Mean [SD]) (Master students)

Category	Leadership M (SD)	Prestige M (SD)	Belonging M (SD)	Security M (SD)	N
Fashion	5.11 (0.79)	4.38 (1.04)	4.24 (1.32)	5.62 (0.75)	24
Lifestyle	5.08 (1.21)	4.27 (1.06)	4.12 (1.61)	5.85 (1.27)	27
Sports	5.79 (0.30)	4.80 (0.68)	5.36 (0.82)	5.94 (0.50)	12
Technology	5.24 (1.01)	4.66 (1.01)	4.56 (1.64)	5.73 (0.95)	13

Note: Values are cluster means (standard deviations) on a 1–7 Likert scale; higher values indicate stronger endorsement of the motive cluster.

5. Discussion

This Work-in-Progress study provides preliminary evidence that brand-following motivations can be organized around evolved coordination motives—prestige/status, affiliation/belonging, resource security/trust, and leadership/followership—rather than reduced to functional utility alone.

From an evolutionary perspective, the descriptive patterns are consistent with three coordination mechanisms: (1) prestige-biased learning and status signaling, which help explain why some brands become imitation targets; (2) coalition-like affiliation motives, which help explain brand community and identity alignment; and (3) trust/security calibration, which helps explain why brands reduce uncertainty and become “safe” choices. Leadership/followership cues offer an additional interpretation for why some brands function as benchmarks that guide behavior beyond product attributes.

For strategic KM, the implication is focused: brand knowledge may be conceptualized as a socially distributed coordination asset that compresses reputational information and stabilizes expectations.

5.1 Managerial Implications

The WIP findings suggest that brand following may be driven by coordination motives (prestige, belonging, leadership, and trust) alongside functional utility. This implies emphasizing consistent symbolic cues that support trust and identity alignment, not only short-term performance messaging. These implications should be interpreted as exploratory and theory-building in nature.

6. Limitations and Future Research

This Work-in-Progress study is exploratory and based on a student sample, limiting generalizability and supporting only pattern-level inferences. Because motive clusters were specified a priori for theory-guided mapping, future work should validate the measurement structure and replicate findings in non-student samples. A next step is to link motive profiles to observed behaviors such as engagement, advocacy, willingness to pay, and brand defense in field settings. Stronger quantitative testing and deeper KM integration would further strengthen the framework.

7. Conclusion

This Work-in-Progress paper provides initial evidence that brand-following motivations can be organized around evolved coordination motives (prestige, belonging, trust/security, and leadership). The value of this approach is to propose a candidate mechanism for why brand knowledge can scale and persist beyond functional utility. Because the study is exploratory and the sample is student-based, claims are limited to pattern consistency and concept development. Future research should extend the framework using stronger empirical validation and broader samples.

Ethics Declaration: Participants provided informed consent and responses were collected anonymously. The study was conducted in a low-risk educational context in line with institutional guidance.

AI Declaration: AI tools were used for language editing and structural refinement; the author verified all content, interpretations, and references.

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Late Submissions

AI-Enabled Digital Knowledge Systems: Implications for Organizational Learning and Strategic Decision-making

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Abstract: Artificial intelligence (AI) is transforming digital knowledge systems (DKS), reshaping how organizations generate, interpret, and apply knowledge in support of organizational learning and strategic decision-making. While AI-enabled systems enhance analytical capability, predictive insight, and information processing speed, their implications for learning quality and epistemic judgment remain insufficiently understood. This study addresses this gap through a systematic literature review that synthesises research across knowledge management, information systems, and organizational learning. Adopting a concept-centric approach, the review analyses peer-reviewed studies published between 2000 and 2026, focusing on how AI-enabled digital knowledge systems are conceptualised and how they influence knowledge processes, organizational learning, and strategic decision-making. The findings indicate a shift from viewing digital knowledge systems as passive repositories toward conceptualising them as mediating infrastructures that augment, generate, and orchestrate knowledge. These systems expand knowledge creation through data-driven insights, enhance knowledge sharing through algorithmic mediation, and increasingly shape how knowledge is applied in decision contexts. However, the analysis also reveals a tension between informational efficiency and authentic learning. While AI-enabled systems support sensemaking and improve decision support under conditions of uncertainty, they may encourage overreliance on algorithmically generated outputs, reduce opportunities for critical reflection, and narrow interpretive perspectives. These dynamics highlight the importance of governance conditions, including epistemic transparency, trust calibration, and learning-oriented organizational practices. The study develops an integrative framework that positions AI-enabled digital knowledge systems as mediating infrastructures linking knowledge processes to organizational learning and strategic decision-making under specific governance and learning conditions. The findings contribute to knowledge management and information systems research by providing a coherent conceptualisation of how AI-enabled systems reshape the epistemic foundations of learning and decision-making in contemporary organizations.

Keywords: Artificial intelligence, Digital knowledge systems, Organisational learning, Strategic Decision-Making, Knowledge management, Governance

1. Introduction and Research Problem

Learning organizations increasingly depend on digital knowledge systems (DKS) to support knowledge creation, sharing, and application in environments characterised by complexity and rapid change. Early knowledge management research conceptualised these systems as repositories and decision-support infrastructures that facilitated access to knowledge, while interpretation and judgment remained primarily human activities (Alavi and Leidner 2001). In this view, digital knowledge systems supported knowledge processes without fundamentally altering how knowledge was constructed or applied.

The integration of artificial intelligence (AI), particularly generative and agentic forms, has significantly transformed this role. AI-enabled digital knowledge systems now analyse large volumes of data, generate insights, and contribute directly to organizational decision processes (Cerchione et al. 2026; Storey et al. 2025). These systems increasingly influence how problems are framed, how information is prioritised, and how decisions are justified. As a result, digital knowledge systems are evolving from passive infrastructures into active mediators of knowledge processes.

While AI-enabled digital knowledge systems extend analytical capability, they introduce a fundamental tension in relation to organizational learning. Learning depends on reflection, sensemaking, and the questioning of assumptions, yet AI-driven processes may encourage reliance on generated outputs, accelerating decision cycles while reducing opportunities for critical inquiry (Böhm 2025; Trunk et al. 2020). In such contexts, organizations risk shifting from reflective learning toward more procedural forms of information processing, where efficiency is prioritised over depth of understanding.

This transformation also reconfigures the epistemic foundations of knowledge within organizations. AI-generated outputs increasingly influence what is considered credible, relevant, and actionable, while often obscuring underlying assumptions, data sources, and reasoning processes (Rezaei 2025). As these outputs become embedded in decision workflows, questions of knowledge authority, validation, and accountability become more complex, particularly in the absence of transparent governance mechanisms (Nakash and Bolisani 2024).

Despite growing scholarly interest in AI within knowledge management, existing research remains conceptually fragmented across technological, organizational, and ethical perspectives (Dwivedi et al. 2021; Chatti and Argoubi 2025). Much of the literature emphasises system capabilities and performance outcomes, with comparatively less attention given to how AI-enabled digital knowledge systems influence learning quality and the epistemic conditions of strategic decision-making. This fragmentation limits understanding of how such systems can be designed and governed to support both authentic learning and effective strategic judgment.

Accordingly, there is a need for a systematic synthesis that examines how AI-enabled digital knowledge systems shape organizational learning and strategic decision-making as interconnected processes, and under what conditions they support or constrain these outcomes.

2. Research Objectives

This study aims to develop an integrated understanding of how AI-enabled digital knowledge systems (DKS) shape organizational learning and strategic decision-making. Specifically, the study seeks:

- To examine how AI-enabled digital knowledge systems are conceptualised in the literature
- To analyse how these systems influence knowledge creation, sharing, and use
- To evaluate the implications of AI-enabled digital knowledge systems for organizational learning and strategic decision-making
- To identify governance conditions that shape the effective and responsible use of these systems

Research Questions

The study is guided by the following research questions:

- How are AI-enabled digital knowledge systems conceptualised in the literature?
- How do AI-enabled digital knowledge systems influence knowledge creation, sharing, and use?
- How do AI-enabled digital knowledge systems affect organizational learning and strategic decision-making?
- What governance conditions shape the use of AI-enabled digital knowledge systems in organizations?

3. Methodology

This study adopts a systematic literature review (SLR) to synthesise research on AI-enabled digital knowledge systems (DKS) and their implications for organizational learning and strategic decision-making. The approach is appropriate given the interdisciplinary nature of the topic, which spans knowledge management, information systems, and artificial intelligence. A systematic review enables the integration of fragmented knowledge and the development of coherent conceptual insights. The review follows established principles of transparency and analytical rigor, informed by PRISMA guidelines (Tranfield et al. 2003).

A structured search was conducted across major academic databases, including Scopus, Web of Science, ScienceDirect, SpringerLink, Emerald Insight, IEEE Xplore, ACM Digital Library, and the AIS eLibrary. Search terms were derived from the research question and combined key concepts related to digital knowledge systems, artificial intelligence, organizational learning, and strategic decision-making using Boolean operators. The search was limited to peer-reviewed journal articles and conference papers published in English between 2000 and 2026.

The study selection process involved screening titles and abstracts, followed by full-text assessment using predefined inclusion and exclusion criteria. Studies were included if they addressed digital knowledge systems, examined artificial intelligence in relation to knowledge processes, and engaged with organizational learning or strategic decision-making. Studies focusing solely on technical AI models without organizational context were excluded. This process ensured that the corpus remained aligned with the conceptual focus of the study. The final corpus consisted of 22 peer-reviewed studies.

Data were extracted systematically to capture key aspects of each study, including research context, methodological approach, conceptualisation of AI-enabled systems, and findings related to knowledge processes, learning, decision-making, and governance conditions. This structured extraction enabled comparison across studies and supported the identification of recurring patterns.

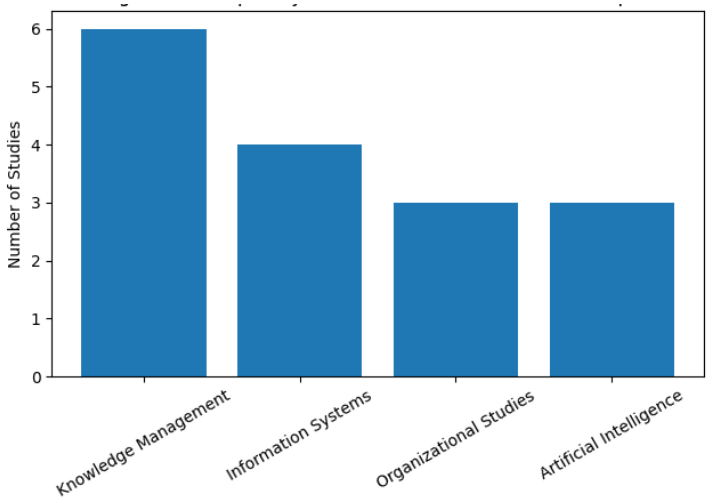
The analysis adopted a concept-centric thematic approach (Webster and Watson 2002), which focuses on identifying key concepts and their relationships rather than summarising individual studies. An iterative coding process was used to group related concepts and refine thematic categories. Through this process, five

interrelated themes were developed: conceptualisations of AI-enabled digital knowledge systems, knowledge processes, organizational learning, strategic decision-making, and governance conditions. These themes provided the analytical foundation for the integrative framework presented in this study.

4. Descriptive Analysis

A descriptive analysis was conducted to contextualise the literature corpus prior to thematic synthesis, focusing on disciplinary distribution, temporal trends, and methodological orientation.

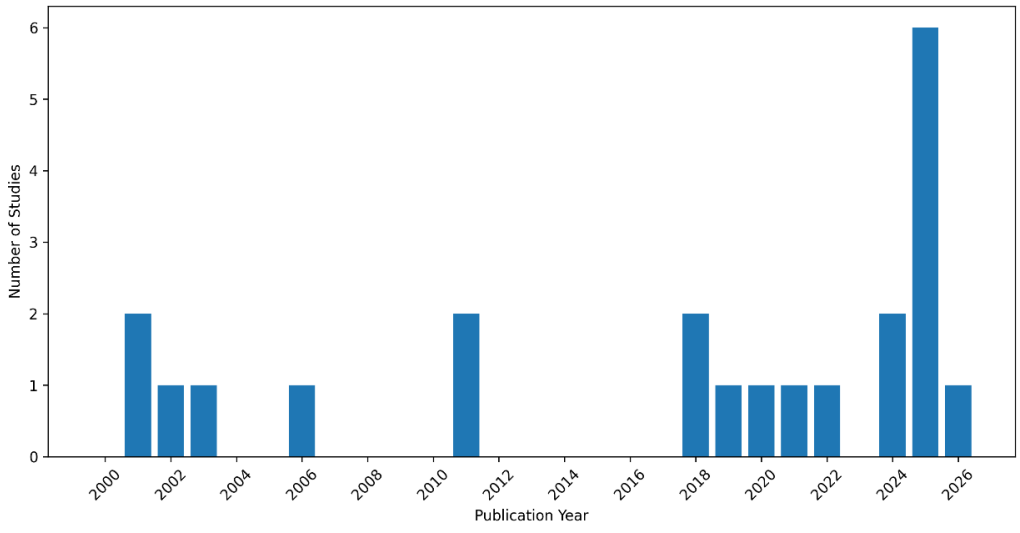
The corpus reflects an interdisciplinary field spanning knowledge management, information systems, organizational studies, and artificial intelligence. As illustrated in Figure 1, the literature is anchored in knowledge management, with complementary contributions from adjacent domains. This distribution highlights that research on AI-enabled digital knowledge systems emerges at the intersection of technological capability and organizational practice.



Source: Author's construction based on systematic literature review (2026).

Figure 1: Disciplinary Distribution of the AI-Enabled Digital Knowledge Systems Corpus

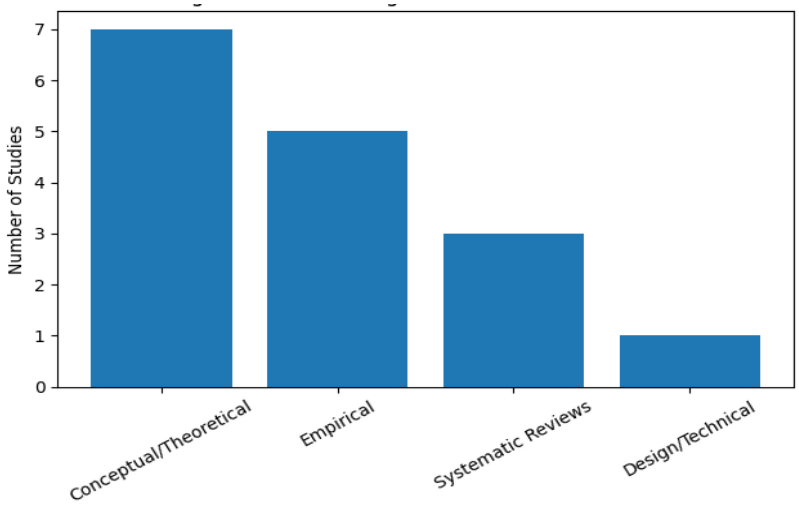
The temporal distribution further indicates the recent emergence of the field within the review period. As shown in Figure 2, the corpus contains limited early contributions after 2000, followed by a marked increase in publications after 2020. This increase corresponds with advances in machine learning, generative AI, and growing scholarly interest in AI-enabled knowledge systems. The pattern suggests that the field is rapidly evolving but remains in a formative stage.



Source: Author's construction based on systematic literature review (2026).

Figure 2: Temporal Distribution of Publications in the reviewed corpus 2026

The methodological orientation reflects this stage of development. As illustrated in Figure 3, the literature is dominated by conceptual and theoretical studies, with comparatively fewer empirical and design-oriented contributions. This imbalance indicates that key constructs and relationships are still being established, reinforcing the need for integrative conceptual work.



Source: Author's construction based on systematic literature review (2026).

Figure 3: Methodological Orientation of Studies in the Corpus

When put together, these patterns suggest that research on AI-enabled digital knowledge systems is interdisciplinary, recent, and conceptually emergent. These characteristics provide a foundation for the thematic analysis that follows, which seeks to synthesise and integrate dispersed insights across the literature.

5. Conceptualisations of AI-enabled Digital Knowledge Systems

The literature indicates a shift in how digital knowledge systems (DKS) are conceptualised within knowledge management and information systems research. Early work positioned these systems as repositories and decision-support infrastructures designed to capture, store, and retrieve organizational knowledge, while interpretation and judgment remained primarily human activities (Alavi and Leidner 2001; Jennex and Olfman 2006). Recent advances in artificial intelligence (AI) have expanded this view. AI-enabled digital knowledge systems are increasingly understood as intelligent knowledge infrastructures that analyse, generate, and prioritise knowledge in organizational contexts (Dwivedi et al. 2021; Pai et al. 2022). These systems extend beyond information management to actively shape how knowledge is produced and used, particularly in environments characterised by complexity and uncertainty (Storey et al. 2025).

Across the literature, three interrelated conceptualisations emerge. First, AI-enabled DKS function as augmentation infrastructures, enhancing knowledge retrieval, pattern detection, and recommendation capabilities while maintaining human interpretive authority. In this configuration, AI extends analytical capacity without fundamentally altering the locus of epistemic control (Dwivedi et al. 2021).

Second, AI-enabled DKS operate as knowledge-generating systems, where generative and agentic AI produce summaries, forecasts, and scenarios that contribute directly to knowledge creation (Cerchione et al. 2026; Hosseini and Seilani 2025). This conceptualisation positions AI as an active participant in knowledge work, shaping problem framing and influencing how organizational understanding is constructed. It also introduces concerns regarding transparency, reliability, and interpretability (Rezaei 2025).

Third, AI-enabled DKS are conceptualised as socio-technical learning platforms embedded within organizational practices. From this perspective, their significance lies not only in their technical capabilities but in how they interact with learning processes, governance structures, and organizational culture (Nakash and Bolisani 2024; Bankins et al. 2024). These systems shape the conditions under which knowledge is interpreted, contested, and applied.

These conceptualisations reflect a progression from repositories to mediating infrastructures that influence knowledge processes, learning, and decision-making. However, the literature continues to treat technological

capability, learning dynamics, and governance conditions in relative isolation, resulting in a fragmented understanding of AI-enabled digital knowledge systems.

In effect, existing research captures important dimensions of AI-enabled digital knowledge systems but lacks an integrated perspective that explains how these dimensions interact. This study addresses this limitation by advancing a conceptualisation of AI-enabled digital knowledge systems as mediating infrastructures that simultaneously shape knowledge processes, organizational learning, and strategic decision-making.

6. The Role of Artificial Intelligence in Knowledge Creation, Sharing, and Use

Artificial intelligence is reshaping the core knowledge processes that underpin organizational learning and strategic decision-making. In traditional knowledge management theory, knowledge creation, sharing, and use are understood as human-centred activities supported by digital infrastructures that enable storage and dissemination (Alavi and Leidner 2001; Malhotra 2001). The integration of AI extends this model by enabling digital knowledge systems to participate more actively in the transformation and application of knowledge.

Across the literature, AI influences knowledge processes in three interrelated ways: by expanding knowledge creation, reconfiguring knowledge sharing, and shaping knowledge use in decision contexts.

In relation to knowledge creation, AI enhances the capacity of organizations to generate insights from complex and heterogeneous data sources. Machine learning techniques enable the identification of patterns that may not be readily observable through human analysis, while generative AI produces summaries, explanations, and scenario-based outputs that contribute directly to organizational sensemaking (Dwivedi et al. 2021; Storey et al. 2025). This results in a hybrid mode of knowledge creation in which human and AI contributions are intertwined, raising questions regarding the transparency and reliability of AI-generated knowledge (Rezaei 2025).

With regard to knowledge sharing, AI enables more dynamic and context-sensitive distribution of knowledge. Traditional systems relied on structured repositories, often limiting accessibility and relevance. AI-enabled systems employ natural language processing and recommendation mechanisms to match knowledge resources with user needs, improving discoverability and flow (Chatti and Argoubi 2025). At the same time, algorithmic mediation introduces selectivity, as system-driven prioritisation shapes what knowledge becomes visible and actionable within the organization (Bankins et al. 2024).

In knowledge use, AI-enabled digital knowledge systems increasingly influence how knowledge informs decision-making. By integrating predictive analytics, simulation, and scenario modelling, these systems support decisions under conditions of uncertainty (Trunk et al. 2020). While such capabilities strengthen analytical support, they may also encourage overreliance on algorithmic outputs, potentially reducing critical reflection and experiential judgment (Njiru et al. 2025).

Collectively, these developments indicate a transition from technology-supported knowledge processes to hybrid human–AI knowledge ecosystems. Artificial intelligence expands the scale and speed of knowledge processes while simultaneously reshaping how knowledge is generated, shared, and applied. The effectiveness of these systems therefore depends on how organizations integrate AI into knowledge practices in ways that sustain critical inquiry and reflective learning.

7. AI-enabled Digital Knowledge Systems and Organizational Learning

Organizational learning involves the development and transformation of knowledge through experience, reflection, and collective sensemaking, where organizational experience interacts with context to create knowledge (Argote and Miron-Spektor 2011). Digital knowledge systems have traditionally supported these processes by enabling access to knowledge, while interpretation remained largely human-driven. The integration of artificial intelligence introduces a shift in this relationship, as AI-enabled digital knowledge systems increasingly shape how knowledge is interpreted, prioritised, and applied.

The literature highlights a tension between learning enablement and learning substitution. AI-enabled systems can enhance learning by supporting sensemaking, expanding access to knowledge, and enabling scenario exploration in complex environments (Dwivedi et al. 2021; Storey et al. 2025). At the same time, reliance on AI-generated outputs may reduce opportunities for reflection and critical inquiry, narrowing interpretive perspectives (Böhm 2025; Rezaei 2025). Learning processes may therefore become more efficient but less reflective.

This tension reflects a distinction between informational efficiency and authentic learning. While AI-enabled systems improve the speed and scale of information processing, deeper learning depends on reflection, questioning, and the transformation of understanding. Their impact on learning outcomes is therefore contingent on how they are embedded within organizational practices and learning cultures.

AI-enabled digital knowledge systems also influence organizational sensemaking by framing problems and prioritising information. While this supports insight generation, it may reinforce dominant perspectives and limit exposure to alternatives (Bankins et al. 2024). Consequently, these systems function as mediating infrastructures that shape both the process and quality of learning, depending on their design, governance, and integration into organizational contexts.

8. Governance, Ethics, and Trust in AI-enabled Digital Knowledge Systems

The integration of artificial intelligence into digital knowledge systems introduces governance, ethical, and trust-related conditions that shape how knowledge is evaluated, validated, and used in organizations. These conditions are not external constraints but integral components of AI-enabled knowledge environments, influencing the quality of both learning and decision-making.

A central concern is epistemic transparency. AI-enabled systems, particularly those based on machine learning and generative models, often operate through processes that are not readily interpretable. When such systems generate knowledge artefacts or recommendations, the underlying assumptions, data sources, and reasoning processes may remain opaque. This opacity limits the ability of users to critically evaluate AI-generated outputs and constrains opportunities for reflective learning (Rezaei 2025).

Closely related is the issue of trust calibration. Effective use of AI-enabled digital knowledge systems requires users to develop appropriate levels of trust in system outputs. Overreliance may lead to uncritical acceptance of AI-generated knowledge, while under-trust may limit the use of potentially valuable insights. Trust is shaped by perceived accuracy, explainability, and prior experience, yet remains difficult to calibrate in dynamic organizational settings (Hosseini and Seilani 2025). Misaligned trust therefore has direct implications for both learning and decision quality.

AI-enabled digital knowledge systems also raise broader ethical considerations, particularly in relation to bias, accountability, and fairness. Systems trained on historical or incomplete data may reproduce or amplify existing biases, influencing what knowledge is generated and how it is interpreted (Bankins et al. 2024). As AI increasingly contributes to knowledge creation and decision processes, questions arise regarding responsibility for outcomes shaped by algorithmic outputs.

Beyond formal governance mechanisms, organizational context plays a critical role. Learning cultures that support inquiry, dialogue, and reflection are more likely to integrate AI in ways that sustain authentic learning. In contrast, environments that prioritise efficiency may reinforce reliance on automated outputs, limiting opportunities for critical engagement (Nakash and Bolisani 2024). Governance, in this sense, extends beyond policies and controls to include the norms and practices that shape how knowledge is questioned and applied.

Accordingly, governance, ethics, and trust function as enabling conditions that shape how AI-enabled digital knowledge systems influence organizational learning and strategic decision-making. Their role is not peripheral but central, determining whether these systems support reflective learning and informed judgment or reinforce uncritical reliance on algorithmic outputs.

9. AI-enabled Digital Knowledge Systems and Strategic Decision-making

Strategic decision-making involves interpreting complex environments, evaluating uncertain alternatives, and committing to action under conditions of risk and ambiguity (Jarrahi 2018). Traditional decision-support systems assisted these processes by providing structured analysis and access to information, while judgment remained primarily human-driven. AI-enabled digital knowledge systems extend this role by embedding predictive, generative, and analytical capabilities directly into decision processes.

The literature indicates that AI-enabled systems influence strategic decision-making in three interrelated ways: by expanding analytical capacity, reshaping how uncertainty is interpreted, and reconfiguring decision authority.

First, AI-enabled digital knowledge systems expand analytical capacity by enabling organizations to process large volumes of data and generate insights through predictive analytics and scenario modelling (Dwivedi et al. 2021;

Pai et al. 2022). These capabilities strengthen the informational basis of decision-making and enhance the ability to anticipate change in complex environments.

Second, AI-enabled systems reshape how uncertainty is interpreted. By producing probabilistic forecasts and data-driven scenarios, they frame uncertainty in quantifiable terms. While this can support more informed decision-making, it may also narrow the interpretive space by privileging data-driven representations over experiential and contextual knowledge (Trunk et al. 2020).

Third, AI-enabled systems reconfigure decision authority. As algorithmic recommendations become embedded in organizational workflows, decision-makers may defer to system outputs, particularly when these are perceived as objective or reliable. While this may improve efficiency, it introduces risks related to reduced critical reflection, diminished accountability, and the potential erosion of managerial judgment (Njiru et al. 2025).

These dynamics highlight a tension between decision efficiency and decision quality. Faster and more data-driven decisions do not necessarily result in better outcomes. Decision quality depends on the integration of AI-generated insights with human judgment, contextual understanding, and organizational experience.

The effectiveness of AI-enabled decision-making is shaped by the governance and learning conditions discussed in the previous section. Transparent systems, appropriately calibrated trust, and strong learning cultures enable organizations to engage critically with AI-generated insights, supporting informed and accountable decisions. In contrast, weak governance and overreliance on AI may result in decisions that are efficient but insufficiently grounded.

In this sense, AI-enabled digital knowledge systems do not merely support decision-making; they reconfigure how decisions are formed, justified, and enacted, reinforcing their role as mediating infrastructures linking knowledge processes, learning, and strategic action.

10. Synthesis of Findings

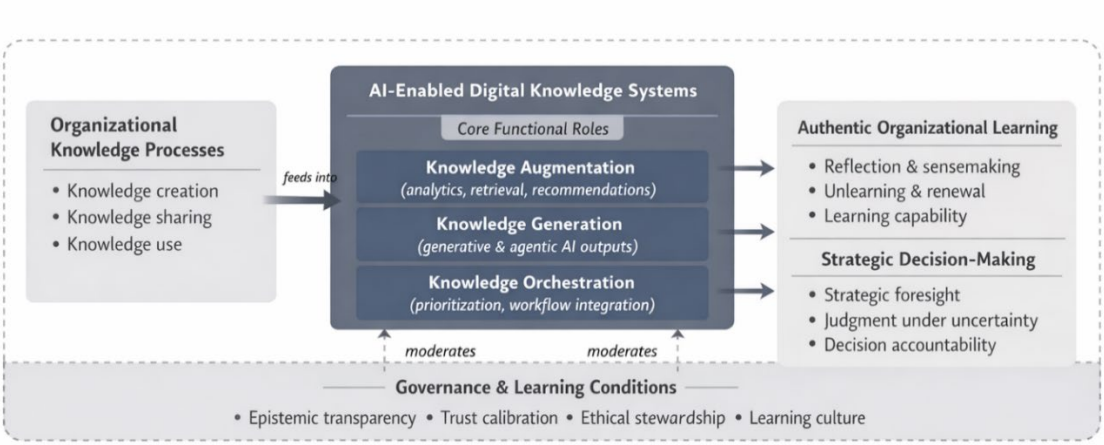
This review highlights a shift in how AI-enabled digital knowledge systems (DKS) are understood within organizations. Rather than functioning as supportive infrastructures for storing and retrieving knowledge, these systems increasingly act as mediating mechanisms that shape how knowledge is generated, interpreted, and applied.

Three interrelated dynamics emerge. First, AI-enabled DKS extend knowledge processes by augmenting analytical capacity and enabling the generation of new knowledge artefacts, reflecting the growing role of generative AI in organizational sensemaking (Dwivedi et al. 2021; Cerchione et al. 2026). Knowledge processes are therefore no longer exclusively human-driven but increasingly hybrid. Second, these systems reshape organizational learning by introducing a tension between learning enablement and learning substitution. While they support access to information and facilitate sensemaking, they may reduce opportunities for reflection and critical inquiry, meaning that gains in informational efficiency do not necessarily translate into deeper learning (Böhm 2025; Rezaei 2025). Third, AI-enabled DKS reconfigure strategic decision-making by influencing how uncertainty is interpreted and how decision authority is exercised, with algorithmic outputs shaping problem framing and justification while introducing risks of overreliance and reduced accountability (Trunk et al. 2020; Njiru et al. 2025).

These dynamics are interconnected and shaped by the interaction between AI capabilities, knowledge practices, and governance conditions. From this perspective, the impact of AI-enabled digital knowledge systems depends not only on technological functionality but on how they are embedded within organizational contexts (Nakash and Bolisani 2024; Bankins et al. 2024). Overall, AI-enabled DKS both enhance analytical capability and reshape the epistemic conditions of learning and decision-making, underscoring the need for an integrated perspective linking knowledge processes, learning, and strategic decision-making.

11. Integrative Framework of AI-enabled Digital Knowledge Systems

Building on the synthesis of findings, this study proposes an integrative framework that conceptualises AI-enabled digital knowledge systems (DKS) as mediating infrastructures linking knowledge processes, organizational learning, and strategic decision-making under specific governance conditions (see Figure 4).



Source: Author's conceptualisation based on systematic literature review (2026).

Figure 4: Integrative Framework of AI-Enabled Digital Knowledge Systems

At the centre of the framework are knowledge processes, encompassing knowledge creation, sharing, and use. AI-enabled digital knowledge systems extend these processes by enabling data-driven insight generation, facilitating context-sensitive knowledge flows, and shaping how knowledge is applied in decision contexts.

These processes influence organizational learning, which is conceptualised as both an outcome and a mediating layer. While AI-enabled systems enhance access to information and support sensemaking, their impact on learning depends on whether they enable reflection or substitute it. The framework therefore distinguishes between informational efficiency and authentic learning, highlighting the conditions under which learning processes are deepened or constrained.

Organizational learning, in turn, informs strategic decision-making. AI-enabled digital knowledge systems shape how uncertainty is interpreted and how decisions are justified by providing predictive analytics, scenario modelling, and algorithmic recommendations. However, the framework emphasises that decision quality depends on the integration of AI-generated insights with human judgment and contextual understanding.

Surrounding these core relationships are governance conditions, including epistemic transparency, trust calibration, and ethical oversight. These conditions moderate how AI-enabled digital knowledge systems influence knowledge processes, learning, and decision-making. Transparent systems and appropriately calibrated trust support critical engagement, whereas weak governance may reinforce overreliance on algorithmic outputs.

The framework thus positions AI-enabled digital knowledge systems as mediating mechanisms within a socio-technical system, rather than as neutral tools. It highlights that the effects of AI are not determined solely by technological capability but emerge from the interaction between system design, organizational practices, and governance conditions.

In doing so, the framework provides a coherent conceptualisation of how AI-enabled digital knowledge systems reshape the relationship between knowledge, learning, and decision-making, offering a basis for both theoretical development and practical application.

12. Conclusion

This study examined how AI-enabled digital knowledge systems (DKS) shape organizational learning and strategic decision-making through a systematic, concept-centric review of the literature. The findings demonstrate that these systems are no longer limited to supporting knowledge storage and retrieval but increasingly function as mediating infrastructures that influence how knowledge is generated, interpreted, and applied within organizations.

The analysis highlights a central tension between informational efficiency and authentic learning. While AI-enabled systems enhance analytical capability, accelerate knowledge processes, and support decision-making under conditions of uncertainty, they may also reduce opportunities for reflection, narrow interpretive perspectives, and encourage reliance on algorithmically generated outputs. This tension underscores the

importance of examining not only what AI-enabled systems enable, but also how they reshape the epistemic conditions of learning and decision-making.

The study contributes to knowledge management and information systems research by advancing an integrative framework that connects knowledge processes, organizational learning, and strategic decision-making under specific governance conditions. In doing so, it provides a coherent conceptualisation of AI-enabled digital knowledge systems as socio-technical mechanisms whose effects depend on their design, use, and organizational context.

From a practical perspective, the findings suggest that organizations should approach the adoption of AI-enabled digital knowledge systems with careful attention to governance, transparency, and learning practices. Ensuring that these systems support critical engagement rather than substitute it is essential for sustaining both effective decision-making and meaningful organizational learning.

Future research should extend this work by examining how AI-enabled digital knowledge systems are enacted in practice, particularly through empirical studies that explore their impact across different organizational contexts. Further investigation is also needed into how governance mechanisms can be designed to balance efficiency with reflection, and how organizations can develop capabilities that support responsible and effective use of AI in knowledge processes.

Ethics Declaration: Ethical clearance for this study was obtained from the College Research Ethics Committee following the vetting and approval of the ethical clearance application at School level. The study is based on a systematic literature review of publicly available sources and did not involve direct engagement with human participants.

AI Declaration: Artificial intelligence (AI) tools were used in the preparation of this manuscript to support language refinement, structuring of arguments, and editing for clarity. All conceptualisation, analysis, and interpretation of the study are the sole work of the author.

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Reclaiming Organizational Knowledge in an Age of Post-truth Disruption

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Abstract: The paper is dedicated to the *post-truth* mini track. There are unprecedented challenges in terms of the reliability of data, knowledge, information that address important questions regarding traditional KM. The paper main goal was to investigate the systemic mechanics of organizational communication and strategic clarity, by isolating the behavioral patterns of the institutional "bullibility" and the cognitive exhaustion. From a methodological point of view, the paper uses mixed-methods that support an interdisciplinary approach. Psychometric scale evaluations demonstrated internal consistency for both the Corporate Bullshit Receptivity Score (CBRS; $\alpha = 0.935$) and the Operational Clarity Baseline (OCB; $\alpha = 0.801$). Pearson's *r* correlations revealed a significant, positive relationship between jargon receptivity and operational data baselines ($r = 0.433$, $p < 0.001$), alongside a significant link between high reliance on operational clarity and heightened crisis-induced jargon exhaustion ($r = 0.220$, $p = 0.011$). The paper argues that, in order to navigate post-truth complexity knowledge-based organizations have to move further the pseudo-profound administrative jargon. We highly recommend that organizations have to apply a more human-oriented transformational leadership model, capable of driving cooperation and collaborative dialogue through decentralized networks of competent teams and communication frameworks rooted in empathy and transparency.

Keywords: Knowledge management (KM), Post-truth era, Artificial intelligence, Human-oriented leadership, Interdisciplinary and intergenerational dialogue

1. Introduction

According to the challenges of the post-truth era many of the traditional approaches of knowledge management (KM) have to be reformulated. Reliability of data within the post-truth era makes more difficult the process of decision making, within all the areas of activities, all over the world. The paper is organized as follows: *Section 2 is dedicated to literature review*; in *Section 3* we described the *research methodology*; *Section 4*, includes our results. The *paper ends with conclusions, main limits and further* possible alternative to continue the research. *Reference* and the two requested Declarations are also included.

2. Literature Review

In order to analyze how modern organizations navigate systemic complex crises, one may anchor the analysis in *Learning Organization (LO)* and *Knowledge Management (KM) theor*ies. The baseline for these organizational perspective are established by ***Peter Senge (1990)***, for LO and correspondingly by ***Nonaka and Takeuchi (1995)***. We focus on a modern perspective of KM, connected with post-truth era. ***Rice and Rice (2005)*** demonstrated the explicit applicability of the SECI, proving that a cross-organizational knowledge loop is necessary to prevent information fragmentation when a variety of independent agencies, academic bodies, and consulting organizations collaborate. ***Farnese et al. (2019)*** operationalized the SECI framework by validating the ***Knowledge Management SECI Processes Questionnaire (KMSP-Q)*** based on a survey design such as to diagnose institutional clarity and epistemic vulnerabilities. ***Hoe (2006)*** expanded upon *the traditional SECI paradigm* by linking it to informal knowledge processes and by showing that when explicit directives lose their utility, quadrants of "*socialization*" and "*internalization*" become survival mechanisms.

Under intense pressure, organic, informal might become the *true operational incubator*s where trust and tacit knowledge are preserved. In order to model this pressure, systems dynamics research by ***Nezafati et al. (2009)*** isolated "*information delay*" and "*transformation speed*" as the critical variables of SECI spiral. Their findings indicated that under conditions of high velocity and low reliability, formal institutional metrics and explicit data streams break down. ***Tammets (2012)*** demonstrated that cross-organizational and intergenerational dialogue serves as powerful corrective measures. ***Faith and Seeam (2018)*** observed that explicit knowledge sharing is continuously undermined by *rigid institutional pressures*. Classical SECI paradigm has to face criticism. ***Gourlay (2003***) identifies empirical shortcomings in the SECI model and argues that model lacks an internal validation mechanism able to verify the qualitative integrity of explicit knowledge. ***Morawski (2023)*** demonstrates that explicit-to-explicit tracking of data sheets, digital metrics, executive strategies, might be designed such as to circulate unverified information, if rigorous human oversight is removed.

2.1 The Sociology and Beliefs of the "Post-Truth" Era and Corporate Semantic Noise

In order to diagnose the vulnerabilities of contemporary knowledge systems, we consider we have to shift from structural models toward *the socio-philosophical and ethical climate of the workplace*. Thus research studies have to look more for *human behavioral dynamics*. ***DePaulo et al. (1996)*** established that deceptive communication is deeply embedded within everyday routine exchanges, with individuals frequently executing low-stakes lies during daily social interactions. *Cross-disciplinary research* demonstrates that modern institutional deception rarely manifests as binary, easily detectable lies. According to *Oxford Dictionary (' 2016)* briefing and ***Lee McIntyre (2018),*** *the "post-truth"* describes an organizational state where objective facts manifest less influence on public and institution than appeals to superficial ideological alignments.

2.2 The Linguistic Breakdown of the SECI Spiral

The operational transmission of *post-truth dynamics* into corporate operations is also a linguistic phenomenon. ***Adachi (2013)*** evaluates *Nonaka and Takeuchi's SECI model* through the lens of *the TEAM linguistic framework*, demonstrating that knowledge conversion relies on linguistic meaning functions. ***Frankfurt (2005)*** argues that lying and "bullshitting" are generating an "information debt"

2.3 The Psychometry of Corporate Receptivity and Behavioral Decision Failures

In order to assess how linguistic noise may impact enterprise workflows, organizations shifted toward *quantitative evaluation*. ***Pennycook et al. (2015***) developed the *Pseudo-Profound Bullshit Receptivity Scale*.

Expanding these insights into institutional settings, ***Ferreira et al. (2020)*** developed ***the Organizational Bullshit Perception Scale (OBPS***). This psychometric framework measures the prevalence, drivers, and cultural outcomes of obscure business jargon within internal corporate networks. One possible behavioral consequence of this vulnerability is documented by ***Petrocelli et al. (2024***). They introduced the construct of *"bullibility*" that illustrates the behavioral tendency of individuals to accept and act upon unverified jargon even when explicit environmental signals indicate the information is non-substantive. To map these institutional drivers and isolate where this vulnerability peaks across modern workforces, ***Littrell (2026)*** has further refined these psychometric metrics. This structural evolution provides the direct empirical foundation for our current survey instrument, capturing whether a corporate culture can actively resist semantic noise or if it will default to costly tactical errors. ***Nagariya et al. 2025***, have shifted rapidly into an "*emergent normal*" characterized by the integration of *Artificial Intelligence (AI), Virtual Reality (VR), Augmented Reality (AR)*. ***Gombar (2025)*** explores how digital algorithms may create a destructive feedback loop characterized by *two core dynamics*: *the "polarization loop"*, which systematically amplifies sensational, emotionally evocative, or rhetorically polished narratives to drive active user metrics, and the *"epistemic barrier*", which actively minimizes alternative, critical, or nuanced data points. ***Gombar*** introduces *the Algorithmic Accountability and Communication Model (AACM)*, bridging technical algorithmic actions with strategic communication outcomes. ***Naukkarinen (2026)*** evaluated this conflict by analyzing the delicate equilibrium between artificial intelligence (AI) and human processes within *modern Knowledge Management* frameworks. The collaborative hybridity is operationalized through the lens of the *Intercultural Domain* introduced by ***Lavis (2021*)**. By functioning within an intercultural domain, an organization mitigates the operational risks **(*Faith and Seeam 2018*)**, ensuring that multi-generational viewpoints are aggregated in order to verify data reliability before it drives strategic execution.

3. Methodology and Data

This study uses *a quantitative, cross-sectional descriptive-correlational research* design such as to examine the relationship between *organizational linguistic framing* (operational clarity versus pseudo-profound corporate jargon) and correspondingly *the employee cognitive exhaustion, perception, and critical crisis assessment.*

A non-probability, purposive sampling approach had been deployed such as to better capture insights from professionals embedded within institutional environments heavily reliant on formal communication channels. The final validated sample comprised *N* = 134 active professionals. Regarding *the sample demographic profile leans* significantly toward experienced decision-makers, with 61.7% of respondents included into the 40–54 and 55 or above age cohorts, representing senior institutional leaders and executive-level managers. Geographically, the sample spans European jurisdictions, with concentrated representation *from Cyprus, Romania, Italy and Germa*ny, allowing for *a robust cross-regional comparison of organizational cultures*.

3.1 Measurement and Instrumentation

In order to develop the questionnaire items we took into account *the pilot testing* and *content validation* performed before by Shane Littrell from *Cornell University* and *Munk School of Global Affairs and Public Policy, University of Toronto* published next on a well appreciated paper entitled *The Corporate Bullshit Receptivity Scale: Development, validation, and associations with workplace outcomes*. We consider this strengthen the confidence in the measurement instruments used within our paper. On *Shane Littrell* study participants completed *the Corporate Bullshit Receptivity Scale* (McDonald's ω = .92; CBSR) created in Study 1, rating the perceived "business savvy" of 10 corporate bullshit statements on a 5-point scale. Higher mean scores indicate greater receptivity to that type of information.

Corporate Bullshit Receptivity Scale items (Corporate Bullshit Statements):

- "Working at the intersection of cross-collateralization and blue-sky thinking, we will actualize a renewed level of cradle-to-grave credentialing and end-state vision in a world defined by architecting to potentiate on a vertical landscape."
- "Our goal is to engage our capabilities by focusing our efforts on executing the current transmission of our empowerment, driving an innovative liquidity with our change drivers, and coaching energetic frameworks to our shovel-ready alignment."
- "This synergistic look at our thought leadership will ensure that we are avoiding reputational deficits with our key takeaways as effectively as we can in order to sunset our resonating focus."
- "This scalable look at our company will ensure that we are executing and minimizing cross-back impact with our conversations as effectively as we can to fundamentally disrupt our ecosystem."
- "We will fundamentally disrupt our conversations in delivering upstream transformational performance-focused key learning like no other company anywhere in the world."
- "By solving the pain point of customers with our conversations, we will ideate a renewed level of end-state vision and growth-mindset in the market between us and others who are architecting to download on a similar balanced scorecard."
- "Our bandwidth comes from the visionary culture-shifting of several new growth-hacked, integrated networks that capitalize on our heritage to engage our future when building bridges to success."
- "We will cover all the bases of our low hanging fruit by joining with our bleeding-edge, results-driven global partners to better grasp our back-end architecture."
- "By getting our friends in the tent with our best practices, we will pressure-test a renewed level of adaptive coherence and culture fit in the market between us and others who are solutioning to download on a similar, value-centered strategic intent."
- "As an emerging leader grounded in a mission to benchmark and nurture the human spirit, we have always aspired to make upstream connections, drilling down one more click on people and communities around the world."

Main results of Shane Littrell:

- Corporate Bullshit Receptivity Scale (CBSR): McDonald's ω = .92.
- Factorial analysis confirmed two factors: 10 items for Corporate Bullshit and, correspondingly 10 items of Real Corporate Discurs

- The final model including 20 items offered two relevant index, namely : TLI = .97 and correspondingly RMSEA = .03
- The relevance of the structure of CBSR: CFI = .95; TLI = .94; SRMR = .06; RMSEA = .05.
- The short form of CBSR-with 10 items had provided relevant correlation: $\chi^2(34) = 42.70$, $p = .145$; CFI = .99; TLI = .98; SRMR = .04; RMSEA = .03.
- Corporate Bullshit Receptivity (CBSR) had illustrated a negative connection for decision made by professional decision makers: $\beta = -0.29$, $p < .001$.
- Correspondingly for short CBSR-10: $\beta = -0.26$, $p < .001$.

Our *questionnaire* was structured into three operational sub-scales in order to better capture distinct dimensions of the corporate communication ecosystem (Table 1):

Table 1: Operational scale architecture and dimensions

Scale Dimension	Operational Target	Items	Linguistic Construct
1. Corporate Bullshit Receptivity Score (CBRS)	Measures an individual's uncritical acceptance or normalization of abstract corporate jargon.	2, 4, 6, 8, 9	High density of buzzwords, low operational density (e.g., "cross-collateralization", "adaptive coherence").
2. Operational Clarity Baseline (OCB)	Establishes the participant's processing metric for concrete, quantitative business data.	1, 3, 5, 7	High operational density, metric-driven targets (e.g., "reduce delivery times by 15%").
3. Jargon Exhaustion & Bullibility Perception (JEBP)	Serves as the primary behavioral dependent variable tracking cognitive friction and communication preferences	10, 11, 12	Focuses on leadership transparency, critical skepticism during crisis, and preference for blunt updates.

Source: Author's work (Andreou, 2026) based mostly on Shane Littrell (2026), https://doi.org/10.1016/j.paid.2026.113699

Items operationalization

- **Item 1 (OCB):** Supply chain optimization metric ("reduce delivery timesby 15%").
- **Item 2 (CBRS):** Pseudo-abstraction ("intersection of cross-collateralization and blue-sky thinking").
- **Item 3 (OCB):** Revenue stream diversification ("expanding digital offerings to mid-market enterprise").
- **Item 4 (CBRS):** Redundant jargon optimization ("de-contenting and avoiding reputational deficits").
- **Item 5 (OCB):** Actionable user engagement data tracking ("deploy weekly updates for client retention").
- **Item 6 (CBRS):** Culture-fit buzzwords ("pressure-test a renewed level of adaptive coherence").
- **Item 7 (OCB):** Direct structural communication protocols ("report budget variances directly to executive leadership").
- **Item 8 (CBRS):** Empowerment jargon abstraction ("executing the current transmission of our empowerment").
- **Item 9 (CBRS):** Integrated network buzzwords ("visionary culture-shifting of several new growth-based networks").
- **Item 10 (JEBP):** Perception of leadership communication opacity ("sound impressive but don't actually tell me anything concrete").
- **Item 11 (JEBP):** Behavioral critical reflection under organizational crisis ("pause, assess the facts, and look past vague directives").
- **Item 12 (JEBP):** Structural preference for explicit leadership transparency ("prefer a leader who gives a blunt, imperfect update").

3.2 Data Cleaning and Processing Protocols

To guarantee dataset integrity for rigorous parametric and non-parametric testing, a multi-phase digital data cleaning protocol was executed using Google Sheets. This pipeline initiated with a phase of linguistic standardization, wherein open-ended demographic strings were systematically audited and normalized. Specifically, geographic variations, such as Bucharest, Romania, and ROMÂNIA were consolidated under a

singular entity descriptor (Romania), while internal language variances like Deutschland were converted uniformly to their English international equivalents (Germany).

3.3 Statistical Analysis

The final, cleaned dataset was exported into *Jamovi (Version 2.7)* for computational analysis. The statistical pipeline initiated with the calculation of *Cronbach's alpha (α) coefficients* to establish *psychometric reliability for the CBRS* and *OCB scales using the specialized 'psych' computation package* (***Revelle 2025***). Following validation, continuous macro-variables were generated by computing the mean scores of the respective scale item buckets (*CBRS_Mean, OCB_Mea*n, and *JEBP_Mean*).

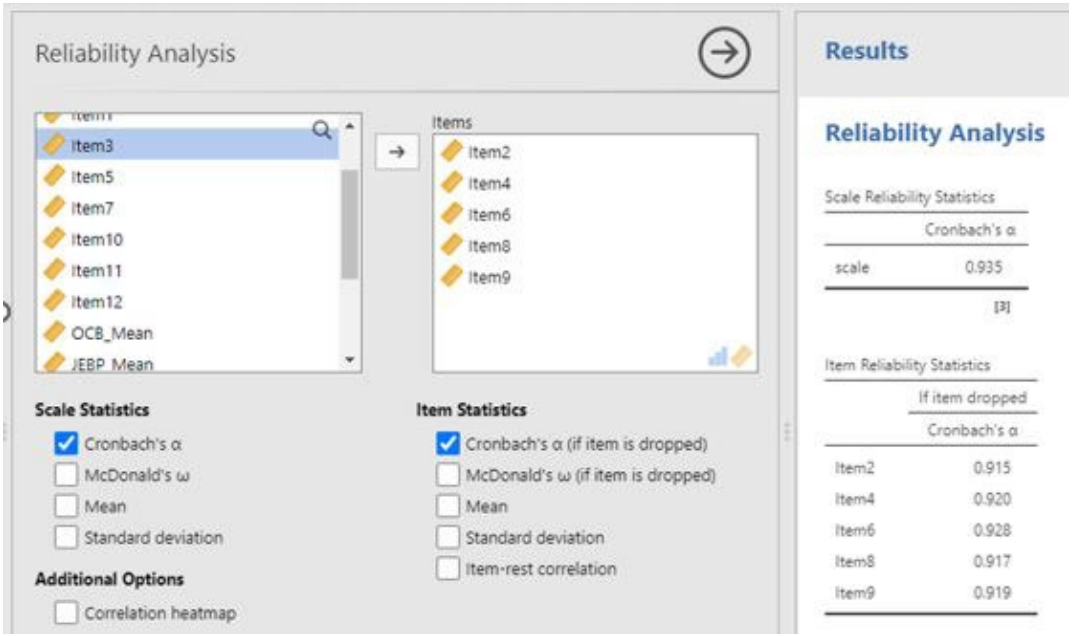
Subsequently, independent samples *t*-tests and *a One-Way Analysis of Variance (ANOVA)* were used to determine variance in jargon receptivity and communication exhaustion across age groups and primary professional sectors (*Corporate versus Academia*). Homogeneity of variance and baseline regression diagnostics were monitored via the 'car' package (***Fox and Weisberg 2024***).

Finally, *Pearson's r correlation coefficients* were calculated to mathematically test the relationship between a high tolerance for abstract jargon and active fact-checking behaviors during organizational crises.

4. Main Results of our Study

4.1 Psychometric Scale Reliability and Instrument Consistency

To establish the psychometric integrity of the primary measurement instruments prior to inferential testing, internal consistency evaluations were conducted by calculating *Cronbach's alpha (α) coefficients for both the Corporate Bullshit Receptivity Score (CBRS) and the Operational Clarity Baseline (OCB) sub-scales.* The 5-item sub-scale tracking an individual's uncritical acceptance or normalization of abstract corporate jargon (Items 2, 4, 6, 8, and 9) demonstrated *a high internal consistency (α =0.935).* A statistical item-deleted reliability analysis indicated that the removal of any single item would drop the overall *alpha score* (with item-deleted values ranging tightly from *0.915* to *0.928*). This confirms that all five constituent items significantly and uniquely contribute to the structural strength of the underlying jargon construct (figure 1).



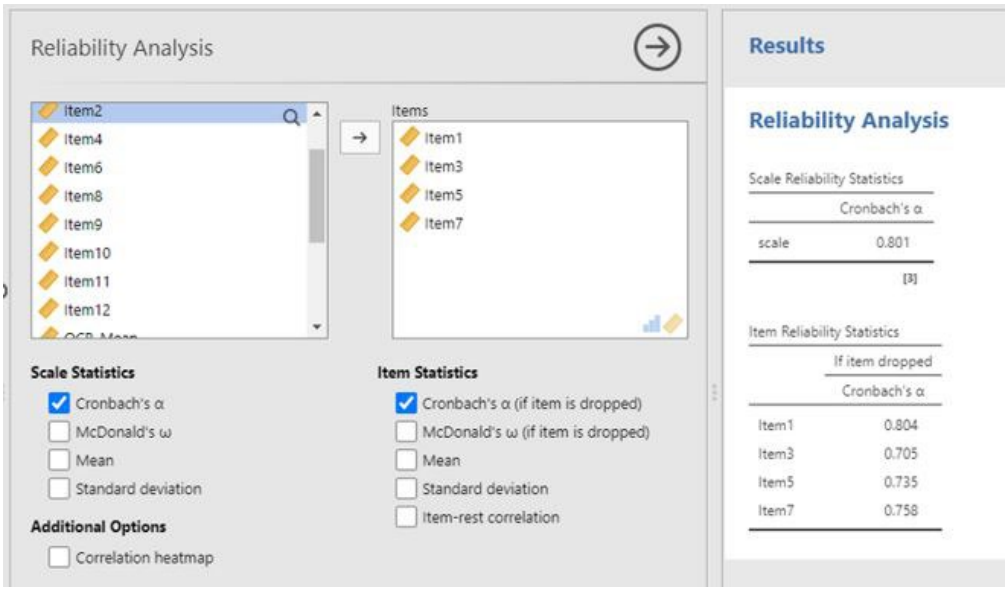
Source: Author's work compiled using Jamovi software (Andreou, 2026)

Figure 1: Reliability Analysis

4.2 Operational Clarity Baseline (OCB)

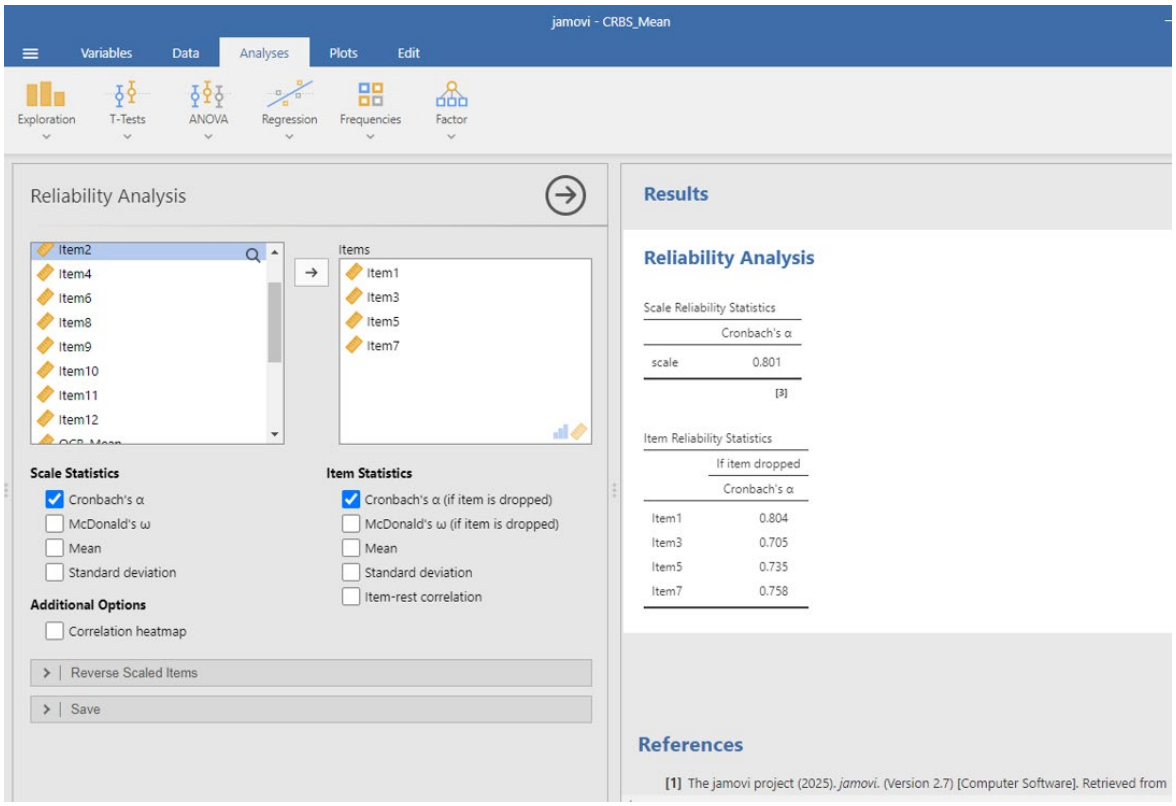
The 4-item sub-scale serving as the processing baseline for metric-driven, structured business communications (Items 1, 3, 5, and 7) displayed strong internal consistency (α =0.801). Item-dropped iterations revealed that omitting Item 1 would result in a negligible, mathematically redundant alpha increase to 0.804. Consequently,

all four original items were retained to preserve complete scale architecture coverage and metric validity (figure 2).



Source: Author's work compiled using Jamovi software (Andreou, 2026).

Figure 2: Reliability analysis statistics for the OCB sub-scale



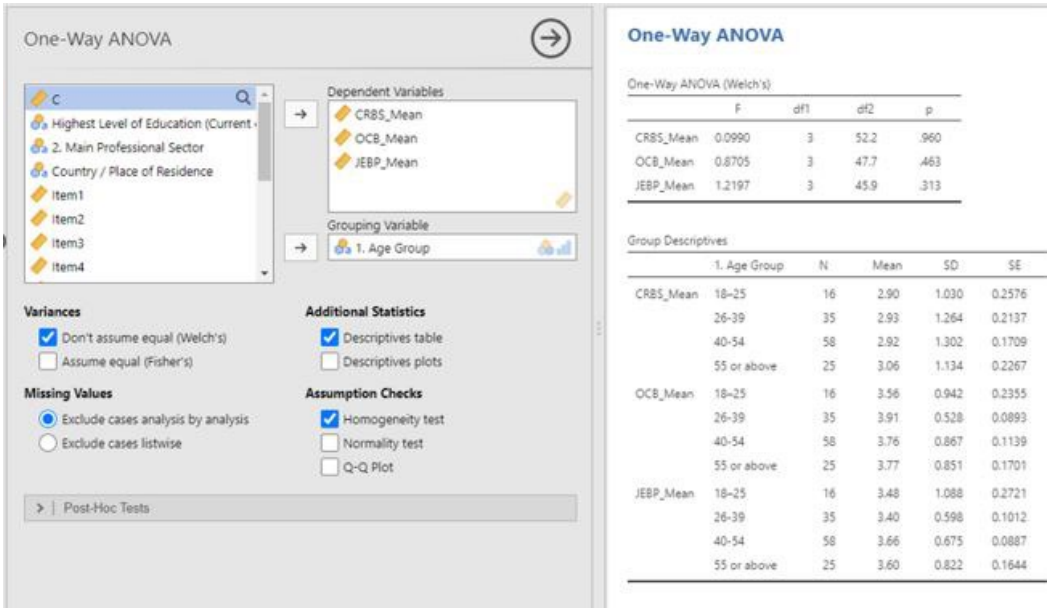
4.3 Inferential Variance Testing Across Demographic Groups. Institutional Sector Variance

A One-Way Welch's ANOVA was executed to determine if variance in corporate jargon receptivity (CBRS) and communication exhaustion (JEBP) existed across distinct institutional sectors. For Corporate Bullshit Receptivity, no statistically significant difference was observed between the groups, ***F* = 0.485; d.f. = 2, 27.9; *p* = 0.621**, indicating uniform baseline thresholds for jargon normalization across institutional contexts. For *Jargon Exhaustion and Behavioral Preference (JEBP)*, the model demonstrated a marginally significant trend across sectors, ***F* = 3.161; d.f. = 2, 27.2; *p* = 0.058**.

This suggests subtle variations in cognitive communication noise thresholds between environments that merit descriptive exploration, though the overall effect did not meet the strict frequentist alpha threshold (*α* = 0.05).

4.4 Generational Cohort Variance

A One-Way Welch's ANOVA was conducted to assess if variance in corporate jargon receptivity (CBRS_Mean), operational clarity processing (OCB_Mean), and jargon exhaustion (JEBP_Mean) existed across distinct generational cohorts (18–25, 26–39, 40–54, and 55 or above). The inferential models revealed no statistically significant differences across age cohorts for any of the macro-constructs. Corporate jargon receptivity was uniform across generations, **F = 0.099; d.f. = 3, 52.2; p = 0.960**, with mean scores remaining tightly clustered between 2.90 (SD =1.03) and 3.06 (SD =1.13). Processing baselines for operational clarity data showed no significant generational variance, **F = 0.871; d.f. = 3, 47.7; p = 0.463**, with means clustered between 3.56 and 3.91. Finally, communication noise fatigue and preference for crisp crisis transparency (JEBP_Mean) did not systematically vary by age, **F = 1.220; d.f. = 3, 45.9; p = 0.313**, remaining steady and high across all groups (ranging from 3.40 to 3.66). These findings collectively suggest that individual psychological thresholds for jargon acceptance and the resulting cognitive communication friction are structural or environment-driven characteristics, rather than generational or demographic traits within the professional ecosystem (figure 3).



Source: Author's work compiled using Jamovi software (Andreou, 2026).

Figure 3: One-Way Welch's ANOVA results and group descriptive statistics across age cohorts

4.5 Bivariate Correlation Analysis

To evaluate the mathematical relationships between corporate jargon receptivity (CBRS_Mean), operational clarity baselines (OCB_Mean), and jargon exhaustion/crisis behaviors (JEBP_Mean), a Pearson's r correlation matrix (table 2) was computed across the full sample (*N* = 134).

Table 2: Pearson correlation matrix for macro-variables

Variable	1. CBRS_Mean	2. OCB_Mean	3. JEBP_Mean
1. Corporate Jargon Receptivity (CBRS_Mean)	—	0.433***	0.121
2. Operational Clarity Baseline (OCB_Mean)		—	0.220*
3. Jargon Exhaustion (JEBP_Mean)			—

Source: Author's work (Andreou, 2026)

Note. *N* = 134. ***p* < 0.05, ***p* < 0.001**.

A statistically significant, moderate positive correlation was observed between *Corporate Jargon Receptivity* and *the Operational Clarity Baseline*, ***r* = 0.433, *p* < 0.001.** This indicates that individuals with higher thresholds for linguistic jargon normalization also maintain strong dual alignment with structured, metric-driven communication frameworks. Additionally, *a statistically significant positive correlation was identified between the Operational Clarity Baseline* and *Jargon Exhaustion/Behavioral Preferences*, ***r* = 0.220, *p* = 0.011**. This confirms that a higher baseline reliance on data clarity systematically links to increased communication fatigue and an active demand for fact-checking behaviors during organizational crises.

Conversely, *the direct relationship between routine corporate jargon receptivity* and *crisis-specific communication exhaustion* was not statistically significant, ***r* = 0.121, *p* = 0.163**, suggesting that crisis communication noise processing operates via distinct psychological mechanisms separate from day-to-day organizational style adaptation.

4.6 Contextual Qualitative Observations

Linguistic proficiency and structural familiarity with corporate discourse may shape how individuals distinguish between meaningful and pseudo-profound organizational communication. This observation is particularly relevant to the study's focus on organizational communication noise, as it suggests that sensitivity to buzzword-heavy language may not be uniform across respondents. The ability to identify non-substantive or pseudo-profound statements may depend, in part, on *linguistic and cultural familiarity* with the specific corporate discussion itself, providing a key qualitative target for subsequent debate.

5. Discussion

The primary results of this research reveals a statistically significant, moderate positive correlation between Corporate Jargon Receptivity and the Operational Clarity Baseline (**r = 0.433, p < 0.001**). These results challenges classical assumptions as Nonaka and Takeuchi's (1995) SECI model which presupposed a clean, binary separation between substantive, metric-driven data assets and non-substantive communicative noise.

Instead, these results indicate that modern professionals do not operate within an idealized, uncorrupted knowledge pipeline. When assessing against **Adachi's (2013)** linguistic critique of the SECI matrix. This confirms that the "combination phase" (explicit-to-explicit tracking) has become structurally entangled with pseudo-profound corporate jargon. Individuals who maintain high thresholds for navigating complex, data-heavy operational baselines simultaneously display an elevated normalization of abstract administrative style. Rather than rejecting semantic noise, high-performing corporate professionals internalize both communication modalities as a unified survival mechanism. This supports **Morawski's (2023)** constructivist assertion that within high-velocity, tech-driven workspaces, explicit strategic documentation frequently challenges rhetorical frameworks alongside hard operational data to project institutional legitimacy.

5.1 Micro-environments, Crisis Friction, and Information Debt

While day-to-day corporate communication reflects a dual acceptance of data and jargon, this study isolates an acute psychological shift during periods of institutional destabilization. The data demonstrates a statistically significant positive correlation between *a participant's Operational Clarity Baseline* and *crisis-induced Jargon Exhaustion/Behavioral Preferences* (***r* = 0.220, *p* = 0.011**). This relationship provides explicit empirical validation for ***Frankfurt's (2005)*** distinction between structural deception and "bullshit", as well as ***Petrocelli et al.'s (2024)*** behavioral construct of "bullibility". When an organizational crisis emerges, evidence-driven professionals require explicit, objective, and transparent data to execute cognitive processing and tactical decisions. If leadership defaults to non-substantive, buzzword-heavy rhetoric to preserve institutional impression management, a severe "*speed-reliability gap"* occurs (***Nagariya et al. 2025***). This disconnect generates instant cognitive friction, causing rapid psychological fatigue among employees who rely heavily on clarity. This behavioral failure confirms the real-world cost of technical information debt: organizations pay for sophisticated data tracking but hide behind polished, abstract administrative prose when operational resilience is needed most. Under crisis conditions, formal corporate channels fail, forcing employees to execute an emergency cognitive pause to look past vague directives (***Hoe, 2006***).

5.2 The Structural Universality of Jargon Normalization

A compelling and counter-intuitive outcome of the inferential variance modeling is the absence of demographic differentiation. *One-Way Welch's ANOVA testing* revealed no statistically significant variations across age groups or professional cohorts regarding jargon ***F* = 0.099; d.f. = 3, 52.2; *p* = 0.960**. Same for *jargon-*

induced exhaustion, ***F* = 1.220; d.f. = 3, 45.9; *p* = 0.313**. Institutional sector testing across Corporate and Academia showed uniform baseline thresholds for jargon normalization, ***F* = 0.485; d.f. = 2, 27.9; *p* = 0.621.**

These findings strongly suggest that linguistic vulnerability and communication fatigue are not isolated demographic twists, individual psychological traits, or generational gaps (such as a split between emerging scholars and senior managers). Instead, they represent structural pathologies embedded within the modern macro-environment. Whether an employee is a younger professional entering a decentralized multi-agency alliance (***Rice and Rice 2005***) or a senior executive managing an academic repository (***Faith and Seeam 2018***), all are socialized within the same pervasive "post-truth" climate (***McIntyre 2018***). The systemic saturation of algorithmic platform filters (***Gombar 2025***) and generative content engines (***Naukkarinen 2026***) has standardized empty corporate language across all industries, rendering traditional demographic markers irrelevant. When framed through ***Lavis's (2021)*** conceptualization of *the Intercultural Domain*, international corporate English functions as a secondary layer of abstraction that alters standard cognitive validation filters. For non-native English speakers operating within multinational corporate pipelines or European research networks, complex buzzwords may be accepted simply because they mirror the expected, stylized aesthetic of "*professional discourse*". If an employee cannot reliably differentiate between substantive strategic insights and pseudo-profound prose due to subtle cultural or linguistic barriers, the risk of institutional bullibility doubles. This structural opacity allows toxic operational pathologies, such as "knowledge hoarding" (***Faith and Seeam 2018***), to remain hidden behind polished, automated corporate communication.

6. Conclusion

This paper provides quite relevant arguments that contemporary organizations are suffering from *acute informational and linguistic debt*: paying premium capital for advanced tracking, telemetry, and explicit data systems while *relying on non-substantive, buzzword-heavy text* to articulate strategy. The findings reveal that while professionals naturally learn to balance this semantic debt *alongside hard data in routine envi*ronments (*r* =0.433), *an acute operational crisis* highly disrupts this equilibrium. When high-pressure situations emerge, *data-driven employees experience severe cognitive friction* and *communication fatigue* (*r* =0.220) if they are fed superficial administrative prose instead of objective facts.To bridge this data-to-decision gap and pull down these fractured ideological silos, knowledge-based organizations have to move past pseudo-profound jargon and adopt human-oriented transformational leadership (***Bass and Avolio 1994)***.

Organizations might execute a strategic forensic fix by establishing decentralized networks of competent teams capable of bypassing rigid bureaucratic hierarchies. Transformational leaders might introduce strategic pauses during a crisis - forcing teams to execute a critical cognitive reflection to evaluate raw environmental signals rather than rushing to fulfill empty, highly polished directives (***Petrocelli et al. 2024***). By shifting from transactional dashboards to empathetic, radically transparent communication frameworks, leaders cultivate true psychological safety (***Edmondson 1999)***. This ensures that high-value operational indicators and vital data points are translated into actionable tasks rather than being buried in a cemetery of unverified linguistic noise.

6.1 Main Limitations of the Paper

While this research *offers psychometric and inferential validation for structural communication no*ise, several distinct limitations have to be acknowledged. *First*, the sample size (*N* = 134), while statistically sufficient for executing robust *Welch's ANOVA* and *Pearson's r correlation models*, relies on a non-probability, purposive sampling strategy *concentrated within European jurisdictions* (Cyprus, Romania, Germany and Italy).. *Second*, data were captured *at a single point in time*. *A cross-sectional design cannot establish long-term longitudinal shifts in jargon exhaustion as an organizational crisis evolves over extended periods.*

6.2 Recommendations for Future Research

We consider that future studies should investigate how the widespread organizational integration of generative AI systems and automated writing tools accelerates administrative debt (***Naukkarinen 2026***). Researchers should test whether automated content engines compress or widen the "*speed-reliability gap*" by overstuffing corporate databases with statistically optimized. Finally, future research should apply *longitudinal field experiments* within enterprises to track *the long-term effectiveness* of our paper framework. Measuring employee exhaustion levels before and after implementing jargon-reduction communication protocols will provide proof of how closing the data gap directly stabilizes workforce retention and operational clarity.

Acknowledgements

Special thanks to all the responders. We intend to share a published version of the paper.

Ethics Declaration Authors declare the research complies with standard international ethical guidelines as data were gathered via a completely anonymous, voluntary, web-administered survey.

Declaration of AI and AI-Assisted Technologies in the Writing Process During the preparation of this manuscript, authors *used the generative AI tool Gemini strictly for grammar, syntax, and editorial refinement.*

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Integration of AI-generated Information Into Organizational Knowledge Through Coherent HRM - and KMM Processes

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Abstract: This position paper argues that the integration of AI-generated information has the potential to disrupt existing human agencies in organizational routines. This disruption of agency is a result of displacement of judgement particularly when routine automation reduces human agency to higher dependencies on these AI outputs leading to lower sense-making. Reinforcement of agency requires conscious moves between different epistemic modes translated into Human Resource Management (HRM) and Knowledge Management (KMM) frameworks and processes. Such a robust epistemological framework epistemological framework relies on orchestrating coherence between high-level exploratory knowledge and low-level pragmatic knowledge that enables justifying, validating by human agents.

Keywords: Knowledge uncertainty, Human in the loop, Transfer learning

1. Introduction

In an era where artificial intelligence generates vast amounts of information for organisational decision-making, a critical challenge emerges: how can AI-generated information be meaningfully integrated into existing organisational routines and knowledge systems without undermining human judgment or creating epistemic misalignment? This position paper argues that human-in-the-loop mechanisms, grounded in modal consciousness and epistemic functional testing, offer a promising pathway to address this challenge.

We propose the development of integrated HRM–KMM (Human Resource Management – Knowledge Management and Mobilisation) protocols that embed epistemic functional testing as a reciprocal validation process. These protocols systematically compare AI-generated pragmatic outputs against human-mediated epistemic frameworks, drawing on different knowledge modalities: epistemic (what is knowable), doxastic (what is believed), deontic (what is obligatory), and alethic (what is possible or necessary). By enabling continuous iteration and adaptation of knowledge representations in SMEs, such protocols help align pragmatic routines with the theoretical possibilities and limitations of AI tools.

Modal logic and Kripke-frame semantics are used here metaphorically as a lens for mapping “possible worlds” of employee data scenarios against real-world organisational constraints. This approach allows organisations to adopt a proactive stance toward AI in HRM, striking a deliberate balance between technological automation and human judgment. The result is the transformation of epistemic uncertainty into more sustainable knowledge ecosystems.

Building on Wiersma (2026), who highlights the role of human reflective capacity and reinforcement learning in reducing epistemic uncertainty, this paper extends that framework to AI-augmented HRM and KMM contexts. While AI excels at automating closed-loop routine tasks, it remains insufficiently reliable for highly contextual, dynamic, and value-laden HRM decisions (e.g., performance evaluation, talent development, or ethical trade-offs). Such situations require nuanced human epistemic stances and the creation of new semantic codes within everyday routines. Tailored human-in-the-loop approaches are therefore essential to ensure situational accuracy and preserve human agency.

The paper introduces epistemic functional testing as a reinforcement mechanism that reflects AI-derived pragmatic outputs against human-mediated theoretical frameworks. This process supports continuous adaptation of SME knowledge representations through reinforcement and transfer learning, reframing epistemic uncertainty not merely as an opportunity but as a navigable organisational constraint. In doing so, it transforms knowledge inertia into situational certainty modelling, enabling SMEs to incorporate AI responsibly while safeguarding human judgment.

This position paper thus advances a balanced, human-centred approach to AI integration in HRM and knowledge management. It aligns with Wiersma’s emphasis on structured innovation spaces while offering both theoretical depth and practical guidance for building sustainable knowledge ecosystems amid rapid technological change.

The central research question guiding this paper is: How can AI-generated information be effectively and efficiently integrated into existing organisational knowledge and routines using humans in the loop to realise coherent HRM and KMM processes?

The remainder of the paper is organised as follows: After this introduction Section 2 presents key definitions, followed by Section 3 which provides an overview of the relevant literature. Section 4 outlines the methodology, and Section 5 discusses the findings. Consequently a quadrant based typology is presented in Section 6. Finally, Section 7 concludes this paper by answering the research question.

2. Definitions

This paper employs the following key definitions and constructs:

Human Resource Management (HRM) HRM refers to the management decisions and practices related to policies that shape the employment relationship and are aimed at achieving organisational goals (Boselie et al., 2021). In this study, HRM practices are conceptualised as organisational routines that are inherently dynamic. Following Feldman and Pentland (2003), routines possess both an *ostensive* aspect (the idealised script or template that describes the routine) and a *performative* aspect (the actual enactment of the routine by human actors in real time and context).

Modal consciousness refers to the deliberate awareness of multiple possible epistemic states (or "possible worlds") when making choices in organisational routines, situations, or contexts. It emerges through reflective capabilities and enables the integration of new knowledge by linking experience-based choices to logical schemas. Drawing on Wiersma (2026), modal consciousness operates at both individual and organisational levels: it supports assimilation at the individual level and integration at the organisational level through knowledge absorption. This form of consciousness equips agents and organisations with advanced epistemic capabilities to manage uncertainty, experiment with new approaches, and justify knowledge claims in innovative activities.

Knowledge Absorption Capacity Knowledge absorption capacity is the organisation's ability to identify, assimilate, transform, and exploit new external information or knowledge.

Epistemic functionality is defined here as the mutually enabling and sustaining relationship between knowledge and its practical function. In this reciprocal dynamic, knowledge evolves in response to contextual functional needs, and improvements in functionality depend on increasingly context-sensitive knowledge (Schyfter, 2020).

3. Literature

Organisational routines are dynamic systems characterised by a fundamental tension between their ostensive aspect the idealised pattern or script and their performative aspect — the actual enactment by human actors in real time (Feldman & Pentland, 2003). This tension creates opportunities for variation, learning, and innovation, but it can also generate inefficiency, conflict, and modal rigidity when not actively managed through reflection, facilitation, and HRM-supported moderation. Environmental dynamics further shape these routines, resulting in a dualistic ontology in which routines are both stable and changeable.

In this context, human agents play a critical role as intermediaries in the transfer, assimilation, and integration of external knowledge. However, their effectiveness is often constrained by structural limitations. Actors frequently draw on the same social and informational networks that create structural holes, thereby restricting broader knowledge flows (Burt, 2004; Kalish & Robbins, 2008; Soda, 2009). Additionally, the capacity of key individuals to span institutional or organisational boundaries can be undermined by ambiguous role definitions and unclear responsibilities (Jacoby, 2001; Hislop, 2005).

Recent literature highlights the importance of dynamic human capabilities to prevent epistemic misalignment in rapidly changing environments (Aas & Breunig, 2024). In particular, Wiersma (2026) emphasises the central role of modal consciousness in enabling reflective learning and overcoming semantic and epistemic barriers. Modal consciousness allows human agents to navigate multiple knowledge modalities when interacting with AI-generated outputs — for instance, interpreting predictive tools through a doxastic lens (what is believed), assessing epistemic uncertainty in model training, exploring alethic possibilities (what is possible or necessary), or evaluating deontic obligations (what is required).

As artificial intelligence becomes increasingly embedded in organisational routines, epistemic uncertainty — stemming from incomplete identification, validation, and contextualisation of AI-generated knowledge — represents a major challenge to effective knowledge integration. This uncertainty is particularly salient in SME contexts, where resources for validation and boundary spanning are often limited. The integration of generative AI therefore calls for new HRM practices that support human agents in their evolving roles as moderators and reflective practitioners, ensuring that pragmatic routine performance remains aligned with higher-level epistemic frameworks.

3.1 Human Agents and Agency

Epistemic uncertainty differs fundamentally from aleatory (non-epistemic) uncertainty. Aleatory uncertainty arises from inherent randomness or variability in processes and outcomes and cannot be reduced through additional knowledge (Martin-Löf, 1996; Hüllemeier & Waegeman, 2021; Moss, 2018). In contrast, epistemic uncertainty stems from limitations in knowledge representation, incomplete information, or multiple possible interpretations (Angelelli, 2021). It originates from several sources: the inherent complexity of phenomena and processes, gaps or inaccuracies in data collection, and high environmental variability — such as rapid shifts in markets or regional dynamics — which together hinder organisations' ability to accurately assess and absorb knowledge.

At the individual level, routine performance can foster routine proneness highly automatic, low-reflective behaviours that rely heavily on tacit knowledge and closed pragmatic loops (Ersche et al., 2017). These deeply embedded routines are often invisible to traditional HRM practices and offer limited potential for developing dynamic capabilities (Wiersma, 2026). When AI is introduced into such routines, the risk of epistemic misalignment increases because human agency may be displaced by automated outputs without sufficient reflective oversight.

To address this challenge, reinforcement learning (RL) and transfer learning provide promising mechanisms for adaptive knowledge refinement. Reinforcement learning enables agents to learn optimal behaviours through trial-and-error interactions with their environment, gradually reducing uncertainty by rewarding actions that better align knowledge representations with real-world outcomes (Sutton & Barto, 2018). Transfer learning complements this process by allowing pre-trained models from one context to accelerate learning in another, although it introduces its own epistemic challenges when source knowledge is unreliable (Gimelfarb, 2023).

When applied to continuous AI-driven knowledge representations and combined with human feedback loops, these approaches support the creation of situational certainty modelling adaptive, context-sensitive frameworks that dynamically predict and validate knowledge under varying conditions. This extension builds on Wiersma's (2026) human-centric perspective by incorporating AI-augmented co-creation while preserving human reflective capacity and agency.

3.2 Epistemic Uncertainty in Knowledge Transfer

Epistemic uncertainty represents a central challenge in knowledge transfer, especially in multi-agent organisational settings. In contrast to aleatoric uncertainty — which stems from inherent randomness or variability in data — epistemic uncertainty arises from gaps in knowledge representation, incomplete information, or conflicting interpretations (Kudukkil Manchingal et al., 2025).

Wiersma (2026) highlights how pragmatic routines (closed-loop, efficiency-focused practices) frequently clash with theoretical insights, generating semantic noise and trust barriers that hinder effective knowledge integration. For example, differing interpretations of "efficiency" between frontline actors and strategic levels can delay the adoption of new practices in SMEs, as organisations prioritise quick fixes over deeper validation.

Recent literature offers promising avenues for addressing this uncertainty through more structured and AI-supported approaches. Angelelli (2021) proposes a dynamical model of uncertainty in knowledge representation, in which agents actively mediate transfer by comparing and synthesising multiple epistemic states. This formal structure complements Wiersma's emphasis on reflective learning in innovation spaces by providing clearer mechanisms for validation.

Complementing these perspectives, Kudukkil Manchingal et al. (2025) advocate "epistemic artificial intelligence," in which AI systems learn from ignorance by quantifying what is currently unknowable and adapting accordingly. In reinforcement learning (RL) contexts, this approach manifests as epistemic-aware agents that explicitly measure model confidence — for instance through Bayesian methods (Gimelfarb, 2023) — thereby reducing the risk of over-reliance on incomplete or uncertain knowledge.

Collectively, these contributions suggest that epistemic uncertainty in organisational routines can be reframed as a "flux of new possibilities" (Gallagher, 2023). By developing continuous, evolving knowledge representations — such as AI models updated through real-time data streams and human feedback — organisations can move from knowledge inertia toward greater adaptability. This perspective directly extends Wiersma's (2026) call for iterative experimentation and reflective capacity in innovation spaces.

3.3 Reinforcement Learning for Uncertainty Reduction via Transfer

Reinforcement learning (RL) offers a powerful mechanism for reducing epistemic uncertainty by reinforcing behaviours and knowledge representations that better align with real-world outcomes. When combined with transfer learning, RL becomes particularly effective: transfer learning enables the reuse of knowledge acquired from source tasks to accelerate learning and reduce uncertainty in target tasks (Gimelfarb, 2023). In decision-making under epistemic risk, transfer models allow organisations to leverage prior experience while adapting to new contexts.

This approach extends naturally to Wiersma's (2026) framework of innovation spaces and routine dynamics. RL agents operating in multi-agent systems can learn directly from pragmatic feedback generated by SME routines, feeding insights back into higher-level theoretical models. The resulting reinforcement loops reward actions that progressively reduce epistemic uncertainty, creating iterative cycles of knowledge refinement and alignment.

Recent literature supports the integration of RL and transfer learning for managing epistemic uncertainty in dynamic environments. For example, the "curiosity in hindsight" approach (Clark et al., 2025) introduces intrinsic rewards that encourage exploration of unpredictable outcomes in stochastic settings — directly relevant to handling epistemic uncertainty in evolving organisational routines. Similarly, instance-based generalization techniques (Bertran et al., 2020) help bound value gaps between training and test environments, enabling more robust transfer across situational variations.

Complementing these methods, neuro-symbolic AI approaches (Acharya et al., 2025) enhance robustness through ensemble methods and Bayesian uncertainty quantification, narrowing epistemic gaps during knowledge transfer. These mechanisms align closely with Wiersma's emphasis on reflective capacity: RL reward functions can function as "logical principles" that reinforce knowledge renewal, gradually transforming epistemic constraints into actionable possibilities.

3.4 Continuous Knowledge Representations and Epistemic Functional Testing

Continuous knowledge representations — evolving AI models that adapt through ongoing data integration and feedback — form the foundation for reducing epistemic uncertainty in organisational routines. While Wiersma (2026) emphasises iterative refinement of knowledge within innovation spaces, extending this logic to AI environments suggests that knowledge should not be treated as static but as dynamically updated representations. Angelelli (2021) supports this view by proposing dynamical models of uncertainty in knowledge representation, in which agents combine multiple epistemic states. Such approaches are particularly suited to neural networks and other continuous models that evolve through transfer learning.

Gallagher (2023) further argues that knowledge representations must handle constant flux by incorporating metaknowledge, moving beyond closed-loop systems toward more open, adaptive structures. For SMEs, this translates into AI models functioning as "certainty engines" — systems that continuously generate and update situational knowledge, which must then be validated against actual routine performance to maintain alignment between pragmatic action and theoretical possibilities.

3.5 Testing Through Functionality in Routines

Epistemic functional testing provides the mechanism for evaluating these continuous representations within organisational routines. Drawing on Wiersma (2026), who illustrates how theoretical models are iteratively tested against pragmatic routine performance, the proposed test assesses whether AI-generated knowledge effectively informs action and supports adaptation. In AI-augmented contexts, this occurs through reinforcement learning feedback loops, where models are rewarded for compatibility with real-world routines.

Recent contributions reinforce this approach. Amayreh (2025) proposes an interactive AI theory for knowledge production, in which epistemic validation serves as a critical human-in-the-loop layer for testing AI representations in practical settings. Similarly, Agustian et al. (2025) highlight the role of epistemic practices and reflective capacity in addressing wicked problems, showing how models can be refined through situated

testing to reduce uncertainty. Together, these elements create a virtuous cycle: AI models transfer knowledge into routines, receive reinforcement based on performance outcomes, and continuously adapt their representations — thereby extending Wiersma's human-centric co-creation into AI-augmented HRM and KMM processes.

3.6 Situational Certainty Modelling

Situational certainty modelling emerges as the outcome of effective epistemic functional testing. It refers to adaptive, context-specific frameworks that provide probabilistic confidence in knowledge under varying conditions. This concept aligns with Wiersma's (2026) emphasis on contingency and flexibility within innovation spaces, where rigid routines are challenged and reformed.

3.7 The Model of Modal Consciousness and Organisational Routines

Building on Wiersma (2026), who conceptualises modal consciousness as the reflective and intentional movement of human agents between different epistemic modes — epistemic (what is knowable), doxastic (what is believed), deontic (what is obligatory), and alethic (what is possible or necessary) — this paper extends the model to AI-augmented organisational contexts.

Wiersma's work shows that modal consciousness enables individuals and organisations to intervene effectively in routines by bridging pragmatic action with higher-level theoretical understanding. This paper argues that while AI is a powerful driver for automating routine tasks, it currently lacks the contextual adaptability and nuanced judgment required in dynamic HRM environments. In such settings, modal consciousness serves as an essential advanced epistemic layer for sensemaking.

Sensemaking, as defined by Weick (1988), involves ongoing processes of interpreting ambiguous or chaotic situations to create plausible meaning and guide action. When routines lose stability, the absence of deliberate sensemaking can turn them into traps that limit adaptability (Weick, 1988; Weick et al., 2005). Modal consciousness addresses this limitation by enabling deliberate, reflective shifts between epistemic modes. These shifts move beyond purely intuitive or pragmatic sensemaking and are actively orchestrated and supported through coherent HRM and KMM frameworks.

A key function of modal consciousness is to facilitate transfer arenas — spaces in which pragmatic routines are systematically validated against theoretical models, leading to hybrid adaptations rather than wholesale replacement (Wiersma, 2026). In the context of AI integration, such arenas become particularly important. Current AI practices for fully autonomous operation in highly situational and value-laden HRM contexts remain limited and underdeveloped (Sizikova, 2019; Rajaram & Tinguely, 2024; Vandaele, 2026). Modal consciousness, supported by epistemic functional testing, offers a structured human-in-the-loop mechanism to bridge this gap and preserve human agency.

4. Methodology

First, a systematic literature review of routine dynamics and epistemic uncertainty in hybrid human-AI systems is synthesized with modal logic and Kripke-frame semantics to formalize modal consciousness as the meta-cognitive capacity to navigate between epistemic modes. Second, a micro-level decomposition of routines, identifying smallest embedded (atomic) routines as the foundational, closed pragmatic units that underpin higher-order dynamic capabilities. This decomposition is achieved through iterative epistemic mapping and reflective-loop analysis (Epistemic Framing Theory – EFT), whereby high-level theoretical/exploratory loops are systematically tested against and integrated with low-level pragmatic/routine-based loops. Third, the framework is validated through conceptual case illustrations and action-research episodes in SME innovation spaces, in which human agents function as critical moderators who perform deliberate modal-shift acts to resolve ostensive-performative tensions and achieve epistemic alignment. HRM practices are positioned as constitutive mechanisms for selecting, training, and rewarding these moderators, thereby operationalizing the dynamic exchange between AI-generated knowledge and embedded routines. The overall methodology is abductive and iterative, moving from theoretical abstraction to situated application, and explicitly treats epistemic uncertainty not as a barrier to be eliminated but as a generative condition to be managed through conscious, principled reflection. This approach yields both a theoretical model and actionable HRM guidelines for knowledge integration in highly dynamic contexts.

5. Findings

This paper demonstrates that Wiersma's (2026) empirical work on innovation spaces can be meaningfully extended by integrating reinforcement learning and transfer learning mechanisms. By developing continuous AI-generated knowledge representations and subjecting them to epistemic functional testing within organizational routines, epistemic uncertainty can be systematically reduced, ultimately giving rise to situational certainty modelling that are better adapted to dynamic and context-specific realities. The findings underscore the importance of seven interrelated process elements that together enable conscious and effective AI integration in knowledge transfer practices. These elements are: (1) human agency, (2) semantic noise, (3) specific operational environment, (4) reflective capacity, (5) transfer loops, (6) critical moderator, and (7) the design of learning environments. When thoughtfully combined, these components form a robust framework for bridging pragmatic routines and theoretical models in multi-agent systems.

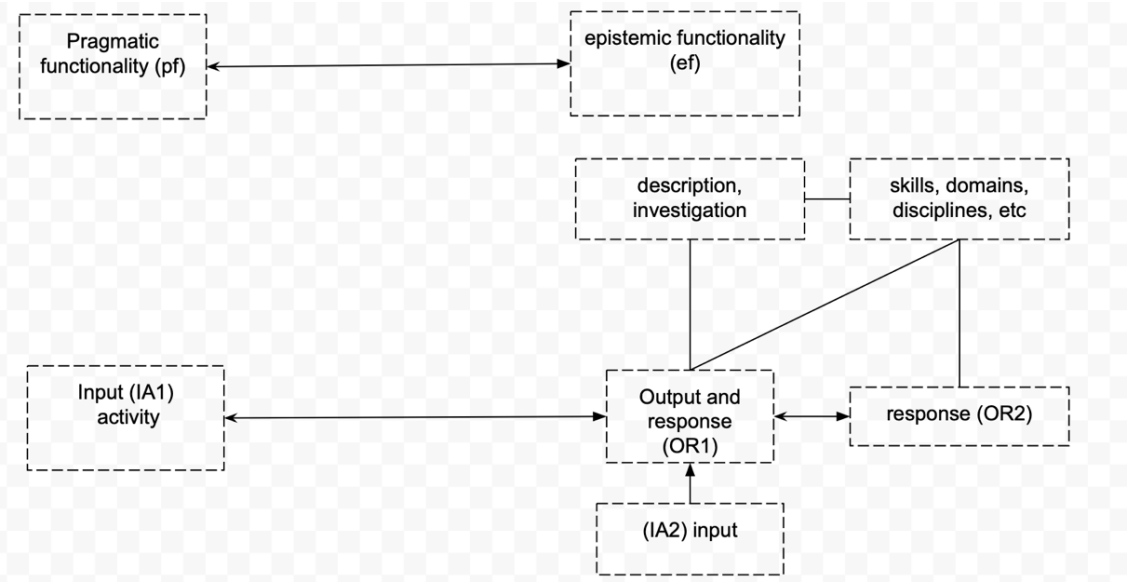


Figure 1: Pragmatic perspective as a foundation for epistemic functionality

Figure 1 illustrates how pragmatic knowledge (routine-level performance) serves as the foundational layer for higher-order epistemic functionality. The diagram shows how the introduction of new AI-generated information perturbs existing activities and outputs, generating compound functionalities and epistemic uncertainty. Epistemic functionality is conceptualised here as an enabling construct that describes the practical capacity of knowledge to inform action and decision-making under conditions of varying certainty.

In the model, input IA2 represents new information entering the system (for example, AI-generated outputs from emerging technologies). This new input influences ongoing activities and alters the original output-response cycle (OR1), leading to modified or additional outcomes (OR2, OR3, etc.). As a result, the original input IA1 becomes compound — it now carries relational, temporal, and situational dependencies with both the new information (IA2) and the resulting outputs. This compounding effect often produces a temporary loss of intentionality and requires organisations to develop denser epistemic representations (e.g., richer concepts, propositions, or judgments).

The framework highlights that effective acquisition (judgments) and assimilation (new beliefs) of knowledge in multi-agent environments demand modal consciousness — the deliberate awareness and switching between different epistemic modes (epistemic, doxastic, deontic, and alethic). By enabling dynamic integration and reflective judgment, modal consciousness helps reduce uncertainty arising from these compound functionalities. Ultimately, the diagram emphasises the need for knowledge engineering practices that explicitly address epistemic doubts and uncertainties through structured human-in-the-loop validation. The model shows how new AI-generated information (IA2) perturbs existing routine activities and outputs (OR1 → OR2/OR3), creating compound knowledge functionalities. Solid arrows represent information flow; dashed arrows indicate validation and reflective feedback loops. Epistemic functionality emerges when pragmatic outputs are tested against multiple epistemic modes via human moderation."

6. Quadrant-based Typology of SME Absorptive Capacity in UAS Collaborations Based on Modal Consciousness

Absorptive Capacity Based on Modal Consciousness and Epistemic Alignment

Modal consciousness refers to the human capacity for reflective awareness and deliberate navigation across different epistemic modes (e.g., epistemic, doxastic, deontic, and alethic). It enables agents to consciously shift between alternative ways of knowing — such as theoretical versus pragmatic perspectives or human-intuitive versus machine-generated knowledge — and to adapt effectively amid uncertainty (Wiersma, 2026). Agents with high modal consciousness can recognise "epistemic twins" (similar but distinct knowledge modes), modulate their epistemic stance, and facilitate the co-creation and absorption of new knowledge.

Epistemic alignment, in contrast, is the degree of coherence and compatibility achieved between different epistemic profiles, perspectives, or sources for example, the alignment between human beliefs/intuitions and AI-generated outputs (Clark et al., 2025).

Table 1 presents a quadrant-based typology that crosses levels of modal consciousness (high/low) with levels of epistemic alignment (high/low). The typology illustrates how these two dimensions influence SMEs' absorptive capacity their ability to recognise, assimilate, and apply new knowledge, particularly when collaborating with universities of applied sciences (UAS) or integrating AI technologies.

Table 1: Quadrant-Based Typology of SME Absorptive Capacity

Quadrant	Modal Consciousness	Epistemic Alignment	Key Organisational Characteristics	Typical Profile / Illustrative Cases
Optimal	High	High	Strong internal reflective practices; low organisational inertia; proactive boundary spanners (e.g., designated champions or receptive managers); dedicated low-risk experimentation environments	Younger or dynamically positioned firms, such as technology-oriented logistics or care-innovation SMEs with leadership open to questioning established heuristics
Reflective but Isolated	High	Low	Reflective capacity exists (e.g., introspective leadership), but structural barriers limit external knowledge bridging (closed networks, lack of boundary roles, or low interaction frequency)	Family-owned businesses with reflective leadership but limited external connectivity
Connected but Passive	Low	High	Good external connectivity and input flow, but weak internal reflective depth; routines remain largely tacit and unquestioned, with minimal deliberate sensemaking or routine revision	Larger SMEs that regularly receive external inputs but lack effective follow-up mechanisms for internal integration
Rigid	Low	Low	High organisational rigidity (e.g., entrenched "this is how we have always done it" culture); minimal reflective agency; few or no boundary-spanning functions; absence of protected experimentation space	Very small, traditional craft-oriented SMEs with strong tacit knowledge cultures and generational inertia

This typology highlights that high absorptive capacity in AI-integrated or UAS-collaborative settings requires both strong modal consciousness (internal reflective capability) and high epistemic alignment (effective integration of external inputs, including AI outputs). The framework can guide HRM practices in designing interventions that strengthen the weaker dimension in each quadrant.

7. Conclusion

This paper poses the following research question: How can AI-generated information be effectively and efficiently integrated into existing organizational knowledge and its routines using humans in the loop realizing coherent HRM and KMM processes?"

As an answer to this question, we propose four distinct HRM approaches.These approaches reflect increasing levels of HRM maturity and reflective capacity:

- **Permissiveness Strategy** (Grieser et al., 2023): Emphasises controlled experimentation within operational routines to ground new information and reduce uncertainty. This approach requires moderate to high HRM maturity.
- **Flexible Arrangements** (Wang et al., 2023): Focuses on designing transferable and adaptable routines that foster innovation-oriented behaviour. It demands significantly greater HRM involvement than traditional knowledge management practices.
- **Inverted Measurement Strategy** (Ersche et al., 2017): Shifts focus from performance metrics to personal development and reflective capacity regarding habitual routines at the individual level.
- **Dynamic Capabilities Arrangement** (Wiersma, 2026): Aims to align organisational routines with evolving environmental dynamics. This approach requires the highest level of HRM maturity to effectively manage complex and deeply embedded routines.

Together, these four approaches illustrate a progression from basic experimentation toward more mature, reflective, and adaptive HRM practices. By embedding modal consciousness and epistemic functional testing into HRM–KMM protocols, organisations — particularly SMEs — can harness the benefits of AI while safeguarding human agency and building sustainable knowledge ecosystems in an era of rapid technological change. These approaches need further empirical validation which further research.

Ethics Declaration: Ethical clearance was not required

AI Declaration: Ai was used enhancing the English quality of the paper.

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Knowledge Management and Public Value in Municipal Mergers: The Nuova Pescara Case

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Abstract: Municipal mergers are commonly examined through their effects on administrative efficiency, expenditure, and service delivery. Yet, their success also depends on the capacity to integrate the knowledge, competences, routines, and institutional memories embedded within previously autonomous organizations. This paper reconceptualizes municipal amalgamation as a knowledge-intensive organizational transformation and investigates how Knowledge Management (KM) can support organizational integration and Public Value co-creation. The study adopts a conceptual research design supported by an exploratory case study of Nuova Pescara, one of the largest municipal merger processes currently underway in Italy. Drawing on documentary and institutional evidence, the analysis interprets the merger's as-is, to-be, and gap analysis phases through the lenses of Knowledge Management, Organizational Learning, and Public Value. The findings suggest that administrative integration should be understood as the outcome, rather than the starting point, of a progressive knowledge integration process. Building on these insights, the paper develops a Knowledge Integration Governance Framework in which knowledge transfer, combination, and creation, supported by organizational learning and Strategic Human Resource Governance, transform distributed knowledge into shared organizational capabilities. The study contributes to Knowledge Management research by positioning knowledge integration as a strategic governance capability enabling institutional transformation and creating the organizational conditions for Public Value co-creation.

Keywords: Knowledge management, Public value co-creation, Municipal mergers, Organizational learning

1. Introduction

Across Europe, municipal mergers have become a common response to the growing complexity of local governance. Financial constraints, demographic change, digital transformation and rising citizen expectations have encouraged governments to redesign local administrative structures in pursuit of efficiency, improved service delivery and stronger institutional capacity (Dollery & Robotti, 2008; Blom-Hansen et al., 2016; Tavares, 2018). Accordingly, amalgamations are usually assessed through their effects on expenditure, governance arrangements and administrative performance.

Yet the results of municipal mergers remain uneven. International evidence shows that many amalgamation processes struggle not because legal integration is impossible, but because organizations fail to integrate people, routines, professional cultures and institutional knowledge (Kuipers et al., 2014; Tavares, 2018). Structural consolidation alone rarely produces organizational integration. Instead, mergers may generate uncertainty, resistance to change and parallel organizational cultures that persist after formal unification. This observation reveals a municipal merger paradox. Top-down standardization seeks administrative homogeneity through common structures and procedures, but it may weaken the informal knowledge networks through which public organizations preserve memory, transfer expertise and coordinate daily practices. Durable institutional transformation therefore requires interaction, learning and collaboration among organizational actors rather than compliance with new formal arrangements alone (Sørensen & Torfing, 2011; Kuipers et al., 2014).

Municipal mergers should therefore be interpreted not simply as institutional reforms but as knowledge integration processes. Each municipality accumulates explicit and tacit knowledge embedded in procedures, professional competences, routines, digital systems, institutional relationships and local cultures (Nonaka, 1994; Nonaka & Takeuchi, 1995; Davenport & Prusak, 1998). When municipalities merge, these knowledge assets do not automatically converge; they must be identified, preserved, transferred, combined and recreated.

Despite these insights, municipal merger research has mostly focused on fiscal outcomes, economies of scale, governance structures and political representation (Blom-Hansen et al., 2016; Tavares, 2018). Less attention has been paid to how organizational knowledge is preserved and transformed throughout merger processes. This is a relevant gap because knowledge integration may be one of the key conditions for organizational continuity, administrative effectiveness and long-term Public Value creation. The creation of Nuova Pescara

offers a significant context for investigating this issue. The merger of Pescara, Montesilvano and Spoltore is one of the largest local government integrations currently underway in Italy. Beyond its institutional dimension, the process requires the convergence of three administrative systems with distinct cultures, professional communities, governance arrangements, routines, digital infrastructures and organizational memories.

The technical documentation supporting the merger reflects this complexity. The transition has been structured through organizational diagnosis (as-is analysis), future institutional design (to-be configuration) and gap analysis. Although developed for managerial purposes, this logic closely mirrors Knowledge Management and Organizational Learning processes: existing knowledge is identified, interpreted, integrated and transformed into new organizational capabilities (Argyris & Schön, 1978; Nonaka & Takeuchi, 1995). Against this background, the paper argues that municipal mergers are knowledge-intensive organizational transformations in which knowledge integration is a prerequisite for administrative integration rather than its consequence. Accordingly, the study addresses the following research question:

How can Knowledge Management support organizational integration and Public Value co-creation during large-scale municipal merger processes?

To answer this question, the paper develops and illustrates a conceptual framework through the Nuova Pescara case.

The study contributes in three ways. First, it extends Knowledge Management research by positioning municipal mergers as knowledge-intensive transformations. Second, it identifies knowledge integration as the mechanism connecting organizational learning, administrative harmonization and Public Value co-creation. Third, it offers a managerial framework for mapping, preserving and integrating organizational knowledge during large-scale local government reforms.

2. Theoretical Foundations

2.1 Knowledge Management and Organizational Learning in Public Administration

Knowledge has become a strategic resource for contemporary public organizations. While traditional administration relied mainly on hierarchy, procedures and compliance, current governance environments require institutions to generate, integrate and mobilize knowledge across organizational boundaries to address complex public problems (Moore, 1995; Bryson et al., 2014; Cepiku et al., 2025). Organizational performance therefore depends not simply on information availability but on the capacity to transform dispersed knowledge into coordinated action, adaptive decision-making and institutional learning (Alavi & Leidner, 2001; Laihonen et al., 2024). Knowledge Management concerns the creation, codification, transfer, integration and application of explicit and tacit knowledge (Nonaka, 1994; Nonaka & Takeuchi, 1995; Davenport & Prusak, 1998). In public administration, this knowledge is embedded in information systems, routines, institutional memory, professional judgement and everyday practice (Wiig, 2002; Massaro et al., 2015). Organizational Learning explains how organizations transform such knowledge into new routines, capabilities and shared practices (Argyris & Schön, 1978; Wenger, 1998). Municipal mergers represent a demanding organizational learning environment because previously independent administrations must integrate accumulated knowledge, professional competences, routines, digital infrastructures and institutional cultures. In this setting, the ability to preserve and recombine knowledge becomes a prerequisite for institutional integration.

2.2 Knowledge Integration as the Core Mechanism of Organizational Transformation

Periods of organizational transformation introduce a specific challenge: integrating previously independent knowledge bases. Knowledge integration refers to the capability to combine heterogeneous experiences, routines, competences and organizational memories into a coherent system supporting collective action. It is not the simple transfer of information; it requires the reinterpretation of existing knowledge, reconciliation of professional practices and construction of shared understandings (Nonaka & Takeuchi, 1995; Wenger, 1998; Alavi & Leidner, 2001).

Organizational studies show that integration success depends less on structural consolidation than on retaining critical knowledge, preserving human capital and facilitating learning between previously independent organizations (Bresman et al., 1999; Ranft & Lord, 2002). Post-merger performance is shaped by deliberate learning processes through which organizations codify experience, adapt integration strategies and develop new capabilities. These mechanisms are highly relevant for public organizations. Municipal administrations must reconcile different administrative cultures, regulatory interpretations, decision-making

routines, professional identities and service delivery practices. Contemporary public-sector KM therefore views knowledge not as a centrally stored resource but as something continuously formed, negotiated and reconstructed during organizational change (Kassa & Ning, 2023; Laihonen et al., 2024).

Knowledge integration should thus be treated as the enabling condition of organizational transformation. Administrative harmonization, process standardization, digital interoperability and governance redesign become sustainable only when supported by mechanisms that preserve organizational memory while generating shared knowledge.

2.3 Municipal Mergers as Knowledge-intensive Organizational Transformations

Municipal amalgamation literature usually interprets mergers as reforms aimed at improving efficiency, service delivery, financial sustainability and governance arrangements (Dollery & Robotti, 2008; Blom-Hansen et al., 2016; Tavares, 2018). This perspective is valuable but often assumes that organizational integration follows automatically from institutional integration.

Creating a new municipality requires the convergence of independently developed routines, competences, digital infrastructures, cultures and institutional memories. Amalgamation is therefore the integration of multiple organizational knowledge systems (Nonaka & Takeuchi, 1995; Davenport & Prusak, 1998; Massaro et al., 2015). Large-scale mergers require procedures, systems, roles and cultures to be aligned through collective learning rather than technical implementation alone (Kuipers et al., 2014; Sørensen & Torfing, 2011). From a KM perspective, as-is analysis, to-be design and gap analysis map, evaluate and recombine existing knowledge into a new institutional configuration (Argyris & Schön, 1978; Nonaka, 1994; Alavi & Leidner, 2001).

2.4 Knowledge Integration as an Enabler of Public Value Co-creation

Public Value should be regarded as the outcome of dynamic organizational processes rather than the automatic consequence of institutional reform (Moore, 1995; Meynhardt, 2009, 2015; Bryson et al., 2014). During municipal mergers, knowledge integration is one of these enabling processes because it allows organizations to reconcile administrative practices, professional competences, technological infrastructures and institutional memories developed independently over time. As knowledge is transferred, combined and recreated, public organizations develop new routines, strengthen organizational identity, improve coordination and build the capabilities required to govern the new municipality. These intermediate outcomes create the conditions for Public Value through better governance, stronger legitimacy, improved service delivery and stakeholder collaboration (Bryson et al., 2014; Pee & Kankanhalli, 2016). This interpretation bridges municipal merger research and Knowledge Management. While amalgamation studies focus on institutional design and economies of scale, KM explains how knowledge is created, transferred, integrated and applied (Nonaka, 1994; Davenport & Prusak, 1998; Alavi & Leidner, 2001). Bringing these perspectives together suggests that administrative integration is the outcome of a prior knowledge integration process.

Building on these theoretical foundations, the proposed framework conceptualizes municipal amalgamation as a knowledge-intensive organizational transformation. It begins with organizational antecedents - institutional context, distributed knowledge assets, human capital and stakeholder expectations - which activate knowledge transfer, knowledge combination, organizational learning and knowledge creation. These processes are supported by leadership, governance mechanisms, communication, organizational culture and digital infrastructures, ultimately generating stronger organizational capabilities and Public Value co-creation. Figure 1 summarizes this conceptual framework by positioning Knowledge Integration at the centre of organizational transformation, connecting institutional antecedents with intermediate organizational outcomes and the co-creation of Public Value through a continuous cycle of learning and adaptation.

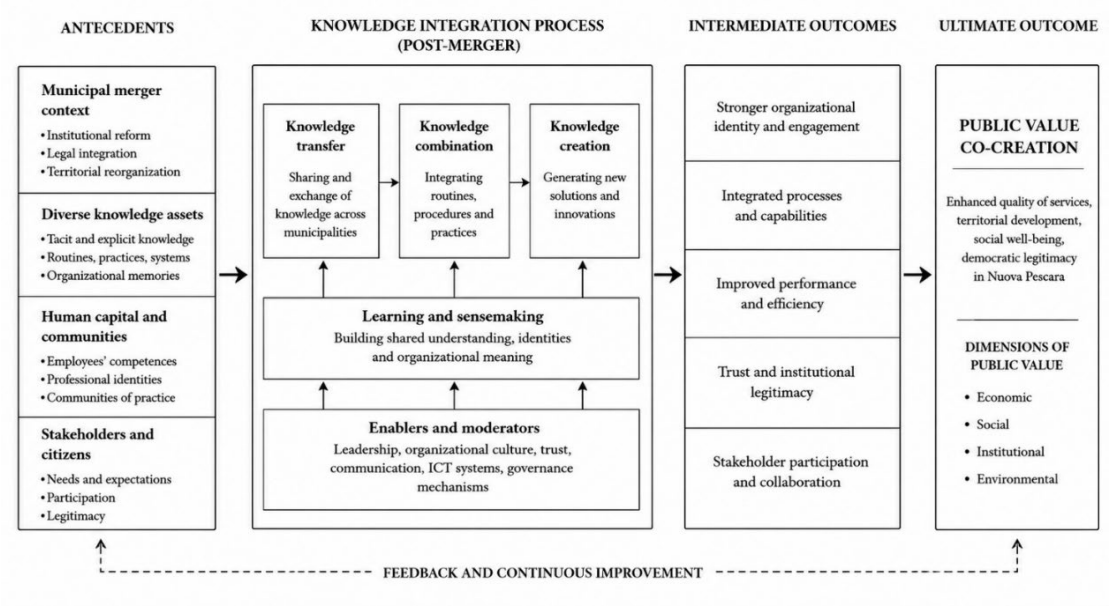


Figure 1: Conceptual framework of Knowledge Integration for Public Value co-creation in municipal merger processes (authors' elaboration)

3. Methodology

3.1 Research Design

This study adopts a conceptual research design supported by an exploratory institutional case study. Rather than testing causal relationships or evaluating merger effectiveness, the research develops a theoretically grounded interpretation of municipal mergers as knowledge-intensive organizational transformations. The objective is explanatory, focusing on the mechanisms through which distributed knowledge may be identified, integrated and mobilized during complex institutional transitions.

Conceptual research is appropriate when emerging organizational phenomena require interpretative frameworks for future empirical investigation (Alavi & Leidner, 2001). The study integrates Knowledge Management, Organizational Learning, Public Value and municipal merger literature (Moore, 1995; Bryson et al., 2014; Massaro et al., 2015; Kassa & Ning, 2023; Laihonen et al., 2024; Tavares, 2018). Nuova Pescara provides an exploratory setting in which the organizational dynamics of knowledge integration can be interpreted.

3.2 Case Selection

The creation of Nuova Pescara is a particularly suitable case because it involves the convergence of three historically autonomous municipalities characterized by different governance arrangements, procedures, professional communities, technological infrastructures, cultures and institutional memories. The merger has also been supported by a structured planning process articulated into as-is analysis, to-be design and gap analysis. This planning logic closely reflects KM and Organizational Learning processes. Identifying existing organizational assets corresponds to knowledge mapping; comparing current and future configurations resembles organizational sensemaking; and redesigning the future municipality represents knowledge recombination and capability development (Nonaka & Takeuchi, 1995; Argyris & Schön, 1978). The case was therefore selected for theoretical relevance rather than statistical representativeness.

3.3 Data Sources

The study relies primarily on documentary and institutional evidence produced during the Nuova Pescara merger, including the Official Merger Report, analyses prepared by the Municipal Merger Office, planning documents, governance reports, organizational mappings and technical materials. These sources are analysed as organizational artefacts describing structures, competences, human resource management, digital interoperability, governance arrangements and planning during the transition from the as-is to the to-be configuration.

3.4 Analytical Approach

The study adopts an abductive and interpretative analytical strategy based on continuous interaction between theory and evidence. The documentary analysis followed a qualitative interpretative approach. Institutional and technical documents produced during the Nuova Pescara merger process were systematically examined to identify recurring organizational themes, governance mechanisms, knowledge assets and integration challenges. These empirical insights were then iteratively compared with the Knowledge Management, Organizational Learning and Public Value literature through an abductive process. Accordingly, the documentary evidence did not serve to test hypotheses, but to inform, refine and theoretically ground the proposed Knowledge Integration Governance Framework.

The analysis follows the logic of the merger planning process: first, the existing organizational configuration is examined to identify distributed knowledge assets; second, the planned configuration is analysed to understand how these assets should converge; third, the organizational gaps are interpreted as knowledge integration challenges requiring learning, capability development and governance coordination. Accordingly, the analysis is organized around four dimensions: organizational antecedents and distributed knowledge assets; knowledge integration processes; organizational learning and capability development; and Public Value enabling conditions. These dimensions form the analytical architecture through which the Nuova Pescara transition is interpreted and translated into the conceptual framework. Figure 2 summarizes the research design adopted in this study, showing how the institutional context, documentary evidence and as-is/to-be/gap analysis are interpreted through Knowledge Management, Organizational Learning and Public Value perspectives.

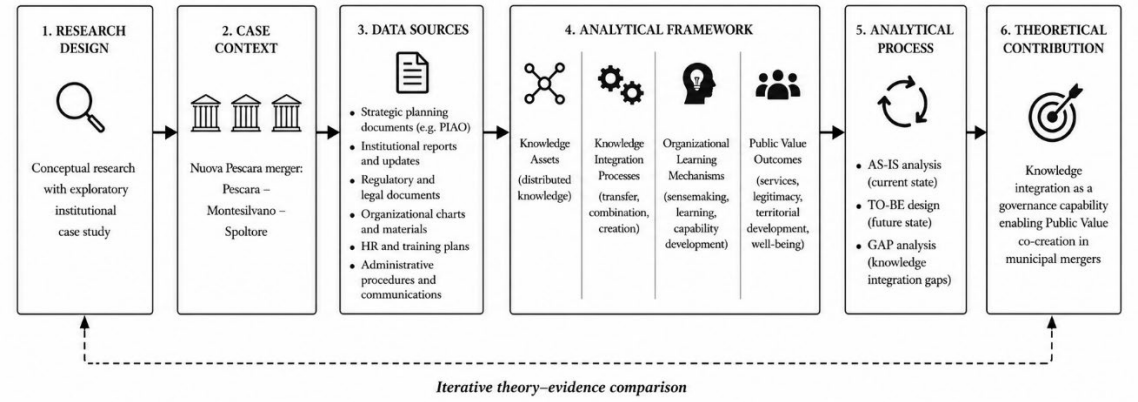


Figure 2: Research design and analytical process (authors' elaboration)

4. Knowledge Integration Challenges in the Nuova Pescara Merger

The Nuova Pescara transition can be interpreted as the progressive integration of three organizational knowledge systems. Knowledge distributed across procedures, information systems, professional expertise, routines and institutional memory must be recombined into a coherent administrative system (Nonaka, 1994; Davenport & Prusak, 1998; Alavi & Leidner, 2001).

Documentary evidence presents the transition as a sequence of knowledge identification, integration and capability development (Nonaka & Takeuchi, 1995; Argyris & Schön, 1978; Laihonen et al., 2024). The as-is phase maps organizational units, procedures, competences, technologies and responsibilities; the to-be phase recombines capabilities and redesigns governance arrangements; and gap analysis identifies where knowledge integration is required before administrative integration can be completed.

4.1 Structural Asymmetries and Organizational Knowledge Gaps

The documentary evidence shows substantial asymmetries in organizational size, staffing allocation, functional specialization, technological maturity and administrative capacity. These differences affect the distribution of organizational knowledge within the future municipality. Pescara constitutes the dominant administrative structure, while Montesilvano and Spoltore operate through smaller configurations. This difference influences not only personnel numbers but also the concentration of specialized competences, routines and institutional experience.

The organizational diagnosis also identifies differences in strategic functions, particularly digital transformation, ICT governance, technical services and local policing. These knowledge-intensive areas depend on specialized competences and organizational continuity. From a KM perspective, such disparities reduce the absorptive capacity of the future organization, making knowledge transfer and capability development essential components of the merger (Alavi & Leidner, 2001; Pee & Kankanhalli, 2016). Financial asymmetries further reinforce these differences because historical budget constraints have generated heterogeneous staffing policies, recruitment capacities and organizational investments. Therefore, organizational knowledge embodied in charts, regulations and procedures cannot simply be merged through administrative harmonization. It requires deliberate knowledge combination capable of balancing capacities while preserving essential public services.

Digital transformation is among the most critical integration areas. The future municipality will depend on interoperable information systems, standardized digital procedures and employees' capacity to operate within common technological environments. Digital upskilling should therefore be interpreted not only as a technological investment but as a strategic Knowledge Management intervention aimed at preserving operational continuity and reducing knowledge fragmentation (Kassa & Ning, 2023; Laihonen et al., 2024). Table 1 provides a quantitative overview of the organizational baseline prior to the merger, highlighting structural asymmetries in staffing levels and administrative capacity.

Table 1: Organizational baseline of the three municipalities prior to the Nuova Pescara merger (authors' elaboration based on the Official Organizational Design Report of the Nuova Pescara Merger Office)

Municipality	Employees (FTE + PT)	Administrative staff (%)	Employees per inhabitant
Pescara	580	45%	1 : 205
Montesilvano	195	38%	1 : 276
Spoltore	72	32%	1 : 263
Future Municipality of Nuova Pescara	**847**	**41%**	**1 : 224**

Taken together, these findings reinforce the central assumption of the paper: the principal barriers to municipal integration are organizational rather than merely structural. Human resources, digital systems, competences and institutional routines are interconnected knowledge assets that must be preserved, recombined and progressively aligned before administrative integration can be fully achieved.

5. A Knowledge Integration Governance Framework for Municipal Mergers

The analysis suggests that municipal amalgamations should be understood as knowledge-intensive governance processes. Their success depends on the capacity to identify, preserve, combine and recreate distributed organizational knowledge. Rather than merely describing the Nuova Pescara transition, the case illustrates how documentary evidence can be interpreted through a Knowledge Management lens to explain why organizational integration emerges from knowledge integration. In this respect, the empirical material provides the practical grounding upon which the proposed governance framework has been developed.

Building on the theoretical discussion and the Nuova Pescara case, this paper proposes a Knowledge Integration Governance Framework explaining how public organizations can govern merger processes while supporting organizational transformation and Public Value co-creation. Unlike studies that examine municipal mergers mainly from institutional, financial or organizational perspectives (Dollery & Robotti, 2008; Blom-Hansen et al., 2016; Tavares, 2018), the proposed framework places Knowledge Integration at the centre of the governance process. Administrative harmonization is interpreted not as the starting point of the merger but as the outcome of organizational learning, through which heterogeneous knowledge assets are transformed into shared capabilities (Nonaka, 1994; Alavi & Leidner, 2001; Laihonen et al., 2024). The framework comprises five interconnected stages linking organizational diagnosis, knowledge integration, Strategic Human Resource Governance, capability development and Public Value co-creation in a continuous learning cycle.

The first stage, organizational diagnosis, corresponds to the as-is analysis. It maps organizational structures, procedures, competences, technologies, governance arrangements and stakeholder relationships, making explicit the distributed knowledge assets upon which future integration depends (Wiig, 2002; Massaro et al., 2015). The second stage concerns knowledge integration. Once organizational knowledge has been identified,

knowledge transfer allows existing practices to circulate across organizational boundaries; knowledge combination reorganizes procedures, competences and routines into new institutional configurations; and knowledge creation generates routines, governance solutions and capabilities that did not previously exist (Nonaka, 1994; Nonaka & Takeuchi, 1995; Alavi & Leidner, 2001). The third stage, Strategic Human Resource Governance, represents the principal managerial contribution of the framework. It aligns organizational development, competence management, leadership, employee engagement, culture and performance management. In this perspective, human resources are not passive administrative resources but the primary mechanism through which organizational knowledge is preserved, mobilized and renewed (Ranft & Lord, 2002; Bresman et al., 1999; Kuipers et al., 2014).

Within the Italian public administration context, this governance infrastructure finds operational expression in the Piano Integrato di Attività e Organizzazione (PIAO). Rather than a compliance document, the PIAO can be interpreted as the managerial architecture through which knowledge integration becomes operational, connecting strategic planning, organizational development, human resource management, training, performance evaluation and organizational well-being (Cepiku et al., 2025). The fourth stage consists of organizational capabilities such as shared identity, employee engagement, integrated processes, coordination, digital maturity, institutional trust and stakeholder collaboration. These capabilities indicate that fragmented knowledge has been transformed into coherent institutional capacity (Bryson et al., 2014; Pee & Kankanhalli, 2016). The final stage is Public Value co-creation. Public Value is not an automatic consequence of institutional reform; it emerges when organizational knowledge is mobilized to improve governance quality, service delivery, democratic legitimacy, territorial development and citizens' well-being (Moore, 1995; Meynhardt, 2009, 2015). Table 2 summarizes the principal knowledge risks emerging from the gap analysis and links them to the corresponding Strategic HR Governance levers embedded within the PIAO.

Table 2: Strategic knowledge integration priorities emerging from the organizational gap analysis (authors' elaboration based on the Organizational Gap Analysis conducted within the Nuova Pescara Merger Office)

Strategic area	Knowledge risk	Knowledge Management priority	Strategic HR Governance lever
Digital transformation & ICT	**High**	Digital reskilling, interoperability of information systems, reduction of operational errors, strengthening digital capabilities	Training programmes, digital transition initiatives, competency development
Local Police & Public Safety	**Medium–High**	Harmonisation of operational procedures, cross-municipal knowledge sharing, Communities of Practice	Inter-organizational Communities of Practice, joint operational training
Social Services (ECAD / Integrated Welfare)	**Medium**	Standardisation of administrative procedures, integration of tacit and explicit knowledge, service coordination	Competency mapping, organizational learning, process harmonisation

Compared with established Knowledge Management research, which mainly examines knowledge creation, transfer and learning within existing organizations, the Knowledge Integration Governance Framework extends the analysis to large-scale institutional transformation. It conceptualizes knowledge integration not only as an organizational process, but as a governance capability that precedes and enables administrative integration. The proposed framework therefore advances a different interpretation of municipal amalgamation. Rather than considering mergers as exercises in consolidation, it conceptualizes them as governance processes centred on knowledge integration, in which strategic human resource management, organizational learning and integrated planning transform dispersed organizational knowledge into Public Value.

6. Implications and Conclusions

6.1 Theoretical Implications

The study contributes to four streams of literature. First, it extends Knowledge Management research by applying KM concepts to large-scale municipal amalgamations, showing that institutional transitions are valuable contexts for observing how distributed knowledge can be preserved, recombined and transformed into organizational capabilities (Nonaka, 1994; Alavi & Leidner, 2001; Massaro et al., 2015; Laihonen et al., 2024). Second, it contributes to Organizational Learning by showing that municipal mergers are continuous learning processes. The transition from as-is to to-be, mediated by gap analysis, illustrates how organizations construct new routines, reinterpret existing practices and develop a shared identity (Argyris & Schön, 1978;

Wenger, 1998). Third, the paper contributes to municipal merger research by suggesting that efficiency, expenditure reduction and governance performance should be interpreted as consequences of a prior knowledge integration process rather than as automatic effects of institutional consolidation (Dollery & Robotti, 2008; Blom-Hansen et al., 2016; Tavares, 2018). Similar integration challenges have been documented in the Danish municipal reform (Blom-Hansen et al., 2016) and in Portuguese territorial consolidation processes (Tavares, 2018), where administrative restructuring alone proved insufficient to ensure organizational integration. The Nuova Pescara case extends these observations by showing how Knowledge Management provides an explanatory framework for understanding these institutional transitions.

Finally, the paper bridges Knowledge Management and Public Value by identifying knowledge integration as an antecedent of Public Value co-creation. Organizational knowledge becomes the mechanism through which institutional reform is translated into societal value (Moore, 1995; Bryson et al., 2014; Meynhardt, 2009, 2015).

6.2 Managerial Implications

The framework offers a governance model for managers involved in complex institutional reforms. Its first implication is the need to replace purely structural approaches with knowledge-based governance. Organizational charts, legal harmonization and procedures remain necessary but should be preceded by systematic processes aimed at identifying critical knowledge assets, mapping competences and preserving institutional memory (Davenport & Prusak, 1998; Wiig, 2002). Second, human resource management should operate as the infrastructure through which knowledge is retained, shared and developed. Competency mapping, targeted upskilling and reskilling, leadership development, digital capability enhancement and organizational well-being initiatives become components of Knowledge Management rather than isolated HR practices (Ranft & Lord, 2002; Bresman et al., 1999; Kuipers et al., 2014). Third, the transition from three municipalities to one institutional identity requires deliberate investment in collaborative learning. Communities of practice, cross-functional working groups and peer-learning initiatives should accompany technical redesign, reducing resistance to change while supporting common administrative routines and professional identities (Wenger, 1998; Sørensen & Torfing, 2011). The Nuova Pescara experience also highlights the importance of integrated planning instruments. The PIAO can be interpreted as the managerial infrastructure through which strategic planning, human capital development, performance management, organizational learning and Knowledge Management converge into a coherent governance system. Stakeholders should be regarded as active contributors to organizational knowledge, enriching decision-making and institutional legitimacy. Municipal amalgamation is therefore a collaborative learning process extending beyond administrative boundaries. Figure 3 presents the practitioner-oriented framework, positioning Knowledge Management as the governance capability connecting diagnosis, knowledge integration, strategic human resource management, capability building and Public Value co-creation.

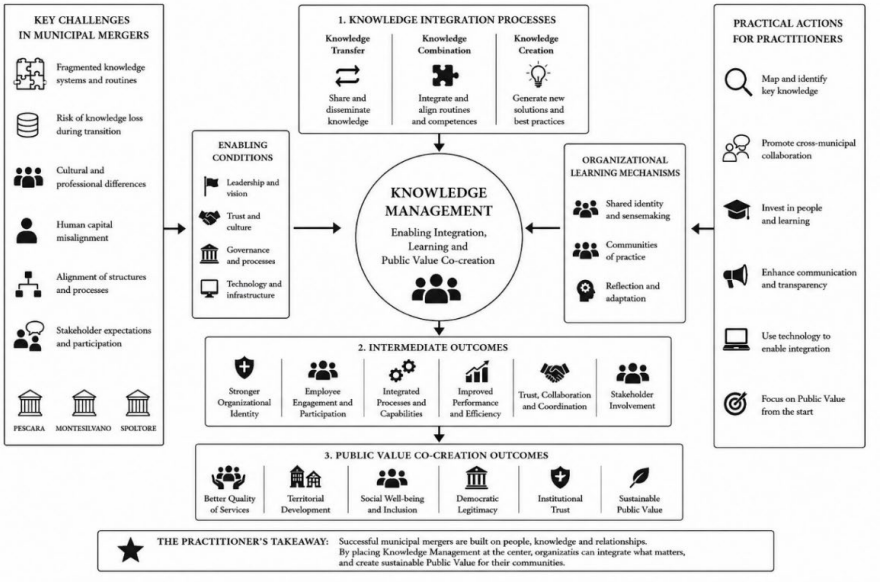


Figure 3: Knowledge Management as the governance capability enabling Public Value co-creation in municipal mergers (authors' elaboration)

6.3 Concluding Remarks

This paper argues that the success of municipal mergers depends less on institutional consolidation than on the ability to govern organizational knowledge. The proposed framework positions knowledge integration, strategic human resource governance and capability development as enabling conditions for Public Value co-creation. Future research should test and refine these relationships through comparative, longitudinal and quantitative studies across institutional contexts.

Ethics Declaration: No ethical approval was required for this study.

AI Declaration: AI tools were used solely for language editing and stylistic refinement. The authors retain full responsibility for the final manuscript.

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Knowledge Transfer in Constructing a Teaching Librarian's Competence Index: Modified Delphi Study

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Abstract: This study aims to develop a competence index for teaching librarians in Malaysian higher education academic libraries. Teaching librarians continue to face structural, professional, and pedagogical challenges in delivering effective instructional information literacy, particularly within evolving digital and institutional contexts. Addressing these challenges requires not only identifying relevant competencies but also understanding how professional knowledge is generated, shared, and validated within the librarian community. This qualitative study employed a modified Delphi method as the research design, utilising a structured, double-round process of expert consultation to elicit, evaluate, and refine professional judgements. Beyond consensus building, the Delphi process functioned as a systematic mechanism for knowledge transfer, enabling the exchange of experiential, contextual, and tacit knowledge among experts. Through controlled feedback across successive rounds, panellists were encouraged to reflect on aggregated responses, reassess their positions, and externalise their implicit professional understandings of instructional information literacy practice. Data generated across the Delphi rounds were analysed using thematic analysis to identify recurring patterns, shared meanings, and knowledge structures emerging from expert interactions. The findings resulted in the development of three interrelated constructs: a core competency index, human attributes, and information literacy modules. These constructs reflect not only agreed-upon competencies but also the cumulative professional knowledge that has been transferred and stabilised through the Delphi process. This study offers both practical and theoretical contributions to librarianship and information management. Practically, it provides an empirically grounded competency framework to guide the training, professional development, and performance enhancement of teaching librarians involved in instructional activities. Theoretically, it extends Delphi-based research by demonstrating how the method supports structured knowledge transfer, expert knowledge codification, and the operationalisation of information literacy competencies. By situating the study within a non-Western higher education context, it further broadens the epistemological and contextual scope of information literacy and competency research in academic libraries.

Keywords: Academic librarian, Competence index, Delphi method, Knowledge transfer, Teaching librarian

1. Introduction

The term teaching librarian is not familiar in the context of Malaysian librarianship, where teaching librarian functions were placed in the reference department or division and were called reference librarians (Dzulkipli, Abu and Shaifuddin, 2024). A preliminary study done to verify on how teaching librarians in Malaysia's academic libraries were given the responsibility of teaching instructional information literacy, findings stated over 55% teaching librarians based on rotation basis, 25% is top management's decision or organisational structure and only 20% from the overall sampling were selected fitting to education background (Dzulkipli, Abu and Shaifuddin, 2025b). In the Malaysian context, teaching librarians are responsible for teaching and learning in information finding, course enrolment, evaluation, assignment assessment, and answering questions within their institution's undergraduates and postgraduates, as well as for external clients (Mohd Hanafi & Ismail, 2020). While information is now accessible 24/7 online, librarian roles remain relevant as advisors and mediators to help users find accurate information. Librarians are not only curators and cataloguers of knowledge, but also active creators of knowledge (Abdul Karim, 2022). Challenges faced by teaching librarians contributed to their inability to perform the instructional task effectively, as evidenced by research showing that teaching librarians in Malaysia are facing five main issues in delivering instructional information literacy. There are modules on information literacy, teaching, information, and technical issues (Dzulkipli, Abu and Shaifuddin, 2025a). There is also little research on the topic in Malaysia, except for teacher librarians, who focus on school librarians; therefore, higher education needs a specific competence index for teaching librarians to deliver instructional information literacy to produce information-literate graduates in the future. Meanwhile, a teacher Librarian is a schoolteacher who manages the school library, aiding the school admin in ratifying the roles of the school library (Abdullah, 1999). Clear gaps in current research on teaching librarians' competency include the geographical factor, and research only highlights certain traits, such as the technological factor, but does not discuss specific human attributes, including knowledge, skills, and abilities.

This research contributes to librarianship, especially in the Malaysian context, by addressing the lack of a standard framework for teaching librarians to deliver instruction in information literacy.

1.1 Problem Statements

The issue is not merely the absence of guidance, but the absence of a clearly defined, standardised competence index that delineates the required capabilities of teaching librarians. The lack of such a framework constitutes a critical gap in professional practice and development. Although librarians across divisions are expected to possess advanced and specialised knowledge beyond core librarianship competencies (American Library Association, 2021), there remains no consolidated competence index that specifically articulates the pedagogical, technological, and instructional competencies required for teaching librarians in academic libraries contexts that has significant implications. Competency frameworks are essential for guiding curriculum design, structuring targeted professional development, evaluating educational programmes, and informing strategic human resource planning (Naveed, Siddique and Mahmood, 2022). In the absence of a standardised competence index, the preparation and performance of teaching librarians remain inconsistent and largely dependent on individual experience rather than systematically defined standards. A key manifestation of this gap is the insufficient pedagogical preparation among librarians. Many enter the profession without formal training in teaching and learning, resulting in limited readiness to deliver information literacy instruction effectively (Moser and Abramovich, 2023). This concern is reinforced by prior literature indicating persistent weaknesses in pedagogical knowledge and instructional practice, as librarians are often required to teach despite lacking formal instructional training (Caffrey et al., 2022; Peacock, 2022). The absence of pedagogical components within library and information science curricula further exacerbates this issue. Additionally, the evolving instructional landscape, particularly the integration of digital and online learning environments accelerated by the COVID-19 pandemic, has intensified the need for clearly defined technological competencies. Teaching librarians are now expected to demonstrate proficiency in hybrid and online instruction; however, without a competency index that explicitly incorporates these skills, their readiness remains uneven (Paliwal and Singh, 2021; Ramos Eclevia, 2022). Collectively, the lack of a standardised competency index results in fragmented competency development, inadequate pedagogical preparedness, and inconsistent technological adaptability among teaching librarians. This, in turn, undermines the quality and effectiveness of instructional information literacy programmes and limits their impact on student learning outcomes and continuous instructional improvement (Diao, 2021).

1.2 Research Objectives

Aligned with the problem statement, the research objectives are to explore the required competencies of teaching librarians in academic libraries in Malaysian higher education and to develop a competence index for teaching librarians in delivering instructional information literacy.

2. Literature Review

The literature on academic librarianship establishes a strong foundation for understanding the evolving roles and expectations of teaching librarians. It also reveals a critical gap that aligns directly with the objectives of this study, the need to identify required competencies and to develop a contextually relevant competence index for teaching librarians in Malaysian higher education. Academic librarians play a central role in supporting the information needs of students, faculty, and researchers within higher education institutions (Nakitare et al., 2020). However, their function has expanded beyond traditional information provision to include leadership, instructional engagement, and collaborative academic roles (Rabasa and Abrizah, 2024; Wong, 2021). Within this broader professional scope, teaching librarians emerge as a specialised group of academic librarians who are directly involved in delivering instructional information literacy, often in collaboration with disciplinary faculty (McCartin and Wright-Mair, 2022). This instructional role underscores the necessity of clearly defined competencies specific to teaching and learning contexts. Despite the recognised importance of information literacy in higher education, existing practices often remain narrowly focused on supporting immediate academic tasks, such as research assignments, rather than fostering long-term, transferable competencies among students (Diekema et al., 2020). At the same time, the increasing complexity of the information landscape particularly with the emergence of digital literacy and the challenges of information overload demands that teaching librarians possess a broader and more sophisticated set of competencies to guide students in accessing, evaluating, and using information effectively and ethically (Azik and Steinerov, 2021; Bernard, 2024). This reinforces the first research objective, which seeks to explore the required competencies of teaching librarians in delivering effective instructional information literacy. The concept of competency itself has long been a focal point in library and information science, encompassing the

integration of knowledge, skills, and attitudes necessary for effective professional performance (Khan and Parveen, 2020; Tang et al., 2024). Existing competency frameworks, including those developed by professional associations, identify a wide range of competencies related to traditional library functions such as cataloguing, reference services, systems management, and collection development (Luo and Tang, 2024). However, these frameworks tend to generalise across roles and are predominantly developed within Western academic contexts. As such, they do not sufficiently capture the specific pedagogical, instructional, and contextual competencies required of teaching librarians, particularly within Malaysian higher education institutions.

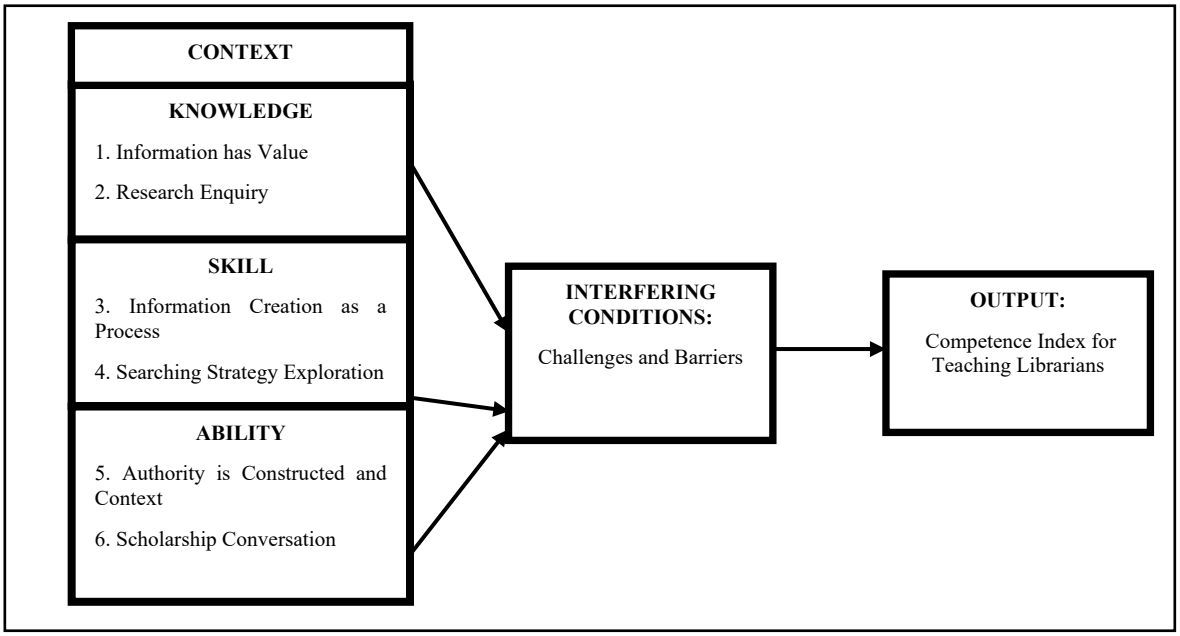


Figure 1: Competence Index for Teaching Librarians in Delivering Instructional Information Literacy Conceptual Framework

To operationalise these ideas, the conceptual framework for this study is structured into three interconnected components: context, interfering conditions, and output, as illustrated in Figure 1. This limitation highlights a significant research gap and directly informs the second objective of this study, the development of a competence index tailored to teaching librarians. There is a clear need for a structured, standardised framework that not only identifies relevant competencies but also organises them systematically and contextually. In addressing this gap, the present study adopts the Knowledge, Skills, and Abilities (KSA) model as an analytical lens to categorise and synthesise the competencies required for instructional practice. The KSA model provides a robust conceptual foundation for competency development, recognising that effective performance is shaped by a combination of cognitive, technical, and behavioural attributes (Nguyen, 2022). By integrating insights from existing librarianship competency frameworks with the KSA model, this study aims to develop a comprehensive, contextually grounded competence index that reflects the realities of teaching librarians in Malaysian academic libraries. Such an index is expected to contribute not only to the standardisation of competencies but also to the enhancement of instructional quality, professional development, and strategic workforce planning in the domain of instructional information literacy. The interfering conditions, represented as instructional information literacy challenges, are a moderating factor. These conditions may either limit the effectiveness of librarians in applying their competencies or influence the extent to which those competencies can be demonstrated. For example, institutional constraints (Väljataga et al., 2020), pedagogical challenges (Caffrey et al., 2022; Cooke, 2020; Peacock, 2022), or technological barriers (Paliwal & Singh, 2021; Peacock, 2022; Ramos Eclevia, 2022) may hinder the translation of knowledge, skills, and abilities into effective teaching practices.

3. Research Methodology

This research aims to construct a novel competency index with embedded knowledge-transfer elements that facilitate the systematic dissemination and application of expertise among panellists. A qualitative approach is adopted to explore and understand the meanings individuals or groups attribute to a social or human problem

(Creswell, 2009). The study employs a modified Delphi method, incorporating two iterative rounds to enable structured knowledge exchange, consensus-building, and validation among domain experts.

3.1 Methodology Procedures

This section outlines the data collection procedures, which consists of three phases. Phase one involves a predetermined theme based on the reviewed literature and the understanding gained from it. This study combines a collection of literature to create a basic list of competence index and uses the Delphi method to reach consensus and achieve the objective of framing the competence index (McMillan et al., 2016; Rajhans et al., 2020). In Phase Two, two rounds of Delphi were conducted, comprising two rounds, and as for Round One, a focus group interview with panellists. Round two individual interview, where panellists were required to rank the importance of the themes and to categorise the themes for human attributes. The final phase is phase three, expert validation. In this phase, the content validity index (CVI) was used to measure the validity of items in the index.

3.2 Characteristics of Delphi Method

The Delphi Method comprises four characteristics: anonymity, iteration, controlled feedback, and statistical group response (Chedi, 2017; Landeta & Barrutia, 2011; von der Gracht, 2012). Panellist and experts in Delphi was chosen because of their knowledge and experience related to the research, capacity and willingness to participate, enough time to participate in the Delphi, having effective communication skills as recommended by Chedi (2017), Adler and Ziglio, (1996) and J. Skulmoski, T. Hartman and Krahn (2007) and additional requirements set by the researcher.

3.3 Sampling Size of Panellist and Experts

For Delphi research, the recommended sampling size ranges from 5 to 10 (minimum) to 20 to 30 (maximum) (Nguyen, 2022). Hence, this study selected 18 panellists and experts with experience ranging from 5 to 30 years. Details of panels and experts involved in the study are in Table 1.

Table 1: Sampling Years of Experience

Expertise	Experiences (Current/Past)	Number of Sampling
Academics/Researchers	5 to 30 years	4
Experts		8
Practitioners		6
Total		18

3.4 Data Analysis

Consensus is determined by the percentage of participants who achieve 90-100% acceptance (Rajhans et al., 2020; Filippone, 2022). Data analysis for this study is thematic analysis which to form a repetition or pattern of words which identifies the essential themes through reading the transcript of findings (Fereday et al., 2006) using six steps of thematic analysis, data transcription and familiarisations, coding, generating themes, reviewing themes, defining themes and writing and reporting the analysis (Clarke and Braun, 2013).

3.5 Validity and Reliability in Data Analysis

Qualitative validity checks the accuracy of the findings by implementing specific procedures, while qualitative reliability shows that the researcher's approach is consistent across diverse researchers and other projects (Creswell & Creswell, 2018). In this study, findings are validated throughout the research process, such as in selecting panellists and experts to avoid bias and in the rigorous and iterative data collection and analysis process. As for this study, several strategies have been implemented in the data collection and analysis: 1) triangulation, the participants or panellists for data collection in this research were selected from four different categories to gain a clear understanding of the panellists' viewpoints and perspectives, 2) member checking, this research employs two rounds of the Delphi method, which consists of focus group interviews and individual interviews to gather the panellists' consensus and feedback or comments after the interview sessions have been conducted and 3) clarifying bias, the study has clarified the selection criteria for all panels and experts, including educational background, employment history, years of experience in the field, and gender. A thorough documentation of the procedures and processes throughout the entire research journey is one way to determine whether the research approach is reliable, allowing other researchers to follow the

procedures and methods (Yin, 2009). To accomplish this, Gibbs (2018) suggested several qualitative reliability procedures: 1) check transcripts, 2) no drift in code definitions, and 3) cross-check codes. This study has followed the first procedures to verify transcription and eliminate transcription errors. A careful transcription was performed twice, listening to the recording piece by piece to avoid tedium and boredom. It took almost two months to complete the whole listening process. The second procedure utilised NVivo software to avoid time-consuming manual coding and redundancy. This software helped transcribe the data and analyse it accordingly. The final procedure involves cross-checking codes, and in this study, the cross-check was conducted using the Content Validity Index (CVI) to validate the findings, rather than the codes themselves.

4. Findings

This chapter presents the findings derived from a two-round data collection process. Round 1 employed focus group interviews to establish consensus on three constructs, while Round 2 involved individual interviews to validate and rank the identified themes. Round 1 comprised structured and semi-structured discussions involving three primary constructs: (i) Core Competence Index, (ii) Human Attributes, and (iii) Instructional Information Literacy Modules. The session utilised items adapted from the Framework for Information Literacy for Higher Education, alongside Knowledge, Skills, and Abilities (KSA) attributes and open-ended questions. A total of 85 items across six frames were presented to the expert panels. Based on the predefined consensus criteria, 77 items were accepted. Eight items were removed, 12 items were refined, and 24 items were merged due to conceptual overlap. For the human attributes construct, 48 items representing KSA components were evaluated. Of these, 46 were accepted, with only 2 removed. This construct examined existing instructional practices across 20 public academic libraries in Malaysia. The analysis identified several gaps and emerging components not consistently addressed in current instructional modules. The six new components were identified:

- Ethics in information sharing
- Identifying information needs
- Application of Bloom's Taxonomy
- Digital literacy skills
- Case study-based learning
- Systematic literature review

These components represent critical areas for enhancing instructional information literacy programmes and provide new insights for academic library practices. A comprehensive competence index for teaching librarians in Malaysian higher education academic libraries is illustrated in Figure 2 below.

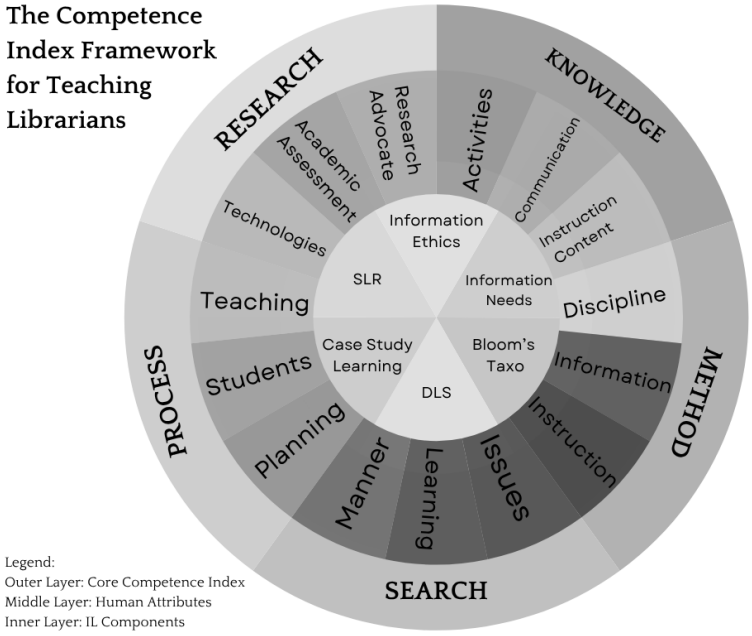


Figure 2: The Three Layers of Competence Index for Teaching

5. Discussion

The proposed competence index for teaching librarians in academic libraries within Malaysian higher education institutions was validated by eight experts using the Content Validity Index (CVI). The results indicate that the acceptance threshold of 0.83 for item-level CVI (I-CVI) was achieved, with 105 items meeting this criterion. At the scale level, the S-CVI (Average) and S-CVI (Universal Agreement) yielded values of 0.97 and 0.80, respectively, indicating high content validity (Dzulkipli, Abu and Shaifuddin, 2025c). The discussion emphasised the critical elements of knowledge, process, method, search, and research as the cycle of seeking information. By understanding the privilege associated with accessing certain types of knowledge, the importance of gathering relevant, specific data, and the role of systems in managing information effectively were also highlighted. The key findings of this study include the new themes identified during data analysis and the components of instructional information literacy modules. Research advocacy is one of the new themes that emerged during the discussion, and it seems that teaching librarians need to familiarise themselves with research, as they need to provide research support (Anna, Kiran and Idaya, 2023), possess research skills, assist with research activities, and understand the standard research process and research methodology. There has been a hike in the need to maximise academic librarians' involvement in research with faculty members (Rabasa and Abrizah, 2024). Malaysian academic librarians have begun to support open science and, through involvement in the Data Stewardship for Open Science Training, have been empowering their roles within librarianship, as the environment of librarianship is evolving (Zainal et al., 2023). This can also reflect teaching librarians as part of research processes. One of the most important parts of a teaching librarian who delivers instructional information literacy is the assessment of the session by students and student learning outcomes. The new modules in instructional information literacy focus on finding and emphasising understanding the audience's needs, digital literacy, and educational strategies, which add value to the competence index and make this study unique and stand out from the previous framework. It provides a new perspective on the information literacy modules in Malaysian academic libraries, offering a standardised set of modules across the higher education system. Bridging these gaps could involve incorporating more audience-focused and ethical considerations into the modules and integrating specific tools and resources into the panellists' strategies. This shows the value and trust placed in the faculty when information literacy is embedded in a multidisciplinary university syllabus that supports the learning outcomes of higher education students (Ford-Baxter, Faulkner and Masunaga, 2022). The changing needs of users for information are leading teaching librarians to use instructional methods to attract and engage them in information literacy content (Mashiyane, Bangani and Van Deventer, 2020). To support users' needs, academic librarians or teaching librarians were tested to respond quickly to ongoing research needs within their academic surroundings and communities online, such as the use of online platforms during the COVID-19 pandemic (Keeran, 2022).

6. Conclusion

This new competence index for teaching librarians in academic libraries in higher education serves as a guideline and standard for practising teaching libraries in delivering instructional information literacy in future professional development for teaching librarians' careers. The three main constructs in the competence index are to cater for the basic proficiency of teaching librarians in delivering instructional information literacy in academic libraries, the functionality of human attributes in the competence index is to add value to the knowledge, skills and ability for teaching librarians since these human attributes chatter to the Malaysian need's environment with the newly added themes to the human attributes. The final construct consists of components of instructional information literacy modules, developed to guide the development of module information literacy that meets current needs and students' learning outcomes. A collaboration with several parties, such as stakeholders, the Malaysian Librarian Association, and *Majlis Ketua Pustakawan Universiti Awam (MKPUA)*, will help promote this new competence index for implementation in all public academic libraries and serve as the main framework for academic librarians to practise teaching librarianship in delivering instructional information literacy. The knowledge contribution of this study is beneficial to librarianship and information science in the Malaysian landscape. This study is limited to information professionals within the scope of public higher education, not in private practice. Future research should include a private practise perspective for a wider locality, audiences and findings.

Acknowledgement

This study was funded by the Ministry of Higher Education under the scholarship of Hadiah Latihan Persekutuan (HLP), Universiti Teknologi MARA (UiTM) and Universiti Teknikal Malaysia Melaka (UTeM).

Ethical Considerations: The UiTM Research Committee approved this study on 15 December 2023 with approval code REC/12/2023/(PG/MR/475). Participants were assured that this study was voluntary and that their data would be kept secret and confidential.

AI Declaration: Artificial Intelligence (AI) tools were used solely to improve the readability and language quality of this manuscript, including sentence restructuring and grammatical correction. The authors take full responsibility for the content of the work, including the accuracy, integrity, and originality of the research.

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Knowledge Governance in the Post-truth Era: The Manosphere as a Competing Knowledge Regime

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Abstract: In the post-truth era, organisations face a critical vulnerability that we frame under epistemic permeability, a process through which external, radicalised digital regimes infiltrate organisational sensemaking and the workplace. These alternative truths, specifically those originating in the manosphere, challenge the foundations of institutional expertise and Equity, Diversity, and Inclusion frameworks. While traditional knowledge management focuses on internal flows, it often remains epistemically blind to the sophisticated architectures of digital subcultures that compete for authority in the minds of the employees. This study employs a netnographic analysis of the French manosphere on mainstream social media platforms Instagram and TikTok to explore the mechanisms through which ideological claims acquire their authority. Our preliminary findings reveal that these regimes are built through four interconnected mechanisms: the construction of experiential authority via embodied proof, the use of intellectual eloquence and the hijacking of academic rhetoric to provide a facade of analytical rigour, the framing of gender hierarchy as an objective biological fact, and the strategic penetration of organisational vocabularies using corporate palatable concepts. By mapping how these sanitised narratives migrate from the digital fringe into the workplace, we argue that organisations must move beyond conventional codification and compliance. Instead, they should develop resilient governance models centred on epistemic literacy and the critical evaluation of contested truths to safeguard institutional integrity.

Keywords: Knowledge governance, Post-truth, Epistemic authority, Digital knowledge Regimes, Manosphere

1. Introduction

The post-truth era has transformed the epistemic foundations upon which organisations build, share, and govern knowledge. As information systems become increasingly entangled with affective, identity-driven, and algorithmically mediated communication, the distinction between credible knowledge and emotionally resonant belief grows hazier.

This paper reconfigures established Knowledge Management (KM) by addressing a critical theoretical vulnerability: the historical focus on internal knowledge flows at the expense of external, competing epistemic regimes. While KM theory has traditionally optimised the transmission and codification of institutional expertise, it has paid comparatively little attention to the sophisticated architectures of digital subcultures that contest that very expertise in the minds of employees. As digital platforms reward engagement over accuracy, they accelerate the circulation of narratives that are epistemically deviant but rhetorically sophisticated – creating a landscape where institutional expertise is no longer a given, but a contested site for struggle.

We argue that to remain resilient, KM must evolve from a technical concern with internal information storage to a sociological discipline focused on the social regulation of epistemic authority. This study introduces epistemic permeability as a primary analytical lens to facilitate this shift. This concept captures the degree to which organisations' internal knowledge systems are porous, allowing external, radicalised logics to seep into employee sensemaking and professional interpretive frameworks.

The manosphere - an online constellation of masculinist and anti-feminist communities – serve as a particularly instructive laboratory for these dynamics. By deploying pseudo-scientific language and hijacking social science rhetoric, the manosphere constructs an internally coherent knowledge system that redefines truth for its participants. The urgency of this phenomenon is underscored by a 2026 Ipsos report across 29 countries, which found that Generation Z men are more likely than older generations to endorse traditionalist and regressive gender roles - a reversal of long-standing trends that signals the potent influence of these digital regimes.

For organisations, the risk is not just a messaging failure regarding Equity, Diversity, and Inclusion (EDI), but a structural problem of epistemic permeability. Without a granular understanding of how these alternative regimes establish their authority and credibility, organisations remain ill-equipped to safeguard their epistemic integrity. This paper, therefore, adopts an exploratory lens to map the supply side of these alternative truths. Using a netnography of the French manosphere on mainstream social media platforms Instagram and TikTok, we analyse the mechanisms through which these logics acquire the appearance of authority. We position this study to recognise and respond to the normalised or sanitised narratives that migrate from the digital fringe into

the workplace. By deconstructing the epistemic architecture of the French manosphere, we seek to inform a more resilient model of knowledge governance.

Our exploratory study is guided by the following research questions: How do manosphere discourses construct and legitimise alternative knowledge regimes on mainstream digital platforms? What specific discursive and epistemic strategies are deployed to establish authority and credibility among participants? How does the mapping of these strategies inform our understanding of epistemic permeability and what are the potential implications for organisational knowledge governance? Together, these questions reframe post-truth disruptions as a challenge of recognition and literacy. By exposing the blueprints of alternative epistemic regimes, this study provides the analytical tools for organisations to navigate an era in which the nature of truth itself is actively contested.

2. Literature Review

2.1 Post-truth, Knowledge Management and Governance

2.1.1 The epistemic shift of post-truth

Post-truth denotes a climate where veracity shifts from empirical evidence to emotional resonance and personal belief (Ahen, 2019). Rather than the disappearance of truth, this era represents a structural transformation in its authentication. While veracity was historically anchored in centralised authorities (religious or institutional), the "new post-truth" leverages 21st century digital ecologies to bypass traditional gatekeepers like peer-reviewed science and legacy media (Ahen, 2019).

A primary characteristic of this condition is a meta-shift in discourse where actors question the broader rules of debate to delegitimise institutional expertise (Fuller, 2018). In the climate change debate, for instance, post-truth actors often bypass empirical data to construct meta-narratives regarding the alleged ideological motivations of scientists (Fischer, 2019). This shift is further facilitated by informalisation, where an erosion of shame regarding exposed untruths allows leaders to be reframed as disruptors rather than liars (Wouters, 1986). At a cognitive level, post-truth functions through naïve realism – a bias where individuals believe they perceive reality objectively while labelling opponents as acting in bad faith – forming a unique climate where not knowing becomes a strategic political resource (Friedman, 2023; McGoey, 2012).

2.1.2 Knowledge management (KM) and governance

In response, KM must evolve from technical information storage to a sociological discipline concerned with the legitimacy of meaning. Knowledge is a social fund – a collective resource that fluctuates based on social interdependencies (Elias et al., 1987; Malcolm, 2021). In post-truth context, the goal of KM moves away from seeking absolute philosophical truth toward achieving relative adequacy, which measures how reality-congruent or useful knowledge is for a specific group's orientation and survival (Wilterdink, 2003). Because individuals perceive reality through fallible human interpretation, they manage knowledge by incorporating new information into existing ideological webs of belief, making organisational systems highly resistant to factual correction (Friedman, 2023).

This internal resistance is further complicated by external technological pressures where KM is increasingly shaped by ontological politics (Rommetveit, 2023). Knowledge governance – the social regulation of epistemic authority – is currently navigating a profound crisis of legitimacy as the democratisation of expertise has dismantled monopolies (Waisbord, 2018). As truth in rational-legal authority erodes, power shifts toward charismatic authority. Digital demagogues act as "high priests of truth" (Rommetveit, 2023, p.8), dictating social reality and allowing alternative knowledge regimes to reshape individuals' standards of evidence (Solea & Sugiura, 2025).

2.2 The Manosphere: Digital Knowledge Regimes and Epistemic Strategies

The manosphere serves as a critical illustration of this structural shift, functioning as a digital ecosystem of masculinist and anti-feminist communities that has constructed its own internally coherent knowledge system. This environment is unified by the belief that men are in a state of crisis due to the social influence of feminism (Ging, 2019; Blais & Dupuis-Déri, 2012). The ecosystem is comprised of Men's Rights Activists (MRAs) focused on legislative reform, the Red Pill which serves as an ontological onboarding for biological determinism, and Pick-Up Artists (PUA) who apply neoliberal market logic to seduction (Ging, 2019; Vallerga & Zurbriggen, 2022). It further encompasses separatist movements like Men Going Their Own Way (MGTOW), and fatalistic groups

such as Involuntary Celibates (Incels), and disciplinarian subcultures like NoFap (Wright et al., 2020; Banet-Weiser & Bratich, 2019; Hartmann, 2021).

2.2.1 The deployment of pseudo-science and epistemic mimicry

The manosphere epistemic authority is built upon the strategic use of pseudo-science, mimicking the aesthetic of objectivity to ground ideological positions in a perceived natural reality. Central to this is a weaponised biological determinism that categorises men into rigid socio-sexual hierarchies of Alphas and Betas, while reducing complex attraction to primitive drives (Han & Yin, 2023). These claims are sustained through troll science, where academic data is deliberately misinterpreted to create a counter-knowledge archive hostile to mainstream consensus (Eslen-Ziya, 2020). This dynamic empowers the ordinary man by suggesting he has more direct access to truth than elite academics or media figures (Eslen-Ziya, 2022).

Beyond biology, the manosphere hijacks social sciences and humanities through epistemic mimicry, co-opting the very concepts developed by progressives to critique patriarchal power (Johansson Wilén et al., 2024). Incels often evoke Gramscian hegemony to argue they are subalterns living under a feminist cultural monopoly, or they twist Critical Masculinity Studies to argue that because masculinity is socially constructed, it is a fragile passport that women can revoke at will (Steinmetz-Jenkins, 2018, Johansson Wilén et al., 2024). This theoretical inversion extends to reinterpreting the male gaze as a retaliatory framework where women are the aggressors, and co-opting Feminist Standpoint Theory to claim that rejected men have a uniquely objective view of human nature (Solea & Sugiura, 2025; Johansson Wilén et al., 2024).

2.2.2 Affective mobilisation and neoliberal logic

The mobilizational power of the manosphere stems from its ability to translate these theories into a visceral hunger for justice through Red Pill ideology – a narrative of awakening to a gynocentric social construct (Ging, 2019). By platforming pain, digital subcultures allow narratives of suffering to be amplified while detached from their material conditions, facilitating the emergence of a regime of male victimhood where hegemonic groups claim the status of the oppressed (Chouliaraki, 2001; García Mingo and Diaz Fernandez, 2023). This affective mobilisation is eventually formalised through neoliberal logics, conceptualising social interaction as a sexual marketplace where human value is reduced to quantifiable KPIs (Han & Yin, 2023).

Within this framework, seduction and self-improvement are managed as a rigorous business process. When individuals fail, the system provides a misattributed explanation rooted in market failure caused by feminist interference rather than the flaws of neoliberal capitalism itself (Banet-Weiser & Bratich, 2019). This logic creates a problematic epistemic framework that marginalises women and racialised individuals by reducing human potential to Eurocentric phenotypes, as seen in the looksmaxxing subcultures (Solea & Sugiura, 2025). By channelling hostility toward market interference, the manosphere creates a highly resilient system immune to institutional debunking or simple fact-checking.

2.3 Epistemic Permeability and Organisational Vulnerability

The migration of these radicalised ideologies into the mainstream is driven by epistemic permeability – the mechanism by which the boundaries of established knowledge systems become porous. According to Digital Subculture Diffusion Theory (DSDT), this infiltration is driven by the strategic manipulation of information flows to bypass institutional safeguards (Solea & Sugiura, 2025). This external diffusion follows a tripartite path beginning with normiefication, where niche terminologies migrate from fringe forums to platforms like TikTok and Instagram as sanitised content. This leads to mainstreaming and eventual normalisation, where previously unacceptable views are absorbed into societal norms, making the ideology appear as common sense before it even enters the workplace (Conway, 2020; Wodak, 2020).

Once in the professional sphere, these concepts manifest as Red Pill leadership, an ideological behaviour that draws upon the manosphere repertoire to justify domination and marginalise inclusive practices (Erbil et al., 2025). This infiltration is facilitated by pre-existing structural gender inequalities and a growing resistance to Equality, Diversity, and Inclusion (EDI) initiatives, which provide a platform for misogynistic scripts to move from implicit undercurrents to overt behaviours (McCarthy & Taylor, 2024; Ng et al., 2025). This represents a profound failure of communicative rationality as Red Pill logics introduce a closed communicative space that suppresses dissent and delegitimises institutional expertise (Habermas, 1990; Erbil et al., 2025).

Ultimately, this infiltration endangers knowledge governance by creating a conflict between the organisation's formal evidence-based systems and the shadow regimes of the manosphere. Organisations often lack the subcultural literacy to distinguish between genuine scientific data and the pseudo-intellectual justifications used

to rationalise social inequalities (Panofsky et al., 2021; Solea & Sugiura, 2025). Consequently, formal policies are subverted as employees may rely on troll science and reactionary narratives to interpret institutional initiatives as existential threats to male career advancement (Erbil et al., 2025). Therefore, our study addresses the lack of granular, empirical exploration into these specific epistemic architectures and their permeability into established knowledge systems by conducting an exploratory netnography of the French manosphere, providing the necessary literacy for organisations to recognise these logics before they manifest in the workplace.

3. Methodology

3.1 Setting and Ongoing Data Collection

This study examines masculinist content produced and disseminated on Instagram and TikTok, two short-form visual mainstream platforms that have become central arenas for the diffusion of anti-feminist ideologies in French-speaking online spaces. Instagram in particular has emerged as a significant infrastructure for community-building around masculinist topics, enabling influencers to cultivate large, engaged audiences through a combination of reels, stories, and static posts. TikTok complements this landscape through its algorithmically-driven content amplification, which has been shown to accelerate the reach of ideologically charged short videos.

The unit of analysis is the individual post or video published by accounts producing masculinist content in French, regardless of whether the account belongs to a public influencer or an anonymous user. Content analysis was conducted on a corpus of posts featuring masculinist themes, collected between January 2026 and March 2026. Data collected for each post included: account characteristics (follower count, account type), content format, persuasive appeals, engagement metrics (likes, views, comments, shares), and the presence of specific discursive markers of masculinist ideology.

Table 1: Observation corpus: Platforms, accounts and data collected

Platform	Observation Context	Type of Data Collected
Instagram	Accounts: @raptorsvsfonte (133,000 followers) @ugogiljimenez (160,000 followers) @lefrenchhitch (124,100 followers) @alexhitchens (125,000 followers) @******_alpha (8,418 followers) @jpfanguin (1,100,000 followers) @jp.fn (368,000 followers)	Posts, stories, videos, captions, hashtags
TikTok	Accounts: @alex_hitchens_.off (325,100 followers) @lefrenchitch (126,600 followers) @alexhitchensoffbusiness (150,800 followers) @*********.hommefemme (2,084 followers)	Videos, comments, podcast excerpts, captions, hashtags

Table 1 provides an overview of the accounts included in the observation corpus, detailing the platforms on which they operate, their respective follower counts as of March 2026, and the types of data collected from each. Consistent with contemporary netnographic ethics (Kozinets, 2020), this study employs a visibility threshold to differentiate between professionalised digital actors (i.e. influencers) and ordinary participants who relay manosphere discourse. By pseudonymising accounts below the 10,000 follower-mark, the research mitigates the risk of de-anonymisation for users whose digital presence does not constitute a deliberate public persona.

3.2 Sampling

Initial seed accounts were selected on the basis of their visibility - measured through follower count and engagement metrics - and their production of content explicitly engaging with gender relations from a masculinist perspective. From these seed accounts, additional profiles were identified through a snowball sampling strategy (Noy, 2008), following cross-references in hashtags, mentions, comment sections, and platform recommendation algorithms. This iterative process was particularly suited to the identification of difficult-to-reach or loosely networked groups operating at the margins of mainstream platform visibility (Pelto, 2013), and continued until theoretical saturation was reached, with no new accounts or content patterns emerging from further sampling.

3.3 Coding Scheme

Posts and accounts were classified according to a coding scheme developed inductively from the data and grounded in existing definitions of masculinism in the sociological literature. The central classification variable concerns whether anti-women discourse constitutes a primary or recurrent element of the account's content. An account or post is classified as masculinist when hatred toward, resentment of, or structural hostility to women constitutes a primary theme, whether expressed in isolation or in combination with other topics such as politics, body image, nationalism, or self-development. An account or post is classified as non-masculinist when it focuses exclusively on gender-neutral topics - such as wealth creation, entrepreneurship, fitness, or personal development - with no significant misogynistic content.

The analytical procedure unfolded in three iterative phases. First, open coding was applied to the full corpus to generate an initial inventory of recurring discursive features – lexical choices, rhetorical registers, visual grammars, and engagement patterns – without imposing prior theoretical categories, allowing the data to surface its own organising logics. Second, focused coding consolidated these observations into higher-order analytical categories. A feature was retained as a distinct category only when it recurred across multiple accounts and platforms, could be distinguished from adjacent categories on substantive grounds, and mapped onto a theoretically meaningful distinction in the literature. Ambiguous cases were flagged and resolved through interpretive discussion between the two authors. Third, the four mechanisms were subjected to internal triangulation, with each verified against the full corpus rather than illustrative examples alone. Theoretical saturation was assessed at both the account and category levels: sampling continued until no new accounts or content patterns emerged. While the exploratory nature of this study precludes claims of representativeness, these procedures ensure the transparency, consistency, and theoretical grounding of the interpretive process.

4. Preliminary Findings

This section presents the findings of the content analysis across the 60 posts collected from Instagram and TikTok between January and March 2026. Four interconnected mechanisms, which illustrate how the theoretical post-truth shift – where veracity is anchored in emotional resonance rather than empirical evidence – is operationalised in digital spaces, were identified. French manosphere influencers construct, legitimate, and diffuse alternative knowledge regimes through the construction of epistemic authority, discursive legitimisation strategies, the naturalisation of gender hierarchy, and the penetration of organisational epistemic systems.

4.1 Construction of an Alternative Epistemic Authority

A central finding is the systematic positioning of influencers as holders of suppressed or misunderstood knowledge. This represents a shift from rational-legal authority to charismatic authority, where digital demagogues act as preachers of truth (Rommetveit, 2021). By bypassing institutional validation in favour of embodied and experiential proof such as Lifestyle content - fitness routines, meal preparation, and body optimisation - the ideology presentsthe transformed body as a reality-congruent argument. This logic of embodied proof functions as a strategic response to the post-truth erosion of centralised authority and is reinforced by posts projecting mastery and self-sufficiency, such as @ugogiljimenez's detailed hunting gear breakdowns, which signal competence and autonomy in traditionally masculine domains.

Influencers operating in the pick-up artist (PUA) and investment coaching registers position themselves as practical experts whose authority derives from lived experience rather than formal credentials. This embodies the epistemic shift where truth is authenticated through personal belief and naïve realism (Friedman, 2023). Alex Hitchens exemplifies this pattern, framing his financial success as self-made proof of concept. The "post-truth" dimension of this epistemic construction is particularly salient: ideological claims are systematically repackaged as suppressed truths. @raptorvsfonter articulates this explicitly - "There is an important process of

de-virilisation happening because they want people who don't resist" - casting mainstream institutions as actively concealing knowledge that only the manosphere makes available.

4.2 Discursive Legitimisation Strategies

Beyond the construction of alternative authority, the corpus reveals discursive strategies that mimic the aesthetic of objectivity – a process termed epistemic mimicry (Johansson Wilén et al., 2024). A distinctive feature of the French manosphere from its Anglophone counterparts is the prominent role of intellectual eloquence and rhetorical register. Rather than relying solely on shock content or aggression, several influencers deploy a register of calm, reasoned argumentation that lends ideological claims a veneer of analytical rigour. Coupled to this refurbishment of intellectual composure, these influencers also provide an affective register in that they are often described by their followers as truth liberators. This highlights how knowledge governance is shaped by emotional resonance. One commenter on Alex Hitchens makes the affective function of this register explicit: "Alex Hitchens is like that little voice in our head, he speaks our truth" - positioning the influencer not as an external authority but as the articulation of what followers already feel but cannot express. Appeals to established intellectual figures are used selectively to anchor fringe claims in recognisable cultural tradition. This aligns with the theoretical observation that post-truth actors do not abandon truth but rather transform its authentication to bypass traditional gatekeepers (Solea & Sugiura, 2025; Ahen, 2019). @******_alpha, for instance, cites philosopher Alain Soral to support assertions of male superiority, lending ideological content an appearance of academic grounding and building counter-knowledge archives (Eslen-Ziya, 2020). At the structural level, fragmented multi-platform presence - Alex Hitchens operating simultaneously across @alex_hitchens_.off, @lefrenchitch, and @alexhitchensoffbusiness - simulates scale and ubiquity, reinforcing the impression that this knowledge is both widespread and credible. These legitimisation strategies are also visible at the aesthetic level. Figure 1 illustrates four recurring visual registers identified across the corpus: (1) dark, high-contrast aesthetics evoking authority and dominance; (2) displays of wealth and material success functioning as embodied proof of concept; (3) idealised masculine physicality presented as biological validation; and (4) civilisational and heritage imagery anchoring ideological claims in cultural legitimacy. Together, these registers operate as a non-discursive layer of epistemic authority, reinforcing the mechanisms described of alternative epistemic authority and discursive legitimisation without recourse to explicit argument.



Figure 1: Visual aesthetic registers of the examined manosphere corpus

4.3 Naturalisation of Gender Hierarchy as Objective Knowledge

A third mechanism concerns the consistent framing of gender hierarchy as biological or psychological fact rather than ideological position. Across the corpus, gender dynamics are presented as self-evident truths requiring only recognition, not argument. By stating "We are not equal... I don't see what's so hard to understand... We must be complementary", influencers like Alex Hitchens employ naïve realism (Ahen, 2019) to foreclose debate, positioning hierarchy as a natural order. This represents a profound failure of communicative rationality, as it creates a closed communicative space that suppresses dissent and delegitimises institutional expertise (Fuller, 2018).

Women are recurrently constructed as inherently irrational and manipulative, requiring active management by men. @*********hommefemme explicitly compares women to children who overstep boundaries, framing male emotional control as the natural relational order. Female sexuality is simultaneously pathologized and policed: Alex Hitchens advises checking a partner's phone to verify her sexual history, framing refusal as evidence of dishonesty. Notably, cross-gender validation is mobilised discursively - women present in comment sections raising equivalent questions are absorbed into the narrative as further confirmation of the ideology's universal applicability, neutralising potential counter-evidence and making the internal knowledge system highly resistant to factual correction.

4.4 Penetration into Organisational Epistemic Systems

The final mechanism illustrates epistemic permeability – the process by which organisational boundaries become porous to external radicalised logics. Manosphere discourse effectively interfaces with professional and organisational vocabularies. The investment and self-optimisation register deployed by influencers such as Alex Hitchens - built around concepts of performance, discipline, and return on investment - can circulate within workplace cultures without explicit ideological flagging. The ideological content is carried by professionally palatable frames. This infiltration is operationalised through the tripartite path of Digital Subculture Diffusion Theory (Solea & Sugiura, 2025), beginning with normiefication, a phase in which niche and often extreme terminologies migrate from fringe forums to mainstream audiences. As these narratives undergo mainstreaming, their organisational permeability is carried by established managerial logics. For instance, @raptorvsfonter's invocation of Elon Musk's productivity governance - "What did you get done this week? If the answer is shaky, you're fired" - maps extreme productivity governance onto gender relations, normalising a transactional and evaluative gaze toward women through the language of workplace performance. Concepts such as "complementarity," "mental strength," and "emotional regulation," drawn from mainstream management and positive psychology discourse, lower the barrier and normalise the introduction of manosphere-adjacent ideas into professional settings while retaining their ideological content beneath a respectable surface. By adopting these sanitised terms, “Red Pill” logics can circulate within the workplace without triggering explicit ideological flagging or policy violations (Erbil et al., 2025).

Finally, a civilisational register adds a further layer of legitimisation, linking individual gender claims to broader cultural defence narratives. @ugogiljimenez frames the celebration of Western heritage as inseparable from gender order: "The more violent and stateless barbarians there are in our streets, the more we must celebrate the grace of our beautiful civilisation." This embedding of misogyny within ostensibly respectable cultural discourse represents a sophisticated legitimisation strategy that extends the reach of manosphere ideology well beyond its core audience.

5. Conclusion

This study advances Knowledge Management by conceptualising digital radicalisation through the notion of epistemic permeability, highlighting how porous organisational boundaries allow external “shadow” knowledge regimes, such as the French manosphere, to infiltrate professional sensemaking. Rather than viewing radicalisation as the spread of isolated extremist claims, the study demonstrates how the manosphere functions as a competing epistemic system that challenges institutional expertise and evidence-based diversity, equity, and inclusion (EDI) frameworks.

Findings identify four interrelated mechanisms underpinning this process: (1) the replacement of rational-legal authority with charismatic authority based on embodied proof; (2) epistemic mimicry, whereby intellectualised rhetoric simulates analytical credibility; (3) naïve realism, which frames social hierarchies as objective fact and resists institutional correction; and (4) Digital Subculture Diffusion, through which radical logics are normalised via sanitised corporate vocabularies centred on performance, discipline, and ROI. Together, these mechanisms enable radical ideologies to circulate within organisational contexts while bypassing traditional safeguards.

The study argues that addressing epistemic permeability requires a shift in knowledge governance from passive compliance toward epistemic literacy, equipping organisational members to critically evaluate and deconstruct alternative digital knowledge regimes. In doing so, the research contributes a framework for understanding the post-truth challenge not simply as misinformation, but as a structural competition over the epistemic foundations of organisational reality.

Ethics Declaration: This study meets the criteria for minimal-risk Internet-mediated research (Dixon-Ward & Chan, 2022). All data are publicly accessible, and no interaction with participants occurs.

AI Declaration: During the preparation of this work, the authors used GPT-4 and Grammarly for: grammar, syntax, and spelling correction and translation from French. After using these tools/services, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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