Università di Genova

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Proceedings of the

6th International Conference on AI Research

Hosted by University of Genoa, Italy

11-12 December 2025

Edited by

Renata Paola Dameri

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A conference managed by ACPI, UK

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ICAIR 2025

A Conference

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Professor Renata Paola Dameri

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E-Book ISBN: 978-1-917204-69-9

Print version ISBN: 978-1-917204-68-2

Print Version ISSN: 2633-3058

Published by Academic Conferences and Publishing International Limited Reading, UK

+44 (0) 118 324 6938

www.academic-conferences.org
info@academic-conferences.org

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About the 6th International Conference on AI Research, 2025

The International Conference on AI Research (ICAIR) is becoming a key forum for academics and students, whether social scientists, natural scientists or philosophers come together to explore the future of society in the context of AI. Many aspects of AI are now the subject of peer reviewed academic research, including the increasing use of Chatbots and GenAI in academe and in society at large.

The conference was initially launched in 2019 as the European Conference on Artificial Intelligence and Robotics. After a success inaugural event in Oxford the conference fell victim to Covid and the following three years where held online. Time was taken in 2023 to refocus this fast developing area of research and the name of the conference was changed this year to the International Conference on Artificial Intelligence.

The Proceedings of the 2025 edition of the conference include academic research papers, PhD research papers, Masters Research papers and work-in-progress papers, all of which have been presented and discussed at the ICAIR 2025 conference. The proceedings are of an academic level appropriate to a professional research audience, including graduates, post-graduations, doctoral and post-doctoral researchers. All papers have been double-blind peer reviewed by members of the Review Committee.

Aims and Scope

The International Conference on AI Research (ICAIR) is an opportunity for academics, practitioners, and consultants from around the world who are involved in the study, management and development of artificial intelligence related issues in education, in business or in the public sector to publish and present their research. It seeks to bridge the gap between academic research, practical applications and policy-making. With a multi and trans-disciplinary scope the conference attracts research from diverse settings.

Topics Covered

The call for papers for ICAIR 2025 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.

- The consequences of AI on work and society
- The governance of AI and AI in governance
- Regulations for AI safety
- Enabling knowledge networks with cognitive computing and other technologies
- Ethical and acceptable social behaviours
- Organisational and social impact of AI
- How can AI explain its thinking?

  Further applications of AI including:

- GenAI and AI Chatbots

- Fintech and the financial services industry
- Life sciences and healthcare
- Utilities and transport management services
- In the development of Smart-cities
- In education and training
- In scientific research
- In healthcare
- Collaborative robots and human-robot interaction
- Society 5.0

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.

Mini Tracks

- Governing AI: Organizational Adaptation and Societal Alignment in the Age of AI
- Artificial Intelligence in Academic and Scientific Research
- AI in Education: Empowering Students, Educators, Families and Policymakers
- AI and Ethical Norms: Rethinking Rights, Justice, and Responsibility in the Algorithmic Age

The programme for the 2025 conference can be downloaded from here and full details about the conference can be found on the conference website:
https://www.academic-conferences.org/conferences/icair/

ICAIR Preface

These proceedings represent the work of contributors to the 5th International Conference on AI Research (ICAIR) hosted by ACPI and the University of Genoa, Italy on 11-12 December 2025. The Conference Chair is Renata Paola Dameri from University of Genoa, Italy.

ICAIR is now a well-established event on the academic research calendar and now in its 5th 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 Valentina Di Gregorio, from the University of Genoa, Italy, who will talk about *European Regulation of AI systems: Data circulation, Liability and Protection of Fundamental Rights*. The second keynote on day one of the conference will be from Professor Lorenzo Rosasco, from the University of Genoa, Italy, who will discuss *Can we make Artificial Intelligence Sustainable?* The second day of the conference will have a final keynote presentation from Professor Daniela Mancini, from the University of Teramo, Italy who will talk about *Artificial Intelligence for Accounting and Management Control.*

With an initial submission of 174 abstracts, after the double blind, peer review process there are 67 Academic research papers, 8 PhD research papers, 2 Non- Academic Research Papers and 6 work-in-progress papers published in these Conference Proceedings. These papers represent research from Canada, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, India, Indonesia, Ireland, Italy, Lithuania, Malaysia, Mexico, Nigeria, Poland, Portugal, Romania, Serbia, Singapore, Slovenia, South Africa, Spain, Sweden, Switzerland, Taiwan, Turkey, United Kingdom and the USA.

We hope you enjoy the conference.

Renata Paola Dameri

Genoa, Italy

December 2025

Biographies of Chairs and Keynote Speakers

Conference Chair

Renata Paola Dameri has been a professor of Business Economics at the University of Genoa since 1999 and is currently Vice-Rector for International Affairs. Graduated in Management in 1990 with a thesis on artificial intelligence and decision support systems in business, her research interests have since focused on information systems, smart cities, intellectual capital and technological investments. She has been a visiting professor at the Université Paris Dauphine in Paris and at Georgetown University in Washington D.C. She collaborates with supranational institutions such as the European Union and the OECD, with the Ministry of Foreign Affairs and International Cooperation, and with local institutions such as the Municipality of Genoa and the Metropolitan City of Genoa. She is the director of the Master in Entrepreneurship, of the advanced course in Smart city and of the Innovation Hub in tourism and cultural heritage.

Keynote Speakers

Valentina Di Gregorio is Professor of Private Law at University of Genoa, Department of Law (DIGI) and she is a lawyer since 1991. She is coordinator of the degree course in Social Service and Social Policy at the University of Genoa where she is also Director of the master on Family Mediation and member of the Board of the High School for legal professions. She is Member of the Board of National PhD course on Bioengineering and Robotics, and of Italian Center of Excellence for Logistics, Transport and Infrastructure (CIELI). She is coordinator and member of many international and national research projects and author of numerous works on contracts, torts, family law, legal profiles of AI and new technologies. She is a conference chair and speaker at various conferences on the these topics.

Lorenzo Rosasco is a professor at the University of Genova. He is a visiting scientist at the Italian Technological Institute (IIT). He is a founder and serves as a coordinator of the Machine Learning Genova center (MaLGa) and the Laboratory for Computational and Statistical Learning, focusing on the theory, algorithms, and applications of machine learning. He obtained his PhD in 2006 from the University of Genova and was a visiting student at the Center for Biological and Computational Learning at MIT, the Toyota Technological Institute at Chicago (TTI-Chicago), and the Johann Radon Institute for Computational and Applied Mathematics. From 2006 to 2013, he worked as a postdoc and research scientist at the Brain and Cognitive Sciences Department at MIT. He is a fellow at Ellis and serves as the co-director of the "Theory, Algorithms and Computations of Modern Learning Systems" program as well as the Ellis Genoa unit. Lorenzo has received several awards, including an ERC consolidator grant.

Daniela Mancini is professor of Performance Measurement and Business Analytics at the Department of Law of the University of Teramo, where she is Dean of the PhD programme in Economic and Social Sciences and directs the Msc in Law, Economics and Business Strategy. Before joining the University of Teramo, she was a member of the faculty at the Parthenope University of Naples, the University of Macerata, the University Politecnica delle Marche, and the University of Pisa. She received her PhD in Business Administration from the University of Pisa, and was visiting professor at IESEG School of Management, and the Université Catholique de Lille. She is a member of the Board of Directors of

the Italian Academy of Business Administration (AIDEA) with responsibility for training, European projects, and relations with scientific societies. She is a member of the Italian Society of Professors in Accounting and Business Administration (SIDREA), and the National Association of Administrative and Financial Directors (ANDAF), where she is a member of the I&CT Committee. Her research focuses on management control and performance measurement, at the intersection of digital technologies, sustainability and carbon reporting, business model innovation, and technology transfer in private and public companies, particularly in the agri-food and aerospace sectors. Her research has been published in prestigious national and international journals in the areas of accounting, management, and information systems.

Mini Track Chairs

Dean Cristol, Ph.D., executive director, Educators for All LLC. Columbus, OH focuses on educational technology professional development within marginalized educational settings, aiming to equip both students and teachers with culturally responsive skills for technology-driven learning environments. Engages in research initiatives funded by international, national, state, and private foundation grants. Contributes extensively to academic discourse through publications in numerous journals, authoring books and chapters, and presenting findings at international, national, and state conferences. He serves as an Associate Editor for the Theory Into Practice journal and is Vice President for the International Association for Mobile Learning, showcasing their commitment to advancing scholarly dialogue and professional development in educational technology on a global scale. Nicholas Giester, MBA, more than 20 years of experience in public and private sector industries of IT, specializing in delivering technological solutions to business partners focused on the automation and improvement of vital business operations, as well as adeptly navigating organizational culture. He is highly skilled in evaluating the compatibility of existing infrastructure and software with fundamental business services, offering strategic guidance on investing in technologies like artificial intelligence or deciding on divestitures to meet business objectives. He excels at building and sustaining critical relationships, enabling him to manage crises efficiently, troubleshoot issues, and broker solutions effectively.

Nicholas Giester, MBA, more than 20 years of experience in public and private sector industries of IT, specializing in delivering technological solutions to business partners focused on the automation and improvement of vital business operations, as well as adeptly navigating organizational culture. He is highly skilled in evaluating the compatibility of existing infrastructure and software with fundamental business services, offering strategic guidance on investing in technologies like artificial intelligence or deciding on divestitures to meet business objectives. He excels at building and sustaining critical relationships, enabling him to manage crises efficiently, troubleshoot issues, and broker solutions effectively.

Belinda G. Gimbert, Ph.D., associate professor, Educational Administration, Department of Educational Studies, The Ohio State University, Columbus, OH. Her research addresses a broad array of human capital policies that impact talent management in low performing K-12 school systems and influence the composition, distribution, and quality of educators in the workforce. Gimbert teaches course related to human resource administration, introduction to educational administration, and K-12 instructional supervision focusing on using AI and mobile learning technologies. She also directs two national projects sponsored by the U.S. Department of Education's Office of English Language Acquisition.

Dr. Mitt Nowshade Kabir is an adjunct professor of Digital Transformation at Ecole de Management Léonard De Vinci. He is a serial entrepreneur, knowledge evangelist, business accelerator, and an investor. Dr. Kabir has a master's degree in computer science, an MBA, a Ph.D. in Information Technology, and a DBA in Management. His current interests include AI, innovation, entrepreneurship, and strategic management.

Raeal Moore, Ph.D., Executive Director of Evaluation Data Solutions, LLC. She specializes in providing comprehensive, high-quality research, evaluation, and assessment services to deliver reliable and accurate information about the implementation and outcomes of programs and projects. She uses mixed methods approaches to answer programmatic questions. She understands that a credible and comprehensive evaluation is critically important to provide program decision-makers with timely, evaluation results. With 20 years' experience, Raeal spends time strengthening the evaluation capacity and practice of organizations. Moore earned an M.A. and Ph.D. in Quantitative Research, Evaluation, and Measurement at Ohio State University.

Catherine A. Okonkwo is a Nigerian writer, researcher, and information specialist with a Higher National Diploma in Library and Information Science. She has authored multiple books and academic articles, and has presented research on topics including artificial intelligence in education in collaboration with the University of Essex, UK. Catherine is a member of the IFLA, the YALI Network, and several academic and professional networks. She is passionate about advancing knowledge through research, teaching, and global collaboration.

Pardis M. Tehrani, PhD, Associate Head and Associate Professor of the Law School at the University of Sunderland, UK. Her research interests lie at the intersection of information technology law and international law, with a growing focus on artificial intelligence and emerging technologies within legal systems. Her current work explores the legal, ethical, and regulatory challenges posed by AI in both domestic and international contexts. She is the author and co-author of over 70 papers and has delivered talks at various panels, NGOs, research centres, and international organisations, including the International Committee of the Red Cross (ICRC) and other human rights bodies. She has also successfully secured internal and international research funding from a range of organisations across China, Malaysia, Austria, the United Kingdom, and the European Union.

ICAIR Conference Committee

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Artificial Intelligence Leads to Circular Economy: A Bibliometric Review and Future Agenda

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Abstract: Despite extensive research on industry 4.0 and circular economy (CE). There is limited research on nexus between artificial intelligence (AI) and circular economy. AI seems to be driving force for revolutionizing in businesses and industries for unlocking economic, environmental, and social benefits. We investigated how AI transform from linear to circular business models. Authors selected 105 peer-reviewed articles from Web of Science database by using bibiliometric analysis. Authors analyzed the data by using VoSviewer Software. The four core clusters were identified, (1) circular economy a pathway to sustainable business management, (2) big data models enhance CE outcomes, (3) I4.0 technologies leads to future of CE and (4) digitalized supply chains for sustainable development. This review advances our understanding on AI and circular economy in the existing literature due to less focus by prior scholars. More importantly, this review contributes to shifting the focus to technological perspective within circular economy, diverging from traditional linear model based on economic views. This review suggested companies should adopt AI as it plays a pivotal role in facilitating the shift to a circular economy by reshaping and enhancing existing models of product design, manufacturing, consumption, repair, regeneration, recovery, and end-of-life management while simultaneously improving the efficiency of waste management. This research provides fresh perspectives on AI and CE to better understand AI as an opportunity rather than cost due to ongoing fourth industrial revolution.

Keywords: Artificial intelligence, Circular economy, Bibliometric review, Big data models, Digital supply chains

1. Introduction

AI seems to be promising for achieving circular and sustainable goals for business and society (Saha et al., 2025). In a similar fashion, the adoption of new technology has accelerated the shift from linear to CE making it a focal point of sustainability policy agendas on a global and regional scale (Sanchez-Garcia et al., 2024). According to World Economic Forum, AI will revolutionize international trade by improving supply chains, logistics, trade finance, and customs compliance, making global business more equitable, sustainable, and effective (WEF, 2025). In 1955, John McCarthy first used the term "artificial intelligence" to refer to "the technical and scientific process involved in creating machines with intelligence." (Anderson, 2024). AI relied on human-established standards for making decisions, but machine learning and deep learning have enabled algorithms to gain insights from data, enabling goal achievement and task execution through adaptive and rapid learning mechanisms (Haenlein and Kaplan, 2019). AI seem to be potential driver for CE transition for achieving economic, environmental and social sustainability.

Despite the aspirations and high hopes expressed by those policies, the firm's response has been largely indifferent. For instance, 75% of the 618 European SMEs surveyed either did not engage in any CE activities or were just concerned with meeting their recycling legal obligations (Bassi and Dias, 2019), this is because companies can't afford to put money into things like clean production and CE-aligned business models, which demand more resources (Reim et al., 2025). The data demonstrating a decline in the "circularity" of the world economy from 9.1% in 2018 to 7.2% in 2023 provides a picture of the broader impact (Circular Economy Foundation 2023). In today's world, linear models are failed to protect the planet and human societies. By considering this issue, CE transition is an important at this moment for sustainable future.

Over the recent years, AI-CE nexus has been widely recognized (Akhtar et al., 2024; Fallahi et al., 2023; Jain et al., 2025; Tutore et al., 2024). Against this backdrop, the concept of AI has emerged (McCarthy et al., 1956; Turing, 2007). AI may enhance a system's ability to ingest data and acquire knowledge based on it; the knowledge can be leveraged to achieve expected objectives and tasks (Haenlein and Kaplan, 2019). This development has raised the interest of major IT companies in AI solutions. As a result, cloud computing services for machine learning began to be provided by businesses like Google, Amazon, Microsoft, Salesforce, and IBM, making cognitive technologies more accessible and usable (Davenport, 2018). This reflects many companies are investing a huge money on adopting AI for circularity.

There are several reviews discussed barriers and benefits of digital technologies with CE (Chauhan et al., 2022a; Neri et al., 2025), eco-innovations (de Jesus Pacheco et al., 2017; Kuo and Smith, 2018), healthcare waste management (Sharma et al., 2025), building resilient supply chains (Chauhan et al., 2023b), sustainable product management (Rusch et al., 2023), digital health entrepreneurship (Weimar et al., 2025), stakeholder engagement (Prebanić, K. R., and Vukomanović, 2021; Tabas et al., 2025), Industry 4.0 and CE ecosystems in Central and European context (Abbas & Smaliukienė, 2025). Hence, few reviews highlighted role of AI with sustainability and business models (Kar et al., 2022; Jobstreibizer et al., 2025), entrepreneurship (Kalsoom et al., 2025), innovation capabilities (Gama and Magistretti, 2025), family businesses (Kumar & Ratten, 2025), human resource management (Gong et al., 2025). However, less focused has been given to AI with circular economy in existing literature (Agrawal et al., 2022; Huang et al., 2025). Recent studies encouraged to explore AI and CE by using bibliometric analysis technique to provide a clearer picture on it (Aivazidou et al., 2025; Neri et al., 2025). This shows lack of bibliometric review on nexus between AI and CE transition. By doing so, we address two notable research questions:

RQ1. What is the role of AI on CE transition?

RQ2. What are the future agendas on nexus between AI and CE?

2. Research Design

With the goal of consolidating and expanding our knowledge of how AI and circular economy, we deployed bibliometric review (Donthu et al., 2021). Scholars benefit by using bibliometric analysis in several ways. They can use it to find trends in the success of journals and papers, patterns in their partnerships, and trends in the research (Verma and Gustafsson, 2020). With the help of VoSviewer, the authors ran the data for analysis (Wong, 2018). We applied PRISMA by selecting our sample size for bibliometric review.

2.1 Data and Sample

We used Web of Science (WoS) database for selecting the peer-reviewed articles. The WoS is well-known for its tough journal selection standards, which ensure reliable, peer- reviewed articles (Martín-Martín et al., 2021). Many review studies use the WoS as their sole data source, and it is a trustworthy tool for bibliometric reviews, this is particularly relevant for studies focused on significant and prominent studies (Falagas et al., 2008; Visser et al., 2021). After considering other databases such as Scopus and Google Scholar, we settled on WoS due to its extensive indexing period (dating back to 1900), constant indexing of high-quality academic sources, and standardized metadata—all of which are essential for generating reliable and repeatable results (Singh et al., 2021). Despite its size, Scopus has issues with irregular metadata, duplicate records, improper or incomplete retrieval, and incorrect or missing citations (Franceschini et al., 2016).

The inclusion criteria as follows: We searched keywords “artificial intelligence” AND “circular economy”. The data extraction from Web of Science on 10th June 2025. Authors used documents only in English language, and selected Journal articles and followed specific fields, Management, Business, Economics, Engineering Environmental. This research mainly focused on specific fields due to inclusion on business, management and technology. The Table 1 shows identification, screening and eligibility stages by following PRISM. This reflects quality selection criteria for our sample for getting better and comprehensive results and provide rigor methodologically.

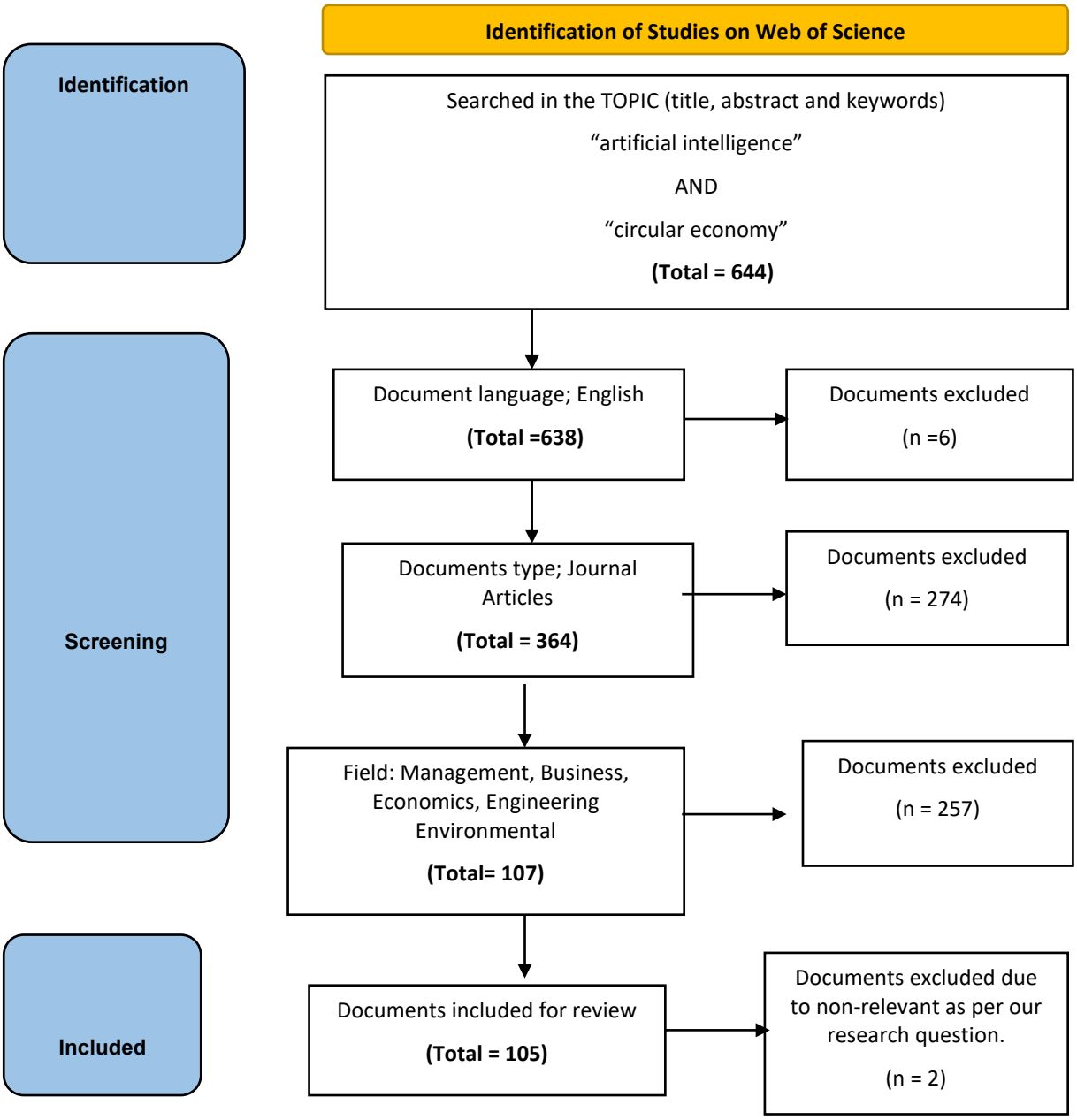

Figure 1: PRISMA adapted from Page et al., (2021)

3. Results

Recent years have seen a rise in the use of survey and case study approaches to discuss AI and the circular economy. Scholars are also doing literature reviews, meta-analyses, and bibliometric reviews to learn more about this new occurrence. The number of papers included in the study's analysis increased over time, as seen in Figure 1. Our sampling begins with an article published in 2019. Papers published up until 2024 are included in our analysis starting from that year. These publications were the most recent ones available when the manuscript was written. Publications grow from 2020 to 2021 as a result of increased digital transformation among businesses. On the flip side, 2023 has a smaller drop with 23 publications. Next year, in 2024, there will be 19 publications.

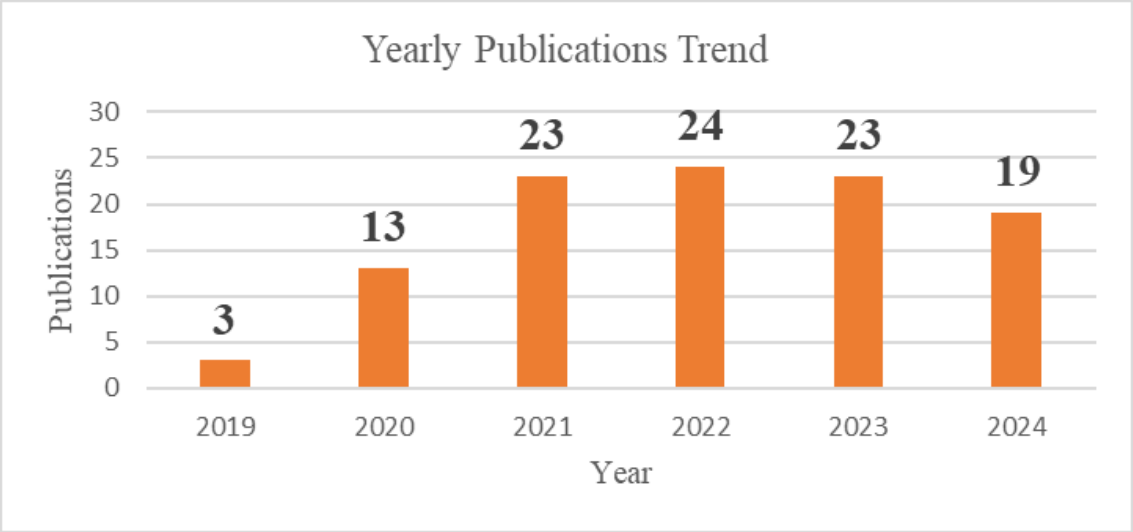

Figure 1: Yearly Publications on AI and CE (Source: Web of Science)

The Journal performance is shown in Figure 2. The sustainability journal is the leading publisher with 18 papers published by writers. Next up is the Journal of Cleaner Production, which features six papers. Therefore, Energy with five articles. Four articles were also published by the authors in the Process Journal and the Applied Sciences Basel. Lastly, the writers' publications may be found in Electronics, the Annals of Operations Research, and Business Strategy and Environment.

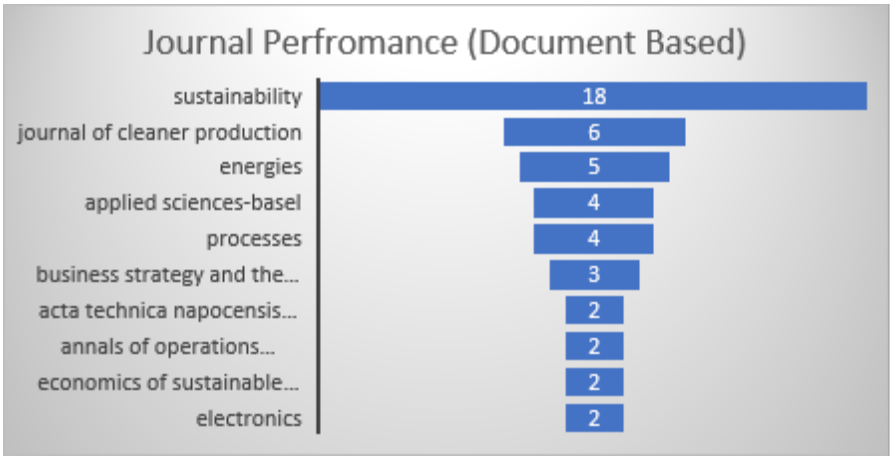

Figure 2: Journal Performance Document Based (Authors' own)

The citation count is a measure of a journal's impact, as seen in Figure 3. The following journals have contributed to this body of work: The Journal of Cleaner Production (508 citations), Journal of Business Research (311 citations), Sustainability (261 citations), Waste management (235 citations), Business Strategy and Environment (176 citations), International Journal of Manpower (144 citations), Processes (130 citations), Transportation Research Part e-logistics and Transportation Review (123 citations), Computers in Industry (122 citations), and Production Planning Figure 3 shows that the top five journals receive a lot of citations.

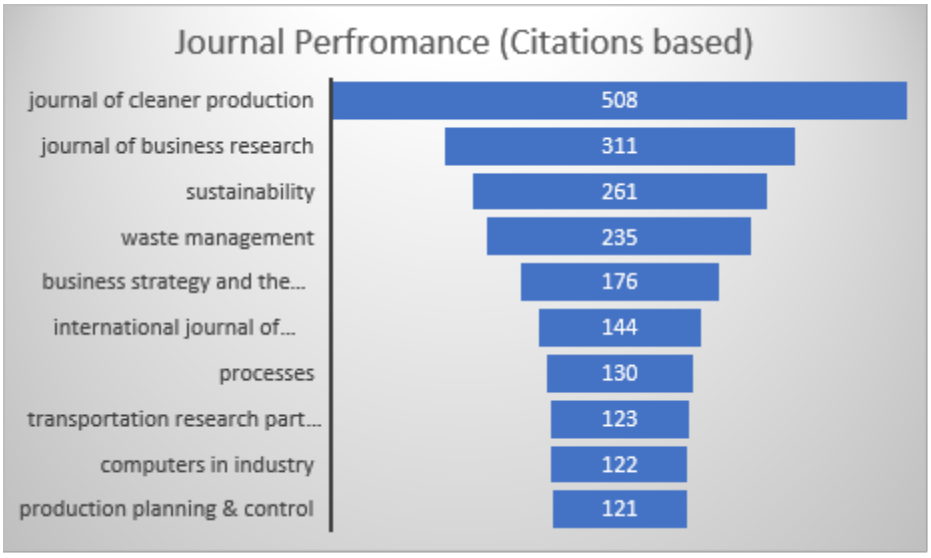

Figure 3: Journal Performance Citations Based (Authors' own)

Figure 4 shows authors conducted research on AI with CE in the Poland with 27 studies. The second most active country is Germany for adopting AI technologies and transformation towards circularity with 26 studies. The third country is Austria which is also quite concern for climate change issues rising from linear economy so they are also transforming to circular economy with 12 studies. The fourth country is Italy as it is also famous for "circular fashion" for using AI technologies into textile and fashion firms with 11 studies. This goup of countires are considered as a Leaders of circular economy and AI technologies. This shows these four countries is implementing Circualr Economy Action Plan and Net-Zero Industry Act quickly and rapidly for achieving their goals towards sustainable future.

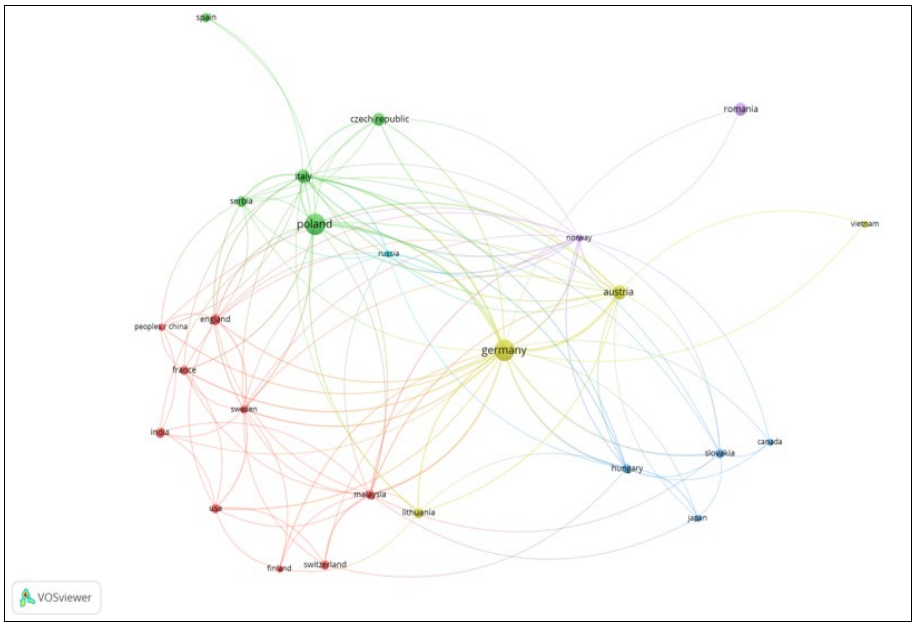

Figure 4: Country scientific production (Source: VOSviewer)

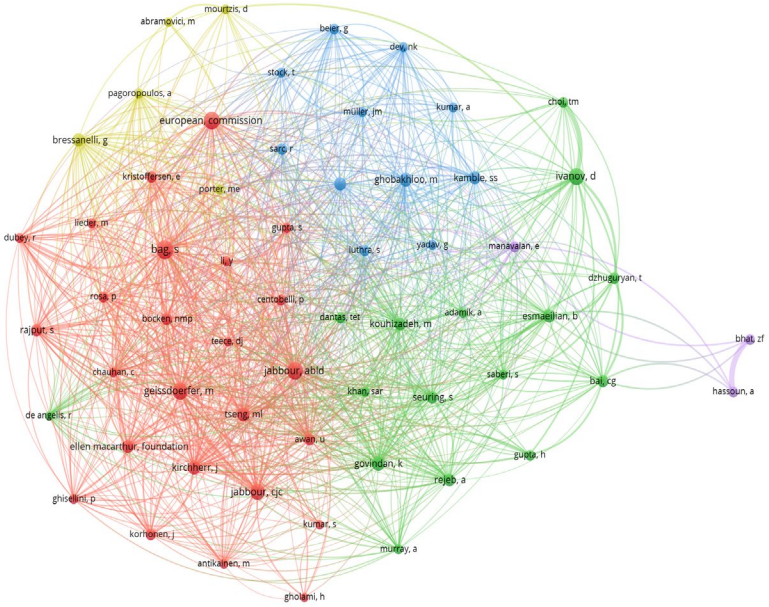

Figure 5: Co-Occurrence Networks Authors (Source: VOSviewer)

This network emphasized key research themes and their interrelations within the domains of AI and CE. The co-occurrence network reveals four main thematic clusters (Figure. 4). The red cluster centers on *circular economy on sustainable business management* which are strongly interconnected with circular economy, sustainability, management, strategies, blockchain, logistics, optimization, reverse logistics, and supply chain. The green cluster focuses on *Leveraging big data models to enhance CE outcomes* which are highly interlinked on bigdata, model, performance, opportunities, innovation, digital transformation, efficiency, and digitization. The blue cluster focuses on *Impact of IR4.0 and digital technologies on the Future of Circular Economy*, which strongly linked to industry 4.0, design, impact, future, smart, internet of things, systems, bigdata analytics. The yellow cluster focuses on *Digitalized Sup-ply chains, A way to foster CE and Sustainable development* which strongly related with supply chain management, sustainable development, digitalization, models, energy efficiency.

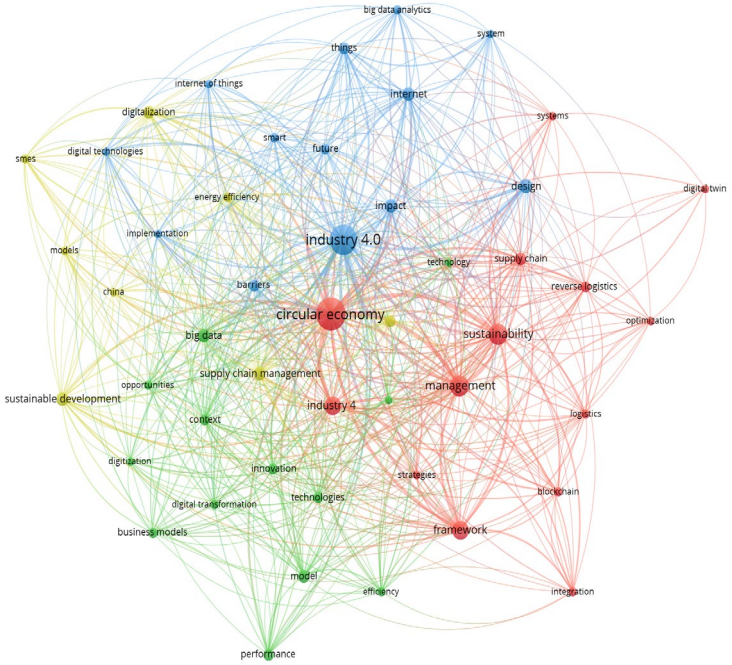

Figure 6: Co-Occurrence network (Source: VOSviewer)

4. Discussions and Implications

4.1 Thematic Analysis

Cluster 1: Circular Economy a pathway towards sustainable business management

The critical importance of sustainable business management is compelling individuals across all industries to adopt sustainability practices for circularity (Kumar and Saravanan, 2019). Recent years scholars realized transformation from linear to circular is an important for sustainable business management to address grand challenges such as climate change and rising temperatures (Agyemang et al., 2025). Notably, researchers have extensively examined how organisations might evolve towards enhanced sustainability; nonetheless, it is only recently that they have started to explore a fundamentally novel approach in sustainability discourse: the circular economy paradigm (Graessler et al., 2024). This reflects sustainable business management is only possible to transform linear to circular business model due to protect the planet for a sustainable future.

Cluster 2: Leveraging big data models to enhance CE outcomes

The circular economy relies on big data for mitigating resource constraints (Modgil et al., 2021). Various ecosystems, from transportation to smart cities, can benefit from big data produced by various platforms in their real-time management of waste, energy, and pollution (Dubey et al., 2019), as a result, big data can make it easier to examine multiple perspectives in order to quickly come to a consensus. The tremendous promise of big data to address business challenges and pave the way for new opportunities has garnered a lot of interest from the business community in the past decade (Raut et al., 2019). This warranted big data is driving circularity in industries, cities and as a whole in society.

Cluster 3: Impact of IR4.0 on the Future of Circular Economy

The industry 4.0 technologies refers to artificial intelligence, internet of things, virtual reality and digital twin. The first IR4.0 technology; AI has advantages in speed, intelligence, and scalability. It turns information into understanding. In doing so, it transforms impersonal procedures into dynamic, tailored workflows. The second technology is internet of things (IoT); the sensors installed in factory machinery can communicate with other web-enabled equipment thanks to their unique IP addresses. The ability to gather, analyse, and share vast amounts of important data is made possible by this network of interconnected machines on smart factories (IBM, 2025). The third technology is digital twin: an item, person, system, or process can have a digital twin if it is digitally replicated and placed in a digital representation of its actual physical surroundings. Some of the benefits by using digital twin: simplified planning and design procedures, scenario modelling, operational optimization, cost reduction, and the integration of industrial and physical AI into buildings (NVIDIA, 2025). This shows industry 4.0 technologies can be good for circular economy and sustainable future.

Cluster 4: Digitalized Supply chains, A way to foster CE and Sustainable development

Digital supply chain refers to the interconnected web of businesses, processes, and tools that use digital technology to manufacture and ship goods and services to consumers (Garay-Rondero et al., 2020). For businesses to make the transition from a linear to a circular economy, companies may have to reevaluate and restructuring their approaches to creativity, cooperation, and business models. The whole value chain is affected by this change, not just internal processes (Hofmann and Jaeger-Erben, 2020). The main goal is to reduce wastage by designing better products, systems, materials, and business models; this will be achieved by optimizing the use of resources and closing loops across value chains (Kirchherr et al., 2017). This shows digital supply chains playing their crucial role in sustainable development for circular economy.

5. Conclusion

This review attempts to address notable shortcoming on under-researched phenomenon of AI and circular economy in existing literature. We analyzed 105 peer-reviewed journal articles by using Web of Science database. Authors conducted data analysis by using VoSviewer software. The results revealed an interesting insight such as *Cluster1: Circular Economy a pathway towards sustainable business management*. This cluster stressed upon sustainable business management is possible by implementing circular business models in the industries. The *Cluster 2: Leveraging big data models to enhance CE outcomes*. This cluster encouraged companies to adopt big data analytics by mitigating technological barriers and improve their decision-making capabilities by using big data models. The third *Cluster 3: Impact of IR4.0 and digital technologies on the Future of Circular Economy*. This cluster shows businesses are realizing the importance of industry 4.0 technologies such as AI, IoT, VR and digital twin and their potential benefits for transition towards circular economy by

considering these technologies as an opportunity rather than cost. The fourth *Cluster 4: Digitalized Supply chains, A way to foster CE and Sustainable development*. This cluster seems to be crucial as digital supply chains increase the profits of companies and improve the customer satisfaction by supplying products on timely-manner with the help of technologies. The main contribution of this review is to advances our understanding on emerging domains e.g. AI and circular economy in the existing literature due to less focus by prior scholars. Notably, another theoretical contribution of this review is to shift the focus to technological perspective within circular economy, diverging from traditional linear model based on economic views.

6. Limitations and Future Agenda

This review has few limitations. We selected single technology such as AI of Industry 4.0. Future scholars may explore several technologies of industry 4.0 such as IoT, VR, Additive Manufacturing, Digital Twin, AI as to see comprehensive reflection of these technologies for CE transition. We selected only journal articles. Future scholars may also use review articles, book chapters, early access and journal articles. We used single Web of Science database. While Web of Science is an extensive and trustworthy academic database, it might miss some publications that are relevant to the study. Future studies may use combination of databases e.g. Scopus, Web of Science, IEEE explore respectively. This review focused on CE transition. Hence, future researchers may examine CE ecosystem to get better understanding on how multi-stakeholders' expectations and interests. This review selected selective period for data collection such as 2019 to 2025 due to ongoing digital and circular transformation. Future scholars may use data from 1990 to 2025 for comprehensive picture on this phenomenon. This review provides an important future research questions as a notable avenue for future scholars to highlight and contribute for scientific progress. Table 1 illustrates several notable shortcomings.

Table 1: Future Research Agenda

Clusters	Future Research Questions
Cluster 1*:* Circular Economy a pathway towards sustainable business management	*RQ1.* How businesses can redesign their linear models into circular for sustainable future? *RQ2.* What is role of Business, Management and Organizational Scholars in addressing climate change issues for circularity? *RQ3.* What is role of multi-stakeholders in achieving circular economy goals for sustainability?
Cluster 2*:* Leveraging big data models to enhance CE outcomes	*RQ1.* Does big data analytics contribute to CE transition in manufacturing and service industries? *RQ2.* How big data analytics achieve organizational performance by considering circularity goals? *RQ3.* How businesses can tackle technological barriers for fulfilling both economic and environmental goals?
Cluster 3*:* Impact of IR4.0 and digital technologies on the Future of Circular Economy	*RQ1.* How AI dynamic capabilities assists firms for circularity and sustainability? *RQ2.* What is role of internet of things technology for sustainable manufacturing? *RQ3.* How virtual reality helps businesses into their training programs, health and safety for transformation towards CE? *RQ4.* Does digital twin contribute in adopting circular business model for sustainable future CE? *RQ5.* How AI changes the future of work in large companies? *RQ6.* Does AI provide potential benefits of future of circular economy?
Cluster 4*:* Digitalized Supply chains, A way to foster CE and Sustainable development	*RQ1.* How digital supply chains improve firm's circularity for sustainable development? *RQ2.* What is role of CE and sustainable development? *RQ3.* How stakeholders respond adopting digital supply chains in business environment? *RQ4.* Do digital supply chains seem to be challenge or opportunity for companies? *RQ5.* How regulatory bodies deal with firm while implementing digital

Clusters	Future Research Questions
	supply chains? *RQ6.* Do digital supply chains create new ecosystem for multistakeholders? *RQ7.* How digital supply chains enhance customer experience especially following sustainable development goals?

Acknowledgement

This research has received funding from the Research Council of Lithuania (LMTLT-Lietuvos Mokslo Taryba), under the project number (no. P-PD-24-075), "Linking Industry 4.0 to Circular Economy Ecosystem in Central and Eastern Europe". Authors are grateful to Vilnius Gediminas Technical University, Vilnius, Lithuania and Alexander Dubcek University in Trencin, Slovakia for their kind support.

Funding: This research was funded by Research Council of Lithuania (LMTLT-Lietuvos Mokslo Taryba), under the project number (no. P-PD-24-075), "Linking Industry 4.0 to Circular Economy Ecosystem in Central and Eastern Europe".

Ethics Declaration: Ethical clearance was not required for the research because this research was based on review method so authors used secondary data accessed from Web of Science Database.

AI Declaration: Authors declare here they have not used AI tool, technologies or softwares for development of this paper.

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How GenAI Use Cases Emerge and Evolve in Organizations: Analysis of a Case Study

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Abstract: The present study investigates how Generative Artificial Intelligence (GenAI) use cases emerge and evolve within organisational settings, challenging dominant "blueprint" perspectives that assume static implementation pathways. While Generative AI offers transformative potential by generating novel content and workflows, research often overlooks the dynamic, socio-technical processes through which its value is realised in practice. Addressing this gap, we conduct a longitudinal case study analysing 18 months of GenAI implementation within the pre-sales processes of a manufacturing firm. Our analysis reveals that GenAI use cases evolve dynamically across two key dimensions: process formalisation (structured vs. emergent) and user type (internal vs. external). Findings indicate use cases emerge organically through user interaction, organizational learning, and strategic imagination, progressing through four distinct phases. This evolution is enabled by specific conditions, including organisational legitimacy, technological flexibility, reflexivity, experimentation, and strategic foresight. The study develops a dynamic framework mapping this use case emergence, identifying key patterns and enabling conditions. Theoretically, this research contributes by shifting focus from static GenAI adoption models to dynamic, path-dependent processes, extending affordance theory through "evolutionary affordances," and deepening understanding of value co-creation and co-destruction dynamics over time. Practically, the framework assists organizations in managing GenAI adoption as an emergent process, guiding capability development and investment strategies for expanding GenAI applications across diverse organizational contexts.

Keywords: Generative AI, Use case evolution, Organizational implementation, Socio-technical systems, Value co-creation

1. Introduction

Generative Artificial Intelligence (GenAI) has emerged as a transformative technology with potential to reshape organizational processes and individual capabilities, driving value creation across diverse sectors. Unlike traditional AI, which excels in analysing predefined data for prediction and classification, GenAI's adaptive nature enables it to generate novel content, solutions, and workflows across organizational contexts (Alavi et al, 2025; Brynjolfsson et al., 2023; Kuss and Meske, 2025). This generative capability creates a unique socio-technical dynamic: as users interact with GenAI, they discover new applications and possibilities that were not initially envisioned, leading to continuous emergence of novel use cases (Möllers, 2025). For organizations, this presents both unprecedented opportunities for value creation and challenges in managing AI adoption strategically (Benbya et al., 2024; Sviokla, 2024).

The extant literature on Artificial Intelligence has predominantly adopted a "blueprint approach," where researchers identify specific use cases and their associated benefits to provide prescriptive guidance for practitioners (Berente et al., 2021; Lacity and Willcocks, 2016). These studies often focus on predefined applications in specific domains, such as manufacturing, healthcare, or software development (Bruhin, 2024; Dakhel et al., 2023; Gupta et al., 2021). Research has explored AI role in specific organizational contexts, examining its contributions to outcomes like operational efficiency, decision-making, or innovation (Brynjolfsson and McAfee, 2016; Shollo et al., 2022). While these studies offer valuable insights, they often assume static or linear adoption pathways, overlooking GenAI's socio-technical nature, which allows users to iteratively design and deploy new applications as they engage with the technology. These emergent dynamics, where use cases continuously evolve through sustained user-technology interaction rather than following predetermined paths, remain underexplored in the literature (Abhari et al., 2025; Möllers, 2025), limiting organizations' ability to fully harness GenAI's generative potential.

To address this gap, our study poses the following research question: *How do GenAI use cases emerge and evolve during organizational implementation*? We explore this question through an in-depth longitudinal case study of a manufacturing firm specialising in sterilisation machinery, where we observed GenAI implementation in pre-sales processes over 18 months. Our analysis reveals that organizational processes exhibit varying degrees of structure and that GenAI applications target different user groups, creating distinct patterns of value creation and evolution. This complexity requires decomposing processes to understand where and how different types of GenAI value creation occur, leading us to develop a framework that maps use case emergence across process formalisation and user targets.

This study offers theoretical and practical contributions to GenAI adoption literature. Theoretically, it advances understanding of GenAI socio-technical dynamics by proposing a framework to model the iterative emergence of use cases. Unlike static blueprint approaches, our framework emphasises the evolutionary nature of GenAI adoption, extending theories of value co-creation and co-destruction (Echeverri and Skålén, 2011) and contributing to affordance theory (Markus and Silver, 2008) by illustrating how GenAI's generative capabilities shape and are shaped by user interactions, offering insights into the mechanisms of use case evolution and enabling conditions that facilitate transitions between application types. From a practical perspective, the framework provides organizations with a structured approach to manage, rather than predetermine, GenAI use case emergence by recognising that successful implementation requires understanding the hybrid nature of organizational processes and sequential development of applications across user groups.

The paper is organized as follows. Section 2 reviews the literature on GenAI and identifies the gap in understanding how GenAI use cases emerge during human-AI interaction. The theoretical framework for mapping these use cases is presented. Section 3 outlines the methodology used to address our research question. Section 4 presents the results of our analysis and maps the emergence of GenAI use cases using the proposed framework. The final section discusses our results in the context of GenAI literature and explores their implications for organizations.

2. Literature Review and Theoretical Framework

The literature on Generative AI in organizations has rapidly expanded, documenting specific applications and benefits across diverse contexts (Brynjolfsson et al., 2023; Shollo et al., 2022). However, it often lacks a deep understanding of how GenAI use cases emerge and evolve through ongoing user-technology interaction within organizational settings (Benbya et al., 2024; 2011; Bruhin et al., 2025; Möllers, 2025; Walenta et al., 2025).

Much of the existing research adopts what we term a "blueprint" approach (Berente et al., 2021; Lacity and Willcocks, 2016). This perspective focuses on identifying predefined GenAI use cases, such as automation in manufacturing or coding assistance in software development, and prescribing their implementation, often assuming static pathways and predetermined outcomes (Bruhin et al., 2025; Dakhel et al., 2023; Mehlet et al., 2024; Negi et al., 2025; Walenta et al., 2025). While valuable, this approach has limitations for understanding GenAI's dynamic nature. It tends to overlook the generative paradigm shift GenAI represents, from deterministic automation of routine tasks (Brynjolfsson and McAfee, 2016) towards creating novel content and workflows. This shift enables users to iteratively discover and design new applications, leading to continuous use case emergence (Brynjolfsson et al., 2023), a process largely missed by static "blueprint" studies.

Furthermore, these approaches often neglect the dual dynamics of value co-creation and co-destruction inherent in GenAI adoption (Bruhin et al., 2025). While GenAI can enhance collaboration and outcomes (Dell'Acqua et al., 2023), it simultaneously poses risks such as skill erosion or over-reliance (Järvi et al., 2018). Additionally, organizational processes vary significantly, ranging from highly structured, rule-based routines to emergent, adaptive activities requiring human judgement and sensemaking (Mintzberg, 1979; Shollo et al., 2022). GenAI impact differs accordingly, supporting efficiency in structured work and augmentation/creativity in emergent work. Similarly, applications serve distinct user groups, internal uses often focus on operational efficiency, while external uses target customer experience or co-creation (Huang and Rust, 2021; Treacy and Wiersema, 1993). However, existing literature often treats these process and user dimensions separately, failing to capture how organizations might transition use cases from, for example, internal automation to external collaboration over time, or how capabilities developed in one context enable evolution into another.

This literature review reveals a gap in understanding GenAI adoption as a dynamic, path-dependent process where use cases emerge and evolve through organizational interaction. Existing research has only partially explored how GenAI transitions between automation and augmentation modes, how value co-creation/destruction dynamics evolve temporally, or the conditions under which early successes enable more ambitious applications. The blueprint orientation misses the interplay between GenAI's generative capabilities and organizational contexts driving continuous evolution. Table 1 summarises the key insights and limitations of the literature on GenAI use cases' emergence.

Table 1: Summary overview of key literature streams and limitations

Research stream	Key references	Key messages	Limitations for understanding GenAI use cases' emergence
AI evolution	Brynjolfsson et al. (2023); Berente et al. (2021); Dell'Acqua et al. (2023)	GenAI shifts from deterministic automation to generative paradigm; Creates socio-technical dynamics where users discover emergent applications	Focuses on capabilities rather than emergence processes; Limited exploration of organizational transition dynamics
Blueprint approach	Berente et al. (2021); Lacity and Willcocks (2016); Dakhel et al. (2023)	Domain-specific studies assume static implementation pathways; Focus on predefined applications with predetermined outcomes	Treats applications as fixed rather than evolutionary; Misses organizational learning and adaptation processes
Value co-creation/co-destruction	Echeverri and Skålén (2011); Bruhin et al. (2025); Järvi et al. (2018)	GenAI simultaneously enables value co-creation through collaboration and co-destruction through over-reliance; Dual impact spans operational excellence, product leadership, customer intimacy	Limited exploration of how dual dynamics evolve over time; Lacks frameworks for managing temporal interactions between enabling and constraining effects
Process and user types	Mintzberg (1979); Shollo et al. (2022); Huang and Rust (2021); Treacy and Wiersema (1993)	Structured vs. emergent processes require different GenAI approaches; Internal vs. external applications follow different value creation logics; Strategic value spans multiple disciplines	Examines process types and user domains separately; Limited understanding of transitions and cumulative capability building across contexts

To address these gaps, we propose an integrated theoretical framework that captures the dynamic, emergent nature of GenAI adoption. Building on value co-creation and co-destruction theory (Bruhin et al., 2025; Echeverri and Skålén, 2011), process theory (Mintzberg, 1979; Shollo et al., 2022), and strategic value perspectives (Treacy and Wiersema, 1993), our framework centres on two key dimensions

Process Formalisation differentiates between structured and emergent organizational processes, acknowledging that GenAI impact varies significantly depending on the nature of the work it supports. Structured processes align naturally with GenAI automation capabilities, while emergent processes benefit from its generative and augmentative potential (Abhari et al., 2025; Möllers, 2025).

User Type distinguishes between internal and external GenAI users, recognising that the value creation logic differs when GenAI supports internal operations versus external customer-facing applications.

Unlike existing approaches that position applications within static categories, our framework conceptualises these dimensions as dynamic spaces through which GenAI use cases can evolve. This evolutionary perspective recognises that GenAI implementations can transition between structured and emergent process support, and can extend from internal to external applications as organizations develop capabilities and experience.

3. Methodology

To investigate how use cases emerge during GenAI projects in organizations, this study adopts a longitudinal qualitative case study design (Langley, 1999; Yin, 2009). Case studies are particularly suitable for answering "how" research questions, allowing in-depth exploration of contemporary phenomena within real-life contexts (Yin, 2009). Given our goal to understand the socio-technical dynamics underpinning GenAI use case evolution, a case study enables detailed observation of contextual and temporal factors influencing these developments.

The research was conducted at SterTech, a medium-sized European manufacturing firm specialising in high-precision sterilisation machinery for healthcare and pharmaceutical sectors. Due to complexity and customisation required for each order, the company's pre-sales process is extensive and knowledge-intensive, often requiring analysis of large technical specifications submitted by clients. This pre-sales process constitutes our unit of analysis. SterTech recently initiated a GenAI project to enhance its pre-sales function, addressing inefficiencies in analysing customer requirements, preparing documentation, and coordinating cross-departmental inputs. Over time, the project evolved from structured task automation to emergent forms of human-AI collaboration, making SterTech an ideal site for investigating dynamic GenAI use case emergence.

Data collection occurred over 18 months (October 2023 to March 2025) through multiple engagement phases with GenAI initiative stakeholders. Semi-structured interviews were conducted with organizational actors

including sales managers, the head of pre-sales, the GenAI project manager, product manager, and IT department members, plus representatives from the GenAI supplier. Since the aim of the study was to capture the dynamics of use cases' emergence and evolution, some informants were interviewed more than once. For example, the Head of Pre-sales, who initiated the GenAI project, was interviewed at the outset of the project and in key moments when GenAI use cases were adopted. Similarly, the technology provider who accompanied the company through the transformation was interviewed twice. Additional data sources included internal presentations, process documentation, project meeting notes, and non-confidential digital artifacts generated during AI implementation. Table 2 summarises the interview participants, the period of the interviews, and the key contributions made to the study.

Table 2: Key informants of the study

Informant role	Interview period	Key input to the study
Sales manager (SterTech)	January 2024	Strategic vision, business needs, and expected benefits
Head of Pre-sales (SterTech)	October 2023 September 2024 March 2025	Workflow details, pre-sales bottlenecks, AI expectations
GenAI project manager (SterTech)	September 2024	Implementation approach, coordination with departments
Product manager (SterTech)	October 2024	Integration with existing tools, feedback loops
IT manager (SterTech)	December 2024	Technical constraints, system integration
GenAI project manager (supplier)	March 2024 February 2025	Delivery approach, customization logic
GenAI technical specialist (supplier)	December 2024	System architecture, model fine-tuning, feedback adaptation process

The analysis of qualitative data followed an iterative approach, moving between theory and data in different cycles. This process involved coding the data and then analysing it to derive patterns. The coding combined deductive, inductive, and abductive strategies to capture both theoretically informed insights and emergent patterns from the data.

Deductive, inductive, and abductive coding contributed to a deeper understanding of the dynamics of GenAI use case emergence. Deductive coding was informed by prior literature on AI in organizations and established theoretical frameworks, including automation versus augmentation (Raisch and Krakowski, 2021) and value co-creation versus co-destruction (Echeverri and Skålén, 2011). For example, the code "efficiency improvement" captured instances where GenAI reduced task completion time. Inductive coding identified patterns and themes that emerged directly from the data, revealing organizational dynamics not anticipated by existing theory. For instance, the code "credibility building" described how early GenAI successes established organizational trust. Abductive coding involved theoretical reasoning where unexpected patterns prompted refinement and new conceptual categories. The code "emergent use case discovery" was developed when interview data revealed that users continuously identified new GenAI applications through sustained engagement, a phenomenon not fully captured by existing adoption models.

The coding process was iterative, with multiple passes through the data to refine and integrate the three approaches. For example, the deductive code "efficiency improvement" was enriched by the inductive code "task complexity variation," leading to the insight that GenAI's impact follows different patterns across structured versus emergent processes, contributing to the development of the process-type dimension in the theoretical framework.

Triangulation strategies enhanced validity and reliability of findings. Source triangulation was achieved by collecting data from diverse organizational roles and external GenAI suppliers, enabling verification across different viewpoints. Data triangulation involved comparing interview insights with documentary evidence. For instance, efficiency improvements claimed by personnel were verified against internal process reports documenting measurable changes in task completion times and resource allocation. Methodological triangulation combined formal interviews, document analysis, and observation of digital artefacts, providing complementary perspectives where quantitative metrics supported qualitative insights.

The longitudinal design (Langley, 1999) was essential to capture the dynamics of use case emergence. By conducting interviews and observations at different stages, we were able to follow how new use cases were proposed, which mechanisms enabled their realisation, and how each use case built on the conditions created by earlier ones. For example, the use of GenAI to facilitate cross-departmental discussions was made possible by the experience gained from the initial application in customer requirements analysis. Similarly, the solid technological foundation established in the early stages, together with growing awareness of GenAI's potential, enabled the subsequent design of new customer-facing services.

4. Findings: The Evolution of GenAI use Cases

Our analysis reveals that GenAI use cases at SterTech evolved through four distinct phases, each corresponding to a specific quadrant in our framework. Rather than following a predetermined implementation plan, use cases emerged organically through user interaction, organizational learning, and strategic imagination. This evolutionary trajectory shows three critical patterns: (1) transition from structured to emergent processes driven by deepening human-AI interaction, (2) expansion from internal to external applications enabled by strategic foresight, and (3) cumulative capability building where each phase creates foundations for subsequent development. This section traces this evolutionary path and identifies the enabling conditions that drove transitions between phases.

4.1 Phase 1: Automating Structured Internal Processes

SterTech faced significant efficiency challenges in their pre-sales process, where analysis of customer requirement documents, often exceeding hundreds of pages of technical specifications, required manual review by sales and technical teams. This time-intensive process could take several days, with teams sometimes discovering deal-breaking requirements only in final stages.

To address this challenge, SterTech implemented GenAI to automate document parsing and analysis. The system was trained to extract key technical requirements, identify potential compliance issues, and flag non-viable opportunities early in the bidding process. This application represented direct substitution of manual labor with automated analysis, focusing on clearly defined, routine tasks within the Internal Users-Structured Processes quadrant (Table 3).

The primary benefit was operational efficiency, with dramatic reductions in analysis time and earlier identification of problematic requirements. As the pre-sales manager explained: *"Before, we could spend three or four days analysing a bid only to find out in the last paragraph that there's a requirement we can't meet. Now, with GenAI, this process is dramatically faster, and we can filter out non-viable opportunities much earlier."*

This phase was enabled by two critical organizational conditions. First, clear efficiency gains provided immediate organizational legitimacy for the GenAI initiative, demonstrating tangible value and securing stakeholder support. Second, technological flexibility of the modular GenAI architecture allowed for rapid training and integration with existing document formats, enabling swift implementation without major system disruptions.

4.2 Phase 2: Augmenting Emergent Internal Processes

As internal users became comfortable with the GenAI tool, they recognised opportunities beyond its original automation purpose. The organization needed better coordination and knowledge sharing between departments during the bidding process, particularly among engineering, sales, and compliance teams who often worked in silos.

Building on Phase 1 foundations, employees began experimenting with GenAI-generated summaries and classifications to facilitate cross-departmental discussions and strategic decision-making. Rather than simply processing inputs, the tool evolved to support collaborative sensemaking, helping teams interpret complex requirements together and develop sophisticated bid strategies.

A product manager captured this evolution: *"It's not just that the AI gives us answers; it's that it stimulates questions we wouldn't have thought to ask. It pushes us to rethink our assumptions."* The IT manager noted: *"We initially thought of GenAI as a tool to extract data. But now, it's become a shared space, a kind of knowledge hub where different departments can find common ground and speak the same language."*

Benefits extended beyond efficiency to include enhanced cross-functional communication, creativity in solution design, and emergence of new collaborative practices around bid management, positioning this use case within the Internal Users-Emergent Processes quadrant (Table 3).

Three interconnected dynamics drove this transformation. User experimentation enabled employees to actively explore applications beyond the tool's intended purpose. Sociotechnical alignment emerged as GenAI became integrated into interdepartmental communication. Organizational learning and reflexivity prompted teams to question established practices in response to AI-generated insights.

4.3 Phase 3: Envisioning Structured External Applications

Encouraged by internal success, SterTech leadership began envisioning how GenAI could address external challenges, particularly in early customer interaction stages. The organization needed to improve quality and structure of information received from potential customers, as poorly defined requirements often led to inefficient communications and suboptimal proposals.

Building on internal capabilities, SterTech planned customer-facing applications to help clients structure and articulate needs more effectively. The proposed solution involved intelligent portals where customers could upload specifications and receive immediate feedback on feasibility and fit with SterTech's capabilities, potentially including guided forms or chatbot interfaces.

A sales manager described the vision: *"We're thinking about a portal where clients can upload their specifications, and GenAI gives them feedback on whether we're a good match. That would save both sides a lot of time."* The business manager added: *"If we can guide the client toward better-structured input from the beginning, we reduce the back-and-forth and improve the quality of the bid."*

Anticipated benefits include service scalability, improved customer onboarding experiences, and higher conversion rates through better initial requirement matching, corresponding to the External Users-Structured Processes quadrant (Table 3).

Strategic imagination allowed internal actors to project their positive GenAI experiences into customer-facing domains, envisioning how internal success could translate to external value creation. Technological flexibility of the existing GenAI platform supported these ambitions by enabling relatively straightforward adaptation to external interfaces.

4.4 Phase 4: Imagining Emergent External Co-Creation

The phase observed in the case emerged from recognising that customer relationships could be fundamentally transformed through GenAI. Rather than simply meeting predefined customer requirements, SterTech began envisioning collaborative innovation processes where they could work jointly with clients to shape and refine specifications in real-time.

This vision addressed a deeper organizational challenge: traditional arm's-length customer relationships often limited innovation opportunities and resulted in suboptimal solutions that met stated requirements but missed underlying needs. SterTech aimed to create dynamic, partnership-oriented relationships driving mutual innovation.

The envisioned application involves GenAI-facilitated collaborative platforms supporting joint design sessions, iterative feedback loops, and interactive specification refinement between SterTech and hospital clients. The AI would capture and learn from past projects to offer design suggestions anticipating customer constraints and goals.

The GenAI supplier's consultant explained the potential: *"We see a lot of potential in using GenAI to bridge the customer-manufacturer gap. If we can capture and learn from past bids, we can start offering design suggestions that anticipate the customer's constraints."* The sales director reflected: *"This could change the way we interact with hospitals. It's not just about meeting requirements, but about jointly shaping them."*

Anticipated benefits include deeper customer intimacy, faster alignment on technical feasibility, and potential to create more tailored and innovative solutions through collaborative design processes, mapping to the External Users-Emergent Processes quadrant (Table 3).

This vision was enabled by accumulation of learning and confidence from previous phases. Strategic imagination reached fullest expression as leadership conceptualised customers as co-design partners rather than simply requirements providers. The culture of reflexivity and learning developed through earlier

experimentation created openness to redefining traditional organizational roles and customer relationships. Growing sociotechnical adaptability demonstrated organizational willingness to explore new engagement forms blurring boundaries between internal and external innovation processes. The following Table 3 summarises the GenAI Use Cases developed in the company, their positioning in the study Framework, their benefits, and enabling conditions.

Table 3: Positioning of the Gen AI use cases in the study framework

Users (Internal vs External)	**External users - Structured processes**	**External users - Emergent processes**
	- Application: Customer interaction tool - Benefits:Scalability and better onboarding - Enabling conditions: Strategic imagination; GenAI platform adaptability	- Application: Co-creation platforms - Benefits: Customer intimacy and agility - Enabling conditions: Strategic vision; reflexivity; sociotechnical reconfiguration
	Internal users - Structureded processes	**Internal users - Emergent processes**
	- Application: Requirement parsing - Benefits: Efficiency and reduced time-to-bid - Enabling conditions: Organizational legitimacy; technological flexibility	- Application: Collaboration platform - Benefits: Cross-functional collaboration; innovation and insight - Enabling conditions: User experimentation; sociotechnical alignment; organizational learning
	Processes (Structured vs Emergent)	

4.5 Evolutionary Patterns and Enabling Conditions

Our analysis reveals three critical patterns governing GenAI use case emergence at SterTech, demonstrating how organizations can manage GenAI evolution by understanding enabling conditions.

Pattern 1: Structured to emergent transition is characterised by deepening human-AI interaction and increasing interpretive complexity. As users move beyond executing predefined tasks, they begin questioning underlying assumptions through reflexivity and organizational learning. User experimentation serves as the primary mechanism for expanding GenAI functionality, while sociotechnical alignment enables tool evolution from isolated automation asset to shared collaboration platform. This trajectory represents a fundamental shift from efficiency logic toward innovation logic.

Pattern 2: Internal to external expansion is driven by strategic foresight and infrastructural capabilities. Strategic imagination enables organizational actors to envision broader applications by building on internal success stories and projecting learned capabilities into customer-facing domains. Technological flexibility supports these ambitions by allowing scalable adaptations without fundamental architectural changes. As applications extend to external stakeholders, trust-building and role redefinition become essential.

Pattern 3: Cumulative capability building follows a path-dependent sequence where each phase creates cognitive and infrastructural foundations for subsequent phases. Early efficiency gains establish organizational legitimacy, providing permission for experimentation and learning. This experimentation generates reflexivity about organizational processes and capabilities, seeding strategic imagination about future applications. Strategic imagination ultimately enables envisioning transformational applications that redefine customer relationships and organizational boundaries. The following Table 4 summarises the enabling conditions in the three identified patterns.

Table 4: Patterns and enabling conditions

Transition patterns	**Key enabling conditions**
Structured → Emergent processes	Reflexivity, experimentation, sociotechnical alignment
Internal → External users	Strategic imagination, technological flexibility, trust-building
Across all phases	Accumulation of legitimacy and learning enabling progression

This evolutionary trajectory shows that successful GenAI adoption differs from traditional technology implementation. Rather than following predetermined plans, effective GenAI adoption requires creating organizational conditions that enable use cases to emerge and evolve through sustained human-AI interaction.

5. Discussion and Conclusion

This study explored the emergence and evolution of generative AI use cases within organizations, moving beyond static "blueprint" models toward a dynamic understanding of socio-technical processes. Through a longitudinal case study of SterTech's pre-sales implementation, we analysed GenAI evolution across process formalisation (structured versus emergent) and user type (internal versus external) dimensions. Our findings reveal systematic progression from internal structured automation to emergent internal collaboration, eventually expanding to structured and emergent external applications. These transitions were facilitated by specific socio-technical conditions including organizational legitimacy, technological flexibility, reflexivity, experimentation, strategic imagination, and trust-building. Our study contributes two key insights to theory and one significant insight to practice.

5.1 Contributions to Theory

First, we enhance existing GenAI adoption research by transitioning from static blueprint perspectives to dynamic views of adoption as emergent, path-dependent processes. While previous studies assume AI applications are designed upfront to meet predefined objectives (Berente et al., 2021; Gupta et al., 2021), our findings demonstrate that use cases emerge iteratively through sustained user-technology interaction, organizational learning, and context-specific adaptation. This reinforces socio-technical perspectives (Markus and Silver, 2008) and value co-creation theories (Echeverri and Skålén, 2011) by showing how GenAI's generative nature influences both task execution and organizational meaning-making over time. SterTech's trajectory from efficiency-driven document automation to cross-functional collaboration platforms illustrates how organizations "discover" applications through experience, emphasising adoption as a journey of unfolding opportunities rather than discrete implementation decisions.

Our framework extends affordance theory (Markus and Silver, 2008) by revealing how GenAI affordances evolve through sequential realisation phases. Early affordance actualisation creates conditions enabling perception and realisation of more sophisticated affordances. In our study “evolutionary affordances" are possibilities that arise only after prior affordances have been actualised and integrated into organizational practice. SterTech's efficiency affordances in document automation established legitimacy enabling collaboration affordances, which inspired strategic imagination for customer-facing applications. This perspective indicates that managing GenAI requires fostering conditions for affordance evolution rather than merely implementing predetermined affordances.

Second, we deepen theoretical understanding of patterns and conditions governing GenAI evolution. Our framework identifies systematic transitions, from structured to emergent processes and internal to external users, and theorises enabling conditions facilitating these shifts. Structured-to-emergent trajectories are driven by reflexivity, experimentation, and socio-technical alignment, while internal-to-external trajectories require strategic imagination, technological flexibility, and trust-building mechanisms. This advances socio-technical theories (Raisch and Krakowski, 2021) by specifying organizational capabilities and contextual factors needed for different evolutionary pathways. These conditions develop cumulatively: organizational legitimacy and early wins in structured internal applications create foundations for experimentation and visioning, subsequently enabling external-facing applications. This theorisation offers a novel lens for understanding GenAI adoption as staged, path-dependent processes building organizational capabilities over time.

5.2 Contributions to Practice

We propose a process-user framework enabling organizations to manage GenAI use case emergence rather than predetermining applications. By situating applications within four-quadrant matrices and identifying enabling conditions, managers can anticipate capabilities and investments required for expansion across quadrants. Transitioning from internal automation to external co-creation necessitates investments in relationship-building and adaptive technology design, while internal innovation transitions require fostering experimentation, psychological safety, and cross-departmental knowledge sharing. The framework encourages strategic sequencing: initiating with structured internal applications establishes legitimacy and user familiarity, creating foundations for ambitious collaborative applications.

SterTech's journey exemplifies this sequential development. Early efficiency gains generated organizational momentum and technology trust, encouraging employees to propose novel applications and adapt tools for creative tasks. This highlights viewing GenAI adoption as dynamic portfolios of evolving applications rather than isolated projects. Organizations should cultivate reflexive infrastructures, routines encouraging questioning and rethinking of applications, and design flexible technical architectures reconfigurable for new

user groups and process types. This shifts managerial focus from fixed implementation plans to adaptive, learning-oriented strategies for realising GenAI's evolving potential.

5.3 Limitations and Directions for Future Research

This study has several limitations suggesting future research directions. First, findings are based on a single longitudinal case study within one manufacturing organization, limiting generalisability across industries and contexts. While rich qualitative insights offer depth and theoretical development, additional comparative cases are needed to validate and refine the proposed framework. Second, focusing on pre-sales processes means dynamics in other functional areas remain unexplored, potentially limiting understanding of framework applicability across different process types. Third, the study primarily captures internal stakeholder and AI supplier perspectives; incorporating external user viewpoints would provide fuller understanding of external-facing transitions and co-creation dynamics.

Future research should address these limitations through multi-case comparative studies across industries and organizational sizes to validate framework generalisability and identify boundary conditions. Process-focused investigations examining GenAI adoption in diverse functional areas would enhance understanding of how process characteristics influence use case emergence. Mixed-method approaches combining qualitative insights with quantitative performance measures could assess both experiential and outcome dimensions. Finally, longitudinal studies incorporating external user perspectives would provide comprehensive understanding of co-creation dynamics and external value generation in GenAI implementations.

Ethics declaration: Ethical clearance was not required for the research.

AI declaration: AI tools were not used for the creation of the paper.

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Generative AI Competencies: Framework and Maturity Model for Users in Their Work Settings

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Abstract: The increasing use of generative artificial intelligence (GenAI) is changing work processes in companies and requires new competencies from employees. While existing competency models primarily focus on general AI, they do not sufficiently account for the unique features of generative systems. The aim of this article is therefore to develop a specific AI competency framework and maturity model for the successful and reflective use of GenAI in a corporate context. Based on a design science approach, relevant skills were tested for their transferability, supplemented with GenAI-specific competencies, and operationalized along defined maturity levels. A consultation with experts was conducted to evaluate the model. The result encompasses three competency areas – digital/technological, social, and cognitive competencies – with a total of 18 individual competencies, mapped to three maturity levels of GenAI use in companies. The model supports researchers and practitioners alike in systematically assessing competency levels within companies, identifying potential areas for improvement, and developing targeted strategies for competency development.

Keywords: Generative AI, GenAI literacy, GenAI skills, GenAI competency framework, GenAI maturity model

1. Introduction

Generative AI (GenAI) currently requires companies to make future-oriented adjustments at all levels of corporate management. Whether in terms of business models, operating models, tasks, or processes, machine-supported systems that operate autonomously to varying degrees, can adapt to their environment, and are thus able to generate predictions, content, recommendations, or decisions and influence their working environment (BITKOM, 2024) are currently demonstrating their eruptive potential more and more clearly. According to McKinsey, GenAI has a value potential of US$6.1–7.9 trillion, achieved through new use cases and different ways of working, as well as associated productivity gains among employees (Chui et al, 2023).

This is already having noticeable consequences: GenAI is increasingly becoming an integrated tool that is changing the nature of work. Studies estimate that GenAI could replace up to 27% of the hours worked in companies; the proportion of replaceable working hours is particularly high in administrative jobs, which are often dominated by standardized routines (Hazan et al, 2024). Changes are emerging not only in the type of tasks but also in how tasks are performed: collaboration is becoming more agile, tasks are becoming more self-organized, and work settings are becoming more hybrid. This requires employees to develop new skill sets to perform effectively in a changing work environment. These skill sets include AI literacy, but above all, skills that help employees navigate the changing corporate landscape, such as social and emotional skills, cognitive skills like analytical thinking, and project management, which also play significant roles (Hazan et al, 2024).

The use of GenAI has not only triggered these changes but also has an impact on how they are managed. Specifically, this means that the use of GenAI in a business context not only requires collaboration based on the principles of agile project management techniques, for example, but also that this AI-induced agile collaboration is shaped by the options offered by AI applications in practice. This idea of the dual impact of GenAI on tasks and their management is not taken into account in most AI competency frameworks.

This is where the present work comes in.

The aim is to answer the following main research question: How does AI, and especially GenAI, influence the work-setting-related competency frameworks according to its dual impact on tasks and work behaviour? The two derived research questions are:

RQ1: What competencies do employees need in their work setting to use GenAI effectively and efficiently to accomplish their tasks, some of which have been changed by GenAI?

RQ2: How can the characteristics of these competencies be described in terms of maturity levels and mapped in a modular, multidimensional maturity model?

The first objective is to create a generic AI-competency maturity model that aligns with the requirements of work-integrated GenAI use and serves as a framework for companies to modify their own competency models. The target audience comprises users of GenAI in a corporate context and is thus deliberately distinct from IT specialists or AI developers. The second objective is to contribute to scientific competence modelling research through the AI-dual impact thesis, which should stimulate in-depth research on the competence-inherent influences of AI.

The remainder of the paper is structured as follows: Chapter 2 addresses the theoretical foundation. This is followed by a description of the underlying methods in Chapter 3 and a presentation of the model itself in Chapter 4. The paper concludes with a discussion and conclusion in Chapter 5.

2. Theoretical Foundation and Related Work

First, a differentiation is required between AI literacy and AI competencies, which are often used synonymously in the literature but are linked rather than identical.

According to Chiu (2025), AI literacy refers "to a foundational conceptual understanding of AI [and] focuses on knowledge, critical thinking, and ethical awareness rather than technical skill" (p. 3225). It thus enables individuals to use AI responsibly, question results, recognize limitations, and make informed decisions (Chiu, 2025).

AI competency refers to the practical ability to utilize AI systems in real-world contexts, interact with them, develop them, or manage them, and thus extends beyond mere knowledge and understanding (Chiu, 2025; Zhou et al, 2025). At its core, this competency involves retrieving relevant dispositions for the situational problem at hand and combining them into action. It thus plays a decisive role in determining a person's future ability to act in new contexts, resulting in situational performance. For this process to be successful, the person must be able to reflect on, adapt, and expand their dispositions in action, which, in turn, enables agile adaptability and the ability to deal with uncertainty (Spöttl, 2011).

Overall, AI literacy refers to the knowledge and understanding of AI, whereas AI competency encompasses the higher-level ability to apply this knowledge to achieve results (Chiu, 2025).

Campion et al (2011) developed the "Framework for competencies", a reference framework for analysing and identifying competencies, based on the approaches used by a wide variety of organizations for competency modelling. In their definition, they refer to "competency models [...] as collections of knowledge, skills, abilities, and other characteristics (KSAs) that are needed for effective performance in the jobs in question" (Campion et al, 2011, p. 229). On this basis, a cascading determination of relevant competencies within an organization is carried out. Based on this, a company-specific, generic competency model is then derived. Various methods of requirements and job analysis are used to derive a job family-specific competency model from this generic, holistic competency model. Finally, these competencies must be operationalized through measurable behaviours so that the model can be applied to operational human resources work.

Maturity levels refer to the progress of a system toward a target state defined by a series of successive stages.

Maturity models (MM) are then defined by Pullen (2007) as "a structured collection of elements that describe the characteristics of effective processes at different stages of development [and] also suggest points of demarcation between stages and methods of transitioning from one stage to another" (p. 9).

MM thus describe the typical development paths of an object class by mapping the sequence of development stages – from the starting point at the lowest level to full maturity in the considered domain (Becker et al, 2009). They capture the current status, existing potential, and specific requirements of a domain (Wendler, 2012) and, through generally accepted growth stages, enable progress to be defined and improvements to be measured (Pullen, 2007). In this way, they support organizations in pursuing gradual development within implementation processes, systematically utilizing existing capabilities, and enhancing their strategic potential (Alsheiabni et al, 2019; Bruin et al, 2005). MM can therefore be considered a strategic tool for future growth by identifying necessary actions and potential transition challenges, facilitating the prioritization of areas for action, and enabling a roadmap for the company's further development (Pullen, 2007).

Although the research literature extensively addresses AI literacy (Chui, 2025), research on GenAI competencies is still in its early stages. Annapureddy et al (2025), for example, formulate 12 general competencies for GenAI, covering essential skills and areas of knowledge required for interacting with GenAI, ranging from "basic AI literacy" to the ability to engage in continuous learning. As a special feature, the competencies follow a logical

sequence to reflect continuous learning in the sense of a learning path. The authors see their literature-based model primarily as a starting point for further research on application and implementation in government and organizations.

Other researchers are developing domain-specific GenAI competency frameworks. Anica-Popa et al (2024), for example, divide the competencies required for accounting and audit professionals into cross-disciplinary skills and profession-specific competencies. In the education sector, in contrast, students must develop GenAI competencies, which consist of application, authenticity, accountability, and agency (Cardon et al, 2022). Furthermore, Burneo-Arteaga et al (2025) developed a GenAI competency framework for higher education that encompasses the domains of GenAI, responsible AI, and pedagogy, with a total of 16 competencies for educators.

The influence of GenAI on the competencies of postgraduate students was addressed by Aladsani (2025). Students developed several competencies, grouped into four key areas: technical and AI competencies, ethical and legal competencies, critical thinking and analytical competencies, and lifelong learning and interpersonal competencies.

Regarding AI maturity models, industry-related models from consultancies (e.g., AppliedAI, 2021) and academic models are becoming increasingly established, with domain-specific models gaining prevalence. These range, for example, from applications in logistics (Ellefsen et al, 2019) to manufacturing (Sonntag et al, 2024) or HR (Armutat et al, 2024). GenAI has also been mapped in maturity models primarily by consultancies and technology companies (e.g., Ey, 2024) to support companies during implementation. However, these models typically focus on individual aspects such as technology and lack empirical evidence (Banh, 2025). Given the nascent state of GenAI research, academic contributions are limited to a few models. For example, Banh (2025) presents a preliminary model for the organizational adoption journey consisting of the five key dimensions (i.e., capabilities): (i) people, (ii) process, (iii) technology, (iv) data, and (v) organization. Skills and competencies are part of the people dimension.

Overall, it can be noted that existing literature does not offer any competency-related frameworks within the context of maturity models for GenAI. Furthermore, no studies could be identified that integrate the aforementioned reciprocal relationship between the competency requirements for GenAI and their influence on competencies.

3. Method

The approach to designing the GenAI competency framework follows a linear logic based on the steps for developing an MM, as outlined by Becker et al (2009), which has proven its practical suitability (Armutat et al, 2024).

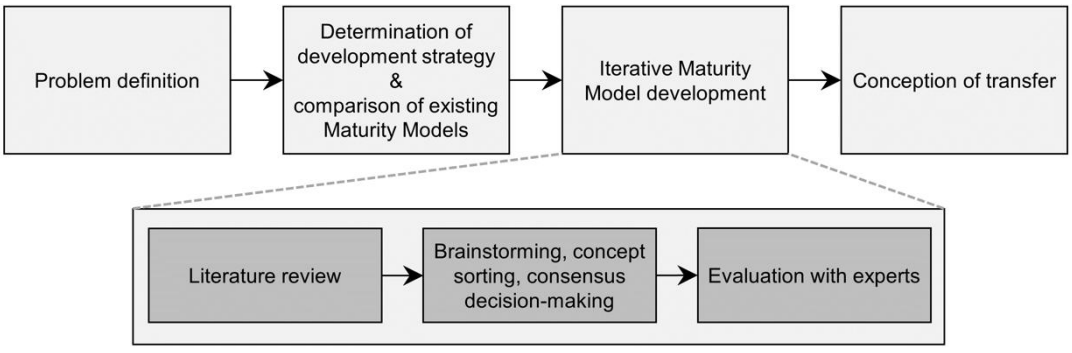

Figure 1: Steps of MM development (Armutat et al, 2024), based on Becker et al (2009) and Bruin et al (2005)

According to Becker et al (2009), the initial phase of the process is dedicated to *problem definition*, encompassing the identification of the domain and target group, the examination of the problem's relevance and anticipated benefits, as well as the specification of the conditions under which the model is to be applied. The target domain and target group of the MM being pursued are the HR sector, specifically HR managers and executives at companies. Additionally, it is necessary to define the objective and the underlying research questions (cf. Chapter 1). Finally, functionality, effectiveness, and comprehensibility must be improved to create the necessary conditions for application.

Regarding the determination of development strategy, a prescriptive model was chosen because significant complexity was anticipated and a high degree of transferability to practice was targeted. Since previous GenAI competency frameworks do not account for the reciprocity described above – competencies are required for the use of GenAI, which in turn influence the competencies – a top-down approach is pursued, in which the maturity levels are first defined. Then the assessment items are developed (Bruin et al, 2005). The AI competency framework developed by Franken et al (2022) was used to develop the dimensions, as it has proven to be remarkably versatile and practical. The framework draws on the core areas of digital, cognitive, and social competencies, which, in the authors' opinion, also represent a promising basis for the use of GenAI, as confirmed by the new studies cited above.

Iterative MM development is divided into three sub-processes, based on the approach outlined by Rigamonti et al (2024), which involve literature research, knowledge-generating techniques, and validation.

The *literature review* was conducted less formally due to the limited number of relevant publications on GenAI competency and the novelty of the topic. Instead, a non-systematic, comprehensive literature review of studies in English was conducted, based on targeted searches in Google Scholar and Google to identify both academic and practice-oriented contributions.

The next sub-process involved using various *knowledge-generating techniques* based on the evaluated literature (McGraw, 1989). This included several brainstorming sessions with the research team to identify items and stages of development, concept sorting to structure items within the proposed dimensions and assign maturity levels, and consensus decision-making to reach a consensus on the maturity level assignments.

The following *evaluation* involved experts from corporate practice, associations, academia, and labor unions, each with proven expertise in the subject area, to ensure the model's valid applicability. These included two company representatives (the head of corporate learning at a multinational corporation and the head of human resources), a scientist specializing in the field of competency mapping, and a union representative with expertise in the human-centred introduction of digital technologies in affiliated companies. Their feedback was integrated through several iterative loops and fed into the preceding sub-processes to refine the model further.

The final step involved the *conception of transfer* and thus defining the transfer medium. The results of the process (model, description, maturity levels) were documented in tabular form (cf. Section 4.2) and visualized in the form of a radar chart (cf. Section 4.3). For this reason, an online format is particularly suitable for reaching the broadest possible target group. The research group's homepage on the university website and the overarching joint project's website (cf. Acknowledgements) were identified for this purpose. Additionally, posts were written on LinkedIn, and joint project partners were informed via email.

4. GenAI Competency Framework

The resulting model describes three levels of maturity in working with GenAI in a corporate context and is based on 18 individual competencies that are classified into three overarching dimensions (digital/technological, social, and cognitive competencies).

4.1 Maturity Levels

The characteristics of these competencies enable the differentiation of three maturity levels in dealing with GenAI in a corporate context. These levels of maturity describe the development from initial engagement with GenAI to its reflective and efficient integration into existing work processes:

- *Maturity level 1:* "I am just starting to explore and experiment with generative AI."
- *Maturity level 2:* "I am systematically experimenting with generative AI to accomplish selected tasks, and I learn from my experiences."
- *Maturity level 3:* "I have fully integrated generative AI into my work context, and I use it efficiently and reflectively to accomplish my tasks. I support the professional use of AI in my organization."

The maturity levels were chosen to reflect a practice-oriented learning journey; in particular, maturity level 1 was deliberately defined as the operational starting point and formulated in a competency-oriented manner to highlight typical challenges when starting out, without depicting them as incompetence.

In the following section, the competencies are assigned to the three maturity levels and described in terms of their respective characteristics.

4.2 Dimensions

This section describes the three dimensions of the model (digital/technological, social, and cognitive competencies) in detail. For each dimension, the associated individual competencies are named and described along the three maturity levels (m1–m3). The development of competencies is presented in tabular form, illustrating how the use of GenAI progresses from initial steps to routine application and ultimately to strategically reflective integration in the work context.

Item (i) and description	m1	m2	m3
AI technology competency: Understanding of technical contexts and generative AI capabilities.	Knows basic terms such as AI, algorithm, model.	Understands the operating principles of general AI applications such as training, probabilities, hallucinations.	Can explain how it works, its limitations, and its impact on work processes in a well-founded manner, acts as a multiplier among colleagues.
Use case competency: Selection of suitable AI tools for the specific work context.	Knows individual AI tools and their general areas of application.	Can differentiate several tools and name suitable use cases.	Actively identifies new tools, evaluates them strategically, and develops application strategies for oneself and the team.
Application competency (prompting): Effective input and further processing of AI outputs.	Formulates simple queries and uses basic functions.	Creates precise prompts, optimizes results, identifies weaknesses.	Uses complex prompting techniques, strategically structures dialogues, automates tasks, shares experiences with colleagues.
Data and information competency: Critical examination of AI results based on the underlying training data.	Is aware of the possible existence of errors and recognizes obvious errors caused by data biases.	Understands data-based biases and checks content for subtle errors or biases in this context.	Has an objective review process and applies it systematically and regularly to validate AI content, supports colleagues with similar questions.
Security competency: Protection of sensitive data and prevention of data protection violations.	Is aware of the existence of fundamental data protection rules (e.g., GDPR, EU AI Act).	Distinguishes between secure/insecure applications, knows company policies.	Proactively implements security concepts, develops them further, and raises awareness among others.

Figure 2: Description of the three maturity levels of digital/technological competencies in dealing with GenAI. Source: Author's own work

Item (i) and description	m1	m2	m3
Critical reflection: Verification of plausible-appearing AI-generated content for accuracy, consistency, and unbiasedness about the work context.	Accepts AI output largely without reflection. Rarely detects errors, distortions, or inappropriate content.	Critically reviews AI results on a case-by-case basis. Begins to question the plausibility and consistency of content in relation to the work context.	Regularly and systematically considers the content, context, and limitations of AI. Integrates reflection as an integral part of work processes and raises awareness of the topic among colleagues.
Ethical awareness: Awareness of the implications of AI-generated content about discrimination and responsible reflection on its use, among other things.	Hardly considers the ethical consequences of using AI-generated content; uses AI and AI-generated content without reflection.	Takes fundamental ethical aspects (e.g., data protection, fairness) into account when using AI and AI-generated content, depending on the situation.	Considers the ethical implications of AI use from the very beginning; helps shape standards and AI guidelines for ethically sensitive AI use; raises awareness among others.
Learning ability: Ability and willingness to acquire the necessary skills to use evolving AI applications.	Reacts hesitantly to new AI tools and concepts. Has few developed strategies for AI-supported independent learning.	Learns selectively and reactively through trial and error, using AI. Independently searches for information when needed and develops initial learning routines.	Learns continuously and strategically with the help of AI. Adapts learning processes flexibly to new developments and supports others in AI-based learning.
Problem-solving competency: Ability to analyze tasks in a structured manner, break them down into solvable sub-problems, and identify suitable application scenarios for AI.	Rarely recognizes where AI can help with real-world problems; tends to use it in a playful manner or according to instructions.	Utilizes AI to handle specific tasks. Links tool functions to problems.	Develops creative, well-thought-out solution strategies using AI; systematically analyzes problems and plans AI-supported solutions in consultation with colleagues.
Process thinking: Understanding of processes and inter-relationships to use AI not only selectively, but also embedded in work processes.	Sees work tasks in isolation. Realizes little potential for integrating AI into processes.	Sees work tasks in the context of operational processes. Recognizes initial potential for supporting processes with AI.	Systematically uses AI to map processes and further develop the process landscape.
Creativity and innovation: Using AI to develop new solutions, products, and ideas.	Is inspired by new ideas when using AI coincidentally and reactively.	Uses AI to generate new ideas and concepts as the situation demands.	Systematically combines AI with creativity techniques to develop new ideas and concepts; supports colleagues with their own experience.
System knowledge: Understanding of how AI architectures work, data protection regulations, legal frameworks, and technical dependencies.	Uses AI as a black box without understanding the technological or legal foundations.	Understands basic system dependencies (e.g., training data, copyright, API usage).	Actively recognizes and considers complex technological, regulatory, and organizational dependencies when working with AI; acts as a multiplier among colleagues.
Holistic thinking: Awareness of the holistic implications of using AI in a business context.	Views AI usage more as a technical tool for work environments, without considering organizational implications.	Recognizes occasional implications of their own AI use in specific situations and takes this into account when performing their work.	Systematically considers the technical, social, and organizational implications of AI use, creates conditions for AI application appropriate to these implications, and acts as a multiplier.

Figure 3: Description of the three maturity levels of cognitive competencies in dealing with GenAI. Source: Author's own work

Item (i) and description	m1	m2	m3
Communication competency: Ability to use AI to improve one's own communication and to communicate the evaluation of AI results clearly, comprehensibly, reflectively, and in a manner appropriate to the target group (in dialogue).	Uses generative AI occasionally to improve their own communication and phrasing; finds it difficult to explain AI results.	Increasingly uses generative AI as a tool for more complex tasks, such as writing and editing emails and simple translations. Increasingly communicates with colleagues about content, benefits, and limitations.	Systematically integrates generative AI into communication processes (e.g., for automated translations and text optimization). Communicates efficiently and in a target group-oriented manner with AI support.
Ability to work in a team: Ability to share generative AI across roles to collaborate constructively on tasks.	Generative AI is rarely used within the team. Team communication and coordination traditionally take place without AI support.	Uses generative AI as needed when collaborating with colleagues, for example for brainstorming or creating team documents. Discusses AI-generated results and gradually learns how to efficiently integrate AI support into collaboration.	Integrates generative AI firmly into teamwork, for example, through automated protocols and joint brainstorming, supports the efficient AI-assisted completion of routine tasks, and the sharing of knowledge.
Interdisciplinary and intercultural cooperation: Using AI solutions together across disciplinary and cultural boundaries, incorporating different perspectives on AI.	Interaction with other disciplines or cultures takes place mainly without AI support. Has difficulty dealing with other disciplines and cultures or perspectives in relation to AI.	Exchange with other disciplines or cultures takes place on an event-related basis with AI support. Cooperates constructively across disciplinary and cultural boundaries, respects different AI perspectives.	Actively uses generative AI to optimize interdisciplinary and intercultural collaboration. Actively builds bridges between disciplines, cultures, and people, integrating diverse perspectives into AI projects.
Ability to handle mistakes: Identify errors or inaccuracies in AI, analyze them systematically, and systematically learn from them.	AI results are accepted uncritically; systematic verification hardly ever takes place. Errors or inaccuracies in AI are rarely reflected upon or corrected.	Recognizes the error-prone nature of generative AI and specifically checks AI results. Corrects errors and learns from them by adjusting inputs (prompts) and procedures.	Utilizes generative AI to specifically detect and correct errors. Systematically analyzes sources of error and uses the findings to continuously improve processes; errors are viewed as learning opportunities, and AI-supported checks are integrated into quality assurance.
Change management: Supporting employees and organizations through the changes brought along by AI and actively shaping change processes.	Is rather skeptical and passive toward new AI tools; change processes are usually initiated by others and there is a lack of initiative. New technologies are only accepted reactively, depending on operational possibilities, and hesitantly.	Shows openness to AI-driven change and actively participates in it. Tests new AI tools depending on the company's capabilities, supports transformation projects, and contributes initial experience with AI to their design.	Proactively drives change processes with the help of generative AI, both for themselves and their colleagues. Initiates the introduction of new AI technologies, makes learning with AI an integral part of the work culture, and supports colleagues in the work process.
Project management: Plan, manage, and complete projects in a structured process using generative AI, taking into account time, budget, and quality.	Plans and manages projects primarily manually without AI support. Project plans and risk assessments are created traditionally.	Uses generative AI tools to support project management, e.g., for initial schedules, risk assessments, or meeting summaries.	Fully integrates generative AI into project planning and management. Plans resources, schedules, and budgets with AI support, creates automated status reports, and uses continuous analysis to identify risks early on and adjust projects efficiently.

Figure 4: Description of the three maturity levels of social competencies in dealing with GenAI. Source: Author's own work

4.3 Visualisation and Calculation

The MM is visualized as a three-dimensional radar chart. There are only minor interdependencies between the dimensions, as the development status of one dimension does not necessarily affect the maturity of other dimensions. This allows all dimensions to be evaluated and developed independently of one another, which supports flexibility and adaptability in the model's implementation and use.

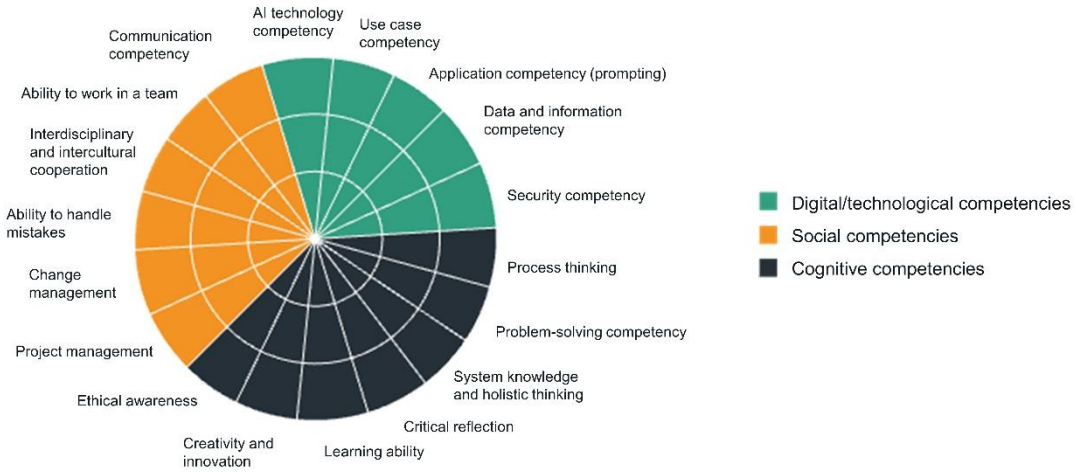

Figure 5: GenAI-competency maturity model with independent dimensions. Source: Author's own work

The overall maturity score M of the model was calculated as the mean of all 18 items, each rated on a scale of 1 to 3. The items are grouped into three dimensions (i = 1,2,3) with n_i items each (n_1 = 5, n_2 = 6, n_3 = 7). Formally, M can be expressed either by dimension or using a sequential index k:

$$M = \frac{\sum_{i=1}^{3}\sum_{j=1}^{n_i} r_{ij}}{\sum_{i=1}^{3} n_i} = \frac{\sum_{k=1}^{18} r_k}{18}$$

Here, r_{ij} denotes the maturity level of the *j*-th item in dimension *i* ($r_{ij} \in \{1,2,3\}$), and r_k the maturity level of the *k*-th item across all dimensions. This approach aggregates the maturity of all dimensions into a single score ranging from 1 to 3.

This also means that the three dimensions of the model are treated equally (none is given special preference or weighting), as the overall maturity level is calculated as the average of all items. Each category, therefore, contributes to the overall result in proportion to the number of items it contains.

5. Discussion and Conclusion

The AI Competency Maturity Model offers companies a systematic framework for identifying, structuring, and developing the specific skills that employees need to utilize artificial intelligence in their work in a reflective, effective, and efficient manner. By focusing on users of GenAI in a corporate context, the model deliberately distinguishes itself from IT specialists or AI developers, whose competencies could not be adequately captured in the selected dimensions and would therefore need to be considered in a separate model. This makes the model manageable and directly applicable to the competency development of the broad workforce.

The model creates the opportunity to expand existing competency models to include AI-related dimensions. This facilitates connectivity to established HR and development processes, ensuring the company's competency landscape remains up-to-date and future-proof.

Additionally, the model enables companies to assess their employees' existing AI competencies transparently. It allows for a differentiated assessment of the current situation, both within individual departments or teams and in comparison with other organizations or industries. Such comparisons are not only valuable for internal personnel development but also promote benchmarking and interorganizational learning processes.

Another key benefit is the ability to create individual competency profiles and derive development plans accordingly. This allows AI-related competency development measures to be tailored precisely to the specific needs of individual employees. This enhances the effectiveness of learning opportunities, boosts motivation, and accelerates strategic competency development.

At the same time, the model combines the perspectives of a competency model and a maturity model: while competencies provide the content basis, maturity levels describe the characteristics and development of these competencies in the context of their application. The chosen three-stage classification represents a practical, understandable, and compatible solution that promotes acceptance among managers and employees, even if empirical validation is still pending and further refinement remains to be conducted.

Overall, the AI competency maturity model thus serves as a bridge between human resources research, technological developments, and individual competency development. It helps to make companies future-proof and prepare the workforce for the demands of an increasingly AI-permeated working world.

Acknowledgements

The results of this paper are based on the research project Kompetenzzentrum Arbeitswelt.Plus. This research and development project is funded by the German Federal Ministry of Education and Research (BMBF) within “The Future of Value Creation – Research on Production, Services and Work” program and managed by the Project Management Agency Karlsruhe (PTKA). The authors are responsible for the content of this publication.

The proposed maturity model can be downloaded via the project's website https://arbeitswelt.plus/.

Ethics declaration: Expert feedback was obtained as part of the conceptual development process. As participation was voluntary, non-sensitive, and limited to professional expertise, no formal ethical approval was required.

AI declaration: In writing this article, the authors utilized DeepL and Grammarly to support the writing process and enhance the linguistic presentation of their thoughts. However, the ideas, concepts, and arguments presented in this article are solely those of the authors.

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Seeds of Deception: Securing AI-Driven Agriculture Against Adversarial Threats

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Abstract: The integration of artificial intelligence (AI) and the Internet of Things (IoT) into agriculture is redefining how crops are cultivated, monitored, and protected. This research builds upon an implemented IoT-driven plant monitoring prototype combined with a convolutional neural network (CNN) for leaf disease classification. The system achieved 96% accuracy on benchmark datasets and 76% accuracy on live samples, demonstrating the technical promise of digital agriculture. However, while effective in functionality, the prototype highlights a broader concern: agricultural digitization is evolving faster than its security safeguards, creating fertile ground for adversarial exploitation. To address this gap, the study applies threat modeling to the implemented prototype, identifying vulnerabilities in sensor integrity, data pipelines, and AI model robustness. Potential adversarial vectors include sensor spoofing, data poisoning, and adversarial image inputs capable of undermining disease detection accuracy. These findings serve as a foundation for expanding the analysis toward two emerging risks that elevate agricultural cybersecurity into the domain of biowarfare. First, the increasing reliance on cloud-hosted genetically modified organism (GMO) repositories presents a novel threat. Adversarial prompt engineering attacks on agricultural AI assistants could leak or corrupt sensitive genetic data, embedding harmful traits within seeds. Such tampering collapses the boundary between digital compromise and biological sabotage, threatening food security at scale. Second, agricultural AI infrastructures are increasingly dependent on high-density data centers that consume large volumes of potable water for cooling. A targeted cyber-physical campaign that overloads these facilities could deliberately drain water reserves, induce man-made drought conditions, and destabilize surrounding ecosystems. This risk reframes data centers not only as computational assets but also as critical ecological choke points. By combining the practical threat modeling of an IoT–AI prototype with conceptual extensions into GMO and data center vulnerabilities, this work establishes a novel framework for agricultural cyber-biosecurity. It underscores the urgency of interdisciplinary safeguards to prevent the transformation of smart farming from a tool of resilience into a vector of biowarfare.

Keywords: Agricultural biowarfare, AI-Driven agriculture, Genetically modified organisms, Adversarial AI, Cyber-Biosecurity; Critical infrastructure

1. Paper Overview

1.1 Conceptual Framework

This research situates modern agriculture within a cyber–bio–physical ecosystem, where IoT devices, AI-driven analytics, biological data repositories, and critical infrastructure are interconnected. The framework is structured around three progressive layers of analysis:

Prototype Layer – IoT and AI Convergence: The implemented IoT prototype integrates soil moisture, temperature, humidity, and PIR sensors with a convolutional neural network (CNN) for plant disease detection. This baseline system demonstrates the technical feasibility of smart farming but also exposes entry points for adversarial manipulation.

Digital-Biological Layer – GMO Repository Exploitation: The migration of genetically modified organism (GMO) repositories to cloud platforms has created new attack surfaces. Agricultural AI assistants that interact with these databases are vulnerable to prompt engineering and adversarial queries, which could allow threat actors to extract, modify, or embed harmful genetic traits within seeds. This collapse of digital compromise into biological sabotage introduces the possibility of food systems as weapons.

Critical Infrastructure Layer – AI Data Center Resource Depletion: AI data centers underpin agricultural decision engines, but their dependence on vast amounts of potable water for cooling makes them ecological choke points. Cyber-physical attacks that overload computational workloads or manipulate cooling schedules could deplete regional water resources, leading to man-made droughts. This represents a form of indirect biowarfare, destabilizing agricultural production through engineered environmental stress.

Together, these layers conceptually illustrate how technical vulnerabilities at the device and data levels may intersect with broader genetic and ecological risks. This relationship is not derived from empirical findings in the prototype but represents a theoretical extrapolation based on trends in cyber-biosecurity research.

1.2 Novelty and Innovation

This work contributes to agricultural cyber-biosecurity through three major innovations. First, it advances grounded threat modeling by beginning with an implemented IoT–AI prototype rather than a purely theoretical construct. Formal methods such as STRIDE analysis and attack trees are applied to this system, allowing practical vulnerabilities to be identified at the sensor, data, and model levels. Second, it introduces the concept of biological exploitation via AI, positioning prompt engineering attacks against agricultural AI assistants as a credible pathway for compromising cloud-hosted GMO repositories. Such attacks could enable adversaries to exfiltrate or manipulate genetic data, transforming crops into vectors of biowarfare. Finally, the study extends agricultural security research into the domain of resource-based sabotage by framing AI data centers as ecological vulnerabilities. These facilities, which consume vast amounts of potable water for cooling, could be deliberately overloaded through cyber-physical attacks, leading to severe depletion of local water resources and destabilization of both agricultural and civic ecosystems. By uniting technical, biological, and infrastructural perspectives, this paper establishes a holistic framework for protecting agriculture from adversarial exploitation while highlighting how neglecting these risks may transform smart farming into a new battlefield of biowarfare.

2. Problem Background

2.1 Review of Prior Events

The increasing integration of IoT and AI in agriculture has already demonstrated both efficiency gains and security challenges. Prior incidents illustrate how smart farming systems are vulnerable to disruption. For example, agricultural IoT devices have been shown to be susceptible to spoofing, jamming, and firmware exploitation, enabling attackers to falsify soil moisture and environmental readings that trigger incorrect irrigation or pesticide responses (M.Gupta et al., 2020). Research has also highlighted how adversarial inputs can compromise deep learning models for crop disease detection, resulting in misclassification that undermines yield predictions and farm decision-making (Gao et al., 2024). These findings indicate that digital agriculture, while technically effective, remains exposed to adversarial manipulation at both the hardware and algorithmic levels.

Beyond direct attacks on IoT–AI systems, the digitization of biological assets has opened a second frontier of vulnerability. Cloud-hosted repositories containing genetically modified organism (GMO) data represent highly sensitive targets. Emerging research in adversarial prompting shows how AI assistants can be manipulated into bypassing restrictions, leaking protected data, or even generating harmful outputs (Perez & Ribeiro, 2022; Greshake et al., 2023). If applied to agricultural contexts, such prompt injection attacks could enable adversaries to access or corrupt proprietary GMO datasets, embedding malicious genetic traits into seeds and collapsing the boundary between digital compromise and biological sabotage.

A third dimension of risk arises from the critical infrastructures underpinning agricultural AI. Large-scale data centers used to train and deploy decision-support pipelines consume enormous volumes of potable water for cooling, with individual sites reported to use millions of gallons per day (Mytton, 2021). These demands have already strained municipal water supplies in drought-prone regions, raising conflicts between industry and local communities (Olson, Grau and Tipton, 2024). While these tensions have so far emerged under normal operations, they reveal a latent vulnerability: a deliberate cyber-physical campaign that forces excessive workloads or manipulates cooling schedules could accelerate water depletion, producing man-made droughts that destabilize both agricultural production and civic ecosystems.

Research on agri-food supply chains has further demonstrated that processing facilities are safety-critical nodes increasingly exposed to cyber threats. Arunthavanathan et al. (2025) show that industrial control systems within food processing plants face systemic vulnerabilities that, if compromised, could cascade into production stoppages and food security risks. These findings directly parallel the weaknesses identified in smart farming prototypes, and by extension reinforce the concern that any compromise—including the mismanagement of GMO crops or bio-engineered inputs—could propagate across the supply chain. A holistic security model is therefore essential, spanning from farm-level IoT to processing infrastructure and extending to the integrity of GMO handling and distribution.

A concrete illustration of agricultural cyber risk occurred in April 2023, when attackers linked to the annual OpIsrael hacktivist campaign disrupted irrigation systems and wastewater treatment controllers in northern Israel. SecurityWeek reported that the adversaries exploited internet-exposed programmable logic controllers (PLCs) that still used default credentials, temporarily disabling automated irrigation across several farms and forcing manual fallback (SecurityWeek, 2023). Although the impact was limited in scope, the incident

demonstrates that agricultural ICS devices are directly targetable and can be compromised with modest technical means. As such, it validates broader concerns that IoT-based prototypes in agriculture are not only theoretically fragile but have already been subject to real-world exploitation.

Together, these incidents and precedents reveal that agricultural digital transformation is not only vulnerable at the system level but also across biological and ecological domains, demanding a more integrated approach to cyber-biosecurity.

2.2 Limitations in Existing Approaches

Despite the growing body of work on IoT-based agriculture and AI-driven disease detection, most approaches prioritize functionality and accuracy over resilience. Prototypes such as IoT crop monitoring systems and CNN-based disease classifiers have demonstrated impressive technical results, often achieving accuracies above 90% on benchmark datasets (Mohanty et al., 2016). However, these systems typically lack mechanisms to authenticate sensor inputs or detect tampering. As a result, they remain vulnerable to spoofing, jamming, and adversarial image perturbations, which could manipulate decision-making processes in ways that directly threaten crop yields and farmer livelihoods (Gao et al., 2024).

A second limitation is the minimal consideration of access control and integrity safeguards in agricultural genomic data management. With GMO repositories increasingly hosted on cloud platforms, their exposure to adversarial prompting and AI exploitation represents a significant blind spot. Current agricultural information systems rarely account for the risk that AI assistants could be manipulated into leaking or corrupting sensitive genomic information (Perez and Ribeiro, 2022; Greshake et al., 2023). The absence of formal governance mechanisms for cloud-based GMO resources leaves this domain highly vulnerable to novel forms of biowarfare.

Finally, existing agricultural cybersecurity research has paid limited attention to the infrastructural dependencies of AI systems. While water and energy demands of hyperscale data centers are well documented in environmental and engineering studies (Mytton, 2021; Olson, Grau and Tipton, 2024), their security implications are seldom integrated into agricultural threat models. In practice, this omission ignores the possibility that a targeted cyber-physical attack could deliberately induce water depletion, creating man-made drought conditions with both agricultural and societal consequences.

Taken together, these limitations highlight a critical gap in the current literature: while digital agriculture continues to expand, its security frameworks have not evolved to address adversarial manipulation, genomic sabotage, or ecological infrastructure attacks. This gap motivates the need for a unified cyber-biosecurity framework that integrates technical safeguards, data integrity controls, and resource-aware resilience planning.

3. System Design / Theoretical Framework

3.1 Baseline Prototype: IoT–AI Agriculture System

The baseline system for this study is an IoT-driven plant monitoring and disease classification prototype that integrates hardware sensors with a deep learning model. The architecture is composed of soil moisture, temperature, humidity, and passive infrared (PIR) sensors connected to a NodeMCU microcontroller. These sensors continuously gather environmental data around the plant, which is then transmitted via Wi-Fi to the Blynk mobile application, providing real-time monitoring and alerts to the planter. Notifications, such as changes in soil moisture content or rodent detection, are displayed on both the mobile app and an LCD interface, enabling proactive plant care.

In parallel, a deep learning pipeline supports disease diagnosis by processing leaf images. The system employs a VGG16 convolutional neural network (CNN) trained on a dataset of 80,000 images sourced from Kaggle, with 75% used for training and 25% for testing. For live deployment, images captured from actual plants are passed through the same CNN model. The architecture incorporates convolutional and max-pooling layers, with ReLU and Softmax activation functions for classification. The model achieved an accuracy of 96% on benchmark datasets and 76% on live hibiscus plant samples, demonstrating the technical feasibility of AI-assisted disease detection in agricultural contexts.

This dual-layer design—combining IoT-based environmental sensing with AI-powered disease classification—exemplifies the direction of smart farming under Industry 4.0. It provides continuous monitoring of plant health conditions and supports data-driven diagnosis without requiring constant farmer supervision. At the same time, by interconnecting sensors, cloud services, and machine learning models, the prototype establishes multiple entry points for adversarial interference, making it an ideal baseline for security-focused threat modeling.

The architecture of the proposed system is shown in Figure 1, where multiple sensors (temperature/humidity, soil moisture, and PIR) interface with a NodeMCU microcontroller that communicates real-time data to a mobile Blynk application and an LCD module for monitoring and control.

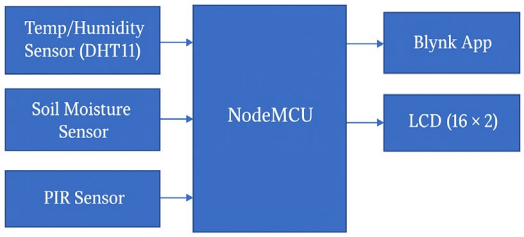

Figure 1: Block Diagram of IoT-AI Plant Monitoring Prototype

3.2 Threat Modeling of Baseline Prototype

The baseline IoT–AI system, while effective for plant monitoring and disease classification, exposes several adversarial entry points. Using the STRIDE framework, vulnerabilities were identified across the sensor, communication, AI, and integration layers.

At the sensor and hardware layer, soil-moisture, temperature, humidity, and PIR modules accept unauthenticated inputs, making them vulnerable to spoofing and physical tampering. Attackers can falsify environmental values, trigger unnecessary irrigation, overload the PIR sensor with repeated IR stimulation, or modify NodeMCU firmware to insert persistent backdoors.

At the communication layer, unencrypted Wi-Fi traffic between the NodeMCU and Blynk app can be intercepted or altered. Session hijacking enables adversaries to impersonate the device and feed false data, while API flooding can delay or block alerts, creating denial-of-service conditions.

At the AI model layer, the VGG16 classifier is vulnerable to adversarial machine-learning attacks. Perturbed leaf images can cause misclassification, poisoned training data can degrade accuracy, and repeated queries may allow model reconstruction.

At the integration layer, replay attacks can mask real-time plant conditions, and a compromised mobile device running Blynk can provide escalated access to IoT firmware or the ML pipeline. A single compromised node can cascade failures across the system.

Overall, the STRIDE analysis shows that the prototype, though technically functional, lacks resilience against low-cost adversarial actions. These vulnerabilities establish the empirical foundation for examining higher-order risks, including AI-mediated GMO exploitation and ecological sabotage through data-center resource manipulation.

3.3 Empirical Outcomes of STRIDE Analysis

Although the prototype was implemented at a small scale, the STRIDE analysis produced concrete empirical observations across the sensor, communication, and AI layers. These results substantiate the methodological claims made in the abstract and innovation sections and demonstrate that the threat modeling was not purely theoretical.

Spoofing (S)

During prototype testing, the NodeMCU accepted unauthenticated soil-moisture and humidity readings. Falsified values successfully triggered irrigation actions even when actual soil conditions were unchanged, confirming susceptibility to spoofing.

Tampering (T)

Physical access to the NodeMCU allowed modification of firmware parameters without triggering alerts. This validated the feasibility of inserting persistent configuration changes or backdoors directly into the device.

Repudiation (R)

The baseline system lacked logging and audit mechanisms. As a result, anomalous sensor readings, communication interruptions, or configuration changes could not be attributed or reconstructed, highlighting an inability to support forensic validation.

Information Disclosure (I)

Unencrypted Wi-Fi transmission enabled passive interception of environmental data during testing. Attackers could infer irrigation schedules, environmental patterns, and plant-stress cycles, demonstrating real privacy and intelligence-extraction risks.

Denial of Service (D)

Flooding the Blynk endpoint with rapid consecutive requests resulted in delayed or dropped notifications. This prevented real-time disease or sensor alerts, illustrating that availability of plant-health feedback can be disrupted with low-effort attacks.

Elevation of Privilege (E)

A compromised mobile device running the Blynk client allowed privilege escalation into the IoT control interface. This confirmed that the mobile layer is a viable pivot point for deeper system compromise.

3.4 Extension 1: GMO Repository Exploitation via Prompt Engineering

Note: The following analysis represents a conceptual extension of the threat-modeling results and is not based on empirical measurements from the prototype.

While the baseline prototype demonstrates how IoT and AI can be used to monitor and diagnose plant health, the broader agricultural ecosystem increasingly depends on centralized genomic resources, particularly repositories of genetically modified organisms (GMOs). These repositories, often hosted on cloud infrastructures, contain proprietary seed sequences and engineered traits that are critical to modern crop development. Their protection is therefore not only a matter of intellectual property but also of national food security.

The rise of AI-driven agricultural assistants, capable of interfacing with genomic databases, introduces a novel threat vector. Recent advances in prompt engineering and prompt injection have shown that large language models and generative AI systems can be manipulated into disclosing sensitive information or executing unintended instructions. In an agricultural context, adversaries could exploit these vulnerabilities to bypass safeguards around GMO repositories. By crafting malicious prompts or queries, attackers might exfiltrate proprietary genetic sequences or alter stored data in ways that embed harmful traits within seeds. Such manipulations blur the distinction between digital compromise and biological sabotage, since the downstream effect would be the propagation of corrupted crops into the food chain.

The implications extend beyond intellectual theft. If adversaries were to tamper with GMO repositories, even minor alterations could destabilize ecosystems by introducing genetic vulnerabilities, reducing crop resistance to pests, or impairing nutritional quality. More severe scenarios include the deliberate design of traits that are toxic to humans or livestock, which could transform agricultural supply chains into vehicles for biowarfare. Importantly, these risks are not hypothetical; prior work in cyberbiosecurity has demonstrated the feasibility of manipulating bioinformatics pipelines to introduce malicious code or alter DNA sequences without detection. In this sense, the very tools that enable rapid agricultural innovation also create pathways for adversaries to weaponize biotechnology.

From a threat modeling perspective, GMO repository exploitation represents an escalation from the vulnerabilities identified in the baseline system. While the IoT–AI prototype is susceptible to spoofed sensors or adversarial images, the compromise of GMO databases represents a higher-order threat in which adversarial access to AI intermediaries directly impacts the biological substrate of agriculture. This stage of analysis demonstrates that agricultural security can no longer be confined to protecting devices and models; it must extend to safeguarding genomic integrity against adversarial manipulation.

3.5 Extension 2: AI Data Center–Driven Drought Sabotage

Note: This section presents a conceptual scenario grounded in cyber-physical security literature, not an empirical outcome of the implemented IoT–AI prototype.

Beyond the vulnerabilities of individual systems and genetic repositories, agricultural AI increasingly relies on large-scale computational infrastructures. Data centers form the backbone of modern agricultural analytics, hosting disease detection pipelines, decision-support systems, and genomic repositories. These facilities, often situated near agricultural regions to minimize latency, consume immense quantities of energy and water to maintain stable operations. In particular, their dependence on potable water for cooling introduces a critical ecological dependency that has direct implications for food security.

Recent studies have shown that hyperscale data centers can require millions of gallons of freshwater daily to support cooling operations, placing considerable strain on local resources in drought-prone areas (Olson, Grau and Tipton, 2024). While these demands are typically a by-product of routine operation, they reveal a latent vulnerability that adversaries could exploit. A targeted cyber-physical campaign, designed to overload computational workloads or manipulate cooling management systems, could deliberately accelerate water consumption. Unlike traditional denial-of-service attacks, which disrupt availability in digital domains, such a campaign would manifest as an ecological denial-of-service, depleting potable water reserves essential not only for agriculture but also for surrounding communities.

The consequences of this form of attack are profound. By artificially inflating the cooling demand of agricultural AI data centers, adversaries could induce localized water shortages, creating conditions akin to man-made drought. Such a scenario would destabilize crop production by depriving farms of irrigation resources, while simultaneously undermining public health and civic infrastructure dependent on the same water supply. Unlike direct sabotage of crops or genetic data, this strategy exploits the ecological choke points created by digital agriculture's infrastructural footprint. In doing so, it reframes cyberattacks as tools for biowarfare, capable of weaponizing resource scarcity rather than pathogens or pests.

From a threat modeling standpoint, this represents the highest-order escalation considered in this framework. The baseline prototype demonstrated how adversarial manipulation of IoT sensors and AI models can misguide farmers. The analysis of GMO repositories highlighted how cloud-based genomic data can be corrupted to weaponize food at the molecular level. At the infrastructural scale, however, the focus shifts to entire ecosystems, where data centers themselves become strategic vulnerabilities that adversaries could exploit to destabilize agricultural regions. Protecting agriculture therefore requires not only securing devices and data but also recognizing and mitigating the ecological risks embedded within the computational infrastructures that sustain AI-driven farming.

The figure below presents a conceptual framework that extends a baseline IoT–AI agricultural system into cyber-biosecurity threat scenarios, emphasizing vulnerabilities from prompt-driven GMO exploitation and AI data center–induced ecological sabotage.

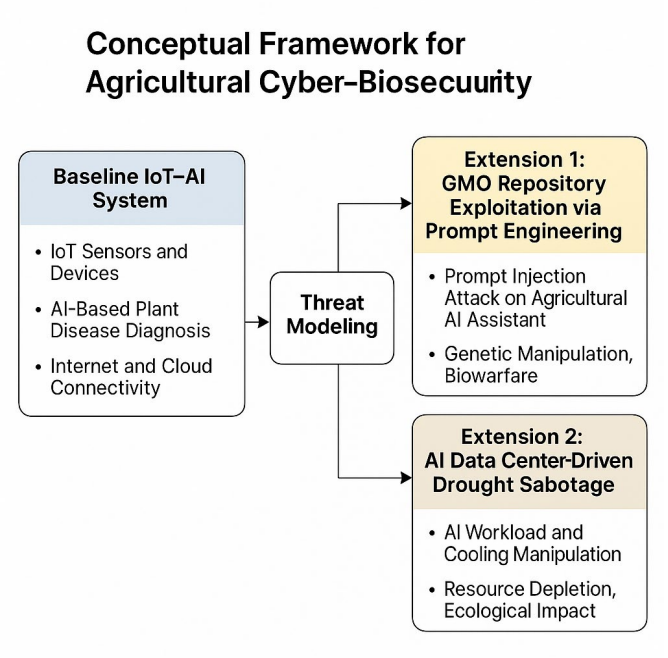

Figure 2: Conceptual Framework for Agricultural Cyber-Biosecurity

4. Results and Analysis

4.1 Evaluation Criteria

The evaluation of threat modeling outcomes was guided by three criteria: vulnerability severity, feasibility of adversarial exploitation, and potential impact on agricultural and ecological systems. Severity was assessed by considering how disruptive a vulnerability would be if exploited, from minor operational inconvenience to full-scale food system destabilization. Feasibility addressed the resources and expertise required for an adversary to execute the attack, ranging from low-cost sensor spoofing to more sophisticated adversarial learning or infrastructure sabotage. Finally, impact was analyzed in terms of scale—whether the consequences were localized to a single farm, extended across regions through compromised genetic repositories, or escalated to ecological disruption through infrastructural sabotage. This layered evaluation ensured that the results were not limited to technical vulnerabilities but also captured their broader implications for food security and biowarfare.

The threat modeling of the baseline IoT–AI prototype revealed that even a simple agricultural system can be undermined through adversarial manipulation. Sensor spoofing, firmware tampering, and adversarial images demonstrated the ease with which attackers can cause misclassifications or false environmental readings. These vulnerabilities are significant because they can be executed with relatively modest technical capabilities, making them accessible to a wide range of adversaries. The outcome underscores that prototypes optimized for functionality and accuracy, such as disease classification at 96% accuracy on benchmark datasets, remain highly fragile when subjected to adversarial pressure.

Expanding the analysis to cloud-hosted GMO repositories illustrated a more strategic form of exploitation. Prompt engineering and injection attacks were shown to create feasible avenues for bypassing AI assistant safeguards, enabling adversaries to exfiltrate or alter genomic data. The consequences of such attacks extend beyond digital compromise: manipulated seed sequences could embed harmful traits that propagate covertly into crops. The outcome here highlights a critical escalation—compromise at the molecular level of agriculture—which transforms a cybersecurity breach into a biowarfare incident. The analysis revealed that current access control and data integrity safeguards are insufficient to defend against such adversarial use of AI, creating an urgent need for bio-cybersecurity standards.

At the infrastructural level, the modeling of AI datacenter operations revealed that water consumption constitutes an overlooked vulnerability. By overloading workloads or disrupting cooling management systems, adversaries could accelerate the depletion of potable water reserves. The outcome of such an attack would be ecological in scale, producing localized drought conditions and destabilizing both agricultural irrigation and civic water supplies. Unlike the baseline system and GMO exploitation, this threat does not target plants or genomes directly; rather, it weaponizes the environmental dependencies of digital agriculture. The results suggest that agricultural AI infrastructures must be considered as critical ecological assets, requiring protections that extend beyond conventional cybersecurity into resource resilience planning.

Taken together, the analysis reveals a cascading risk trajectory. At the lowest level, adversarial manipulation can undermine trust in IoT–AI systems at the farm scale. At the next level, compromised GMO repositories create systemic risks to food security. At the highest level, attacks on AI data centers can destabilize ecological and infrastructural foundations of agriculture. These results confirm that agricultural cyber-biosecurity cannot be addressed in isolation; it demands an integrated framework that spans technical, biological, and ecological domains.

4.2 Observations and Outcomes

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5. Discussion

5.1 Interpretation of Results

The findings of this research reveal that agricultural digitization, while technologically advanced, has introduced vulnerabilities that extend across cyber, biological, and ecological domains. At the prototype level, the threat modeling demonstrated how sensor spoofing, firmware tampering, and adversarial image manipulation can undermine the reliability of IoT–AI systems. This suggests that even highly accurate models, such as the VGG16 classifier with 96% benchmark accuracy, cannot be considered secure without integrated resilience measures. In practice, adversaries do not need to outperform the model's training accuracy; they only need to identify specific weaknesses that disrupt trust in the system.

The analysis of GMO repositories highlighted a second escalation of risk. Unlike the localized consequences of sensor spoofing, adversarial prompt engineering against AI assistants creates a global threat vector. The ability to extract or modify genetic data from cloud-hosted repositories collapses the boundary between digital compromise and biological sabotage, raising the specter of crops themselves being weaponized. These results underscore that agricultural cyber-biosecurity must evolve beyond conventional data protection, extending into the genomic integrity of food systems.

At the infrastructural scale, the modeling of AI data center vulnerabilities reframed agriculture as an ecological security challenge. By overloading workloads or manipulating cooling systems, adversaries could deplete potable water reserves, producing man-made drought conditions that destabilize not only agricultural irrigation but also civic water supplies. This finding demonstrates that cyberattacks need not directly target crops or genetic repositories to disrupt agriculture; they can instead exploit critical resource dependencies. Such attacks weaponize scarcity, transforming digital sabotage into ecological biowarfare.

Together, these interpretations suggest that agricultural security requires a shift in perspective. Traditional cybersecurity frameworks focused on device or network hardening are insufficient. Instead, a multi-layered defense must integrate IoT security, genomic data protection, and ecological resilience to address the cascading risks identified in this study.

5.2 Limitations and Lessons Learned

Although comprehensive in scope, this research presents certain limitations. The baseline prototype was implemented and threat-modeled at a small scale, focusing on a single crop and a controlled environment. While the vulnerabilities identified are broadly generalizable, large-scale agricultural systems may exhibit additional complexities not captured here. Similarly, the analysis of GMO repositories was primarily conceptual, based on analogies from existing prompt injection studies in other AI domains. Empirical testing of prompt-based attacks on agricultural AI systems remains limited due to ethical and practical constraints.

The modeling of AI data center resource depletion likewise relied on scenario-based reasoning rather than live experimentation. Although documented cases confirm the high water usage of hyperscale facilities, deliberately overloading such systems could not be simulated within the scope of this study. Future research should therefore focus on quantifying the thresholds at which workload manipulation translates into measurable ecological impacts.

Another limitation arises from the persistent mismatch between cybersecurity standards and real-world adoption. Kumar, Crowe, and Gu (2025) highlight a perception gap between the intentions of security framework designers and the practices of implementers, particularly in SMEs. In the agricultural domain, where many innovations originate from small-scale AgTech firms, this gap inhibits the translation of threat modeling insights into effective safeguards.

Despite these limitations, the lessons learned are significant. The results demonstrate that security considerations must be embedded at the earliest stages of agricultural technology design. Building IoT prototypes without resilience testing or deploying AI models without adversarial robustness creates blind spots that adversaries can exploit. More importantly, agriculture must be understood as a cyber-bio-physical system, where vulnerabilities at the device level can cascade into genomic compromise or ecological destabilization.

6. Conclusion and Future Work

6.1 Key Takeaways

This research has demonstrated that while IoT–AI systems in agriculture hold tremendous promise for enhancing productivity and plant health management, they also introduce critical vulnerabilities. The baseline prototype, although technically effective with high accuracy in disease classification, was revealed through threat modeling to be fragile against sensor spoofing, firmware tampering, and adversarial image manipulation. These vulnerabilities confirm that accuracy alone cannot ensure trustworthiness in digital agriculture.

The extension of this analysis to cloud-hosted GMO repositories highlighted a strategic escalation of risk. By exploiting prompt engineering techniques against agricultural AI assistants, adversaries could exfiltrate or corrupt genetic data, embedding malicious traits within seeds and weaponizing the food supply. This dimension underscores that food security is inseparable from genomic integrity and that cyber-biosecurity must address the risks of AI-driven biotechnology pipelines.

At the infrastructural level, the analysis of AI data centers revealed an even broader threat: the weaponization of ecological dependencies. Data centers already consume vast amounts of potable water for cooling, and adversaries could exploit this dependency by forcing workload overloads or disrupting cooling systems. The result would be man-made drought conditions, destabilizing both agriculture and civic infrastructure. This scenario reframes agricultural cybersecurity as a matter of ecological resilience and national security.

6.2 Potential Extensions and Impact

The findings of this study suggest several directions for future work. First, there is a need to integrate adversarial robustness testing into the development lifecycle of IoT–AI agricultural systems, ensuring that prototypes are evaluated not only for accuracy but also for resilience under attack. Second, stronger governance frameworks are required for protecting GMO repositories, including access control, integrity verification, and defenses against prompt engineering. Third, agricultural cybersecurity must expand to include ecological dimensions, with resource-aware resilience strategies for AI data centers that account for water and energy dependencies.

Beyond technical contributions, this research has broader implications for policy and strategy. By demonstrating how agricultural infrastructures can be transformed into vectors of biowarfare, it underscores the urgency of developing interdisciplinary approaches that link cybersecurity, biotechnology, and environmental protection. For governments, this means treating agricultural digital systems as critical infrastructure. For researchers, it means advancing cyber-biosecurity as a distinct discipline capable of addressing the complex intersections of digital and biological risk.

In conclusion, the results of this work position agriculture at the frontier of cyber-biosecurity. Without deliberate safeguards, the very technologies designed to secure food production could become instruments of destabilization. With proactive design, however, IoT and AI can serve as powerful tools of resilience, ensuring that future food systems are not only productive but also secure, ethical, and sustainable.

Ethics Declaration: This research did not involve human participants, animal testing, or the use of sensitive biological samples. The IoT–AI prototype was implemented solely for experimental and educational purposes,

and no live plant trials extended beyond routine agricultural practice. All datasets used for training and testing the disease classification model were either open-source (Kaggle PlantVillage dataset) or self-collected leaf images that posed no ethical concerns. Consequently, no formal ethical clearance was required for the conduct of this study.

AI Declaration: Artificial intelligence tools were employed in this study to assist in literature synthesis, drafting, and editing of the manuscript. All conceptual contributions, system implementation, and threat modeling analyses were developed and validated by the authors. AI tools were used exclusively as writing support systems and did not contribute to experimental design, data collection, or interpretation of results. The final responsibility for accuracy, integrity, and originality rests entirely with the authors.

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Teaching Responsible AI Entrepreneurship: Experiences From the Erasmus+ Pathfinder Project

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Abstract: The rapid integration of artificial intelligence in society presents both profound opportunities and urgent challenges for higher education. As future professionals and entrepreneurs will increasingly rely on AI-driven tools, it is essential that universities cultivate AI literacy, critical thinking, and ethical reasoning. In response, this paper presents the design of a new course: AI in Business: Ethics, Applications, and Entrepreneurship, developed under the Erasmus+ Pathfinder project and launched in September 2025. The course is grounded in the UNESCO AI Competency Frameworks, Design Thinking and ENTRECOMP Framework and supports the European Union's Digital Education Action Plan by promoting responsible, human-centered AI integration. Structured around ten thematic modules, the course introduces students to AI ethics, human-centered design, technical applications, and innovation strategies. Delivered online, it leverages group projects, case studies, and real-world problem-solving. A distinctive feature is the use of large language models as learning partners framing AI not merely as a tool, but as a co-creative agent in cognitive and entrepreneurial development. Students work in teams to develop and pitch AI-based business ideas, supported by coaching and expert feedback. The course is informed by a constructivist and sociocultural pedagogical foundation, where knowledge is co-constructed through active engagement and mediated by cultural tools, here, generative AI. It also draws on human-centered design thinking and transformative learning theory, encouraging students to reframe assumptions and design solutions with ethical and societal impact in mind. Though the course is set to end in December 2025, this paper outlines the instructional model, theoretical foundation, and implementation strategy. It offers a scalable, interdisciplinary framework for embedding ethical, inclusive, and innovation-driven AI education within higher education, while empowering educators and students to engage critically and constructively with the evolving digital landscape.

Keywords: AI literacy, Erasmus+, Ethical AI, Entrepreneurship, UNESCO AI framework

1. Introduction

Artificial intelligence is transforming the landscape of higher education, business, and entrepreneurship, emerging as a central driver of innovation and decision-making across all sectors of society (Zouhaier, 2023). Accelerating digitalization, the rise of Industry 5.0, and growing emphasis on sustainability and human-centered innovation are reshaping how knowledge is created, shared, and applied. As future professionals increasingly engage with AI systems to analyze data, generate insights, and design novel solutions, universities are tasked with preparing graduates not only to use these technologies but also to collaborate with them critically and ethically.

This educational transformation is supported by key international policy frameworks. UNESCO's AI Competency Framework for Students (2023) outlines the knowledge, skills, and attitudes needed to engage with AI systems ethically and effectively, emphasising human rights, inclusion, and societal well-being. Similarly, the European Union's Digital Education Action Plan (European Commission, 2020) prioritises the development of digital and AI competences as part of a lifelong learning agenda. Together, these frameworks underscore the urgency of equipping higher education learners with AI literacy, ethical awareness, and innovation capabilities to navigate an increasingly complex and technologically mediated world.

Despite growing interest in AI education, most initiatives remain concentrated within technical disciplines such as computer science and engineering. For non-technical students, particularly those in business, entrepreneurship, and management, AI is often introduced only at a conceptual or strategic level, with limited connection to practical or ethical contexts (Chun and Elkins, 2023). This creates a pedagogical gap: although students increasingly encounter AI-driven decision systems in professional settings, they often lack opportunities to engage with these technologies in ways that foster critical evaluation and ethical application. The challenge lies in teaching AI without requiring coding expertise, while supporting a deeper understanding of how AI systems function, influence decision-making, and shape societal outcomes.

This study addresses that gap by examining the design and implementation of a pilot course, *AI for Business and Entrepreneurship*, delivered at LAB University of Applied Sciences in Finland as part of the Erasmus+ Pathfinder Project (2024–2026). The Pathfinder initiative seeks to enhance AI competences among students

and educators in European higher education through interdisciplinary and ethically grounded teaching methods.

The pilot course was structured as a 5 ECTS online module offered from September to December 2025. It primarily targeted international business students but was also open to participants from technology, healthcare, and design disciplines. The course design integrated three pedagogical frameworks: Design Thinking to guide creative, human-centered problem-solving; the EntreComp Framework to support entrepreneurial skill development; and the UNESCO AI Competency and Ethics Framework to embed ethical reflection and responsible AI literacy.

Methodologically, the study employs a conceptual case study and participatory observation approach, analysing the course's design, structure, and implementation as part of a broader pedagogical experiment in responsible AI education.

The article is structured as follows: Section 2 presents a literature review on AI in higher education, Design Thinking as a pedagogical model, entrepreneurship education through the EntreComp framework, and ethical AI literacy informed by UNESCO's guidelines. Section 3 outlines the methodological approach, explaining how the course was designed and examined as a conceptual case. Section 4 presents findings from the pilot implementation. Section 5 provides discussion and conclusions, relating the findings to ongoing debates in responsible AI education and entrepreneurship pedagogy.

This study contributes to emerging discourse on interdisciplinary AI education by offering a replicable model for embedding AI literacy, ethical awareness, and entrepreneurial competence into applied business curricula. It demonstrates how higher education institutions can respond to the demands of global digital transformation through human-centered, competence-based, and ethically informed AI pedagogy.

2. Literature Review

2.1 AI in Higher Education and Pedagogical Frameworks

Artificial intelligence has become a transformative force in higher education, influencing how institutions teach, assess, and prepare students for an increasingly digital and automated world. Early applications of AI in education focused largely on automation—for example, adaptive testing, grading algorithms, and recommender systems for personalized learning (Zawacki-Richter et al., 2020). More recent developments have shifted toward augmentation, where AI acts as a cognitive partner enhancing creativity, problem-solving, and ethical reasoning. This move from automation to augmentation reflects a paradigm shift: AI is not only a tool to optimize efficiency but also a mediating technology that shapes human thinking, collaboration, and learning itself (Holmes et al., 2024).

The pedagogical implications of this transformation are profound. Integrating AI tools into learning environments requires educators to address new forms of literacy, including understanding how AI systems generate, interpret, and bias information. This has led to a growing recognition of AI literacy as a key educational goal (Tuomi, 2024). AI literacy encompasses not just technical understanding, but also ethical reflection and critical digital citizenship - the ability to interrogate how algorithms affect knowledge production, fairness, and inclusion. Despite the growing adoption of AI in education, challenges persist in developing responsible AI pedagogies that combine technical, ethical, and creative dimensions. Educators still struggle to balance conceptual understanding with practical, interdisciplinary engagement.

2.2 Design Thinking as a Pedagogical Approach

Design Thinking has emerged as a powerful pedagogical methodology for preparing students to navigate complex, uncertain, and innovation-driven contexts. Originally developed within design and engineering fields (IDEO; Brown, 2008), design thinking has evolved into an educational framework for creative problem-solving, emphasizing empathy, iteration, and human-centered innovation. It aligns with constructivist and experiential learning theories, positioning students as active participants who co-create knowledge through exploration, experimentation, and reflection (Liedtka, 2015).

As a pedagogical process, design thinking consists of iterative stages—empathize, define, ideate, prototype, and test—that encourage learners to understand user perspectives, frame problems, generate ideas, and iteratively refine solutions. This cycle supports higher-order cognitive processes such as divergent thinking, metacognition, and reflection (Rauth et al., 2010). In educational contexts, design thinking transforms classrooms into laboratories of inquiry, where failure is reframed as an opportunity for learning.

In recent years, design thinking has been applied in AI and entrepreneurship education, offering a framework for integrating technology with creativity and ethics. For instance, Meinel and Leifer (2021) highlight how design thinking encourages learners to approach emerging technologies with empathy and ethical consideration, enabling "human-centered innovation." This makes it particularly suited to teaching AI ethics, as it foregrounds human needs, societal values, and responsible design principles.

2.3 Entrepreneurship Education and the EntreComp Framework

Entrepreneurship education has undergone a major evolution over the past two decades, shifting from business plan–oriented training toward competence-based, experiential learning. The EntreComp Framework (Bacigalupo et al., 2016), developed by the European Commission, represents a cornerstone of this shift. It defines entrepreneurship as a transversal competence applicable across professional and social contexts, not limited to the creation of new ventures. EntreComp identifies three main competence areas: Ideas and Opportunities, Resources, and Into Action. These competences support learners in developing a mindset of agency, creativity, and responsibility—qualities essential for navigating the ethical and social dimensions of technological innovation.

Pedagogically, EntreComp aligns closely with project-based and experiential learning models, where students learn by developing and testing real ideas. Lackéus (2020) emphasizes the role of value creation - learning through generating value for others as the central mechanism of entrepreneurial education. This aligns with constructivist principles, as learners develop understanding through authentic problem-solving and reflection.

2.4 The UNESCO AI Competency Framework: Ethics, Literacy, and Values

The UNESCO AI Competency Framework for Students (2023) represents one of the first comprehensive global efforts to define what learners should know, do, and value in relation to AI. The framework emphasizes that AI education is not merely technical but ethical, civic, and reflective. It calls for cultivating critical digital citizenship, the capacity to question algorithmic systems, recognize bias, and make responsible choices in human-AI interaction.

Integrating UNESCO's framework into higher education supports curricula that bridge technology, ethics, and social values. Recent scholarship suggests that embedding UNESCO's competencies fosters ethical reasoning and empathy among students (Holmes, 2024).

3. Methodology

3.1 Research Design and Approach

This study adopts a conceptual case study design (Merriam, 1998; Yin, 2018) focusing on the design and implementation of an innovative course rather than its evaluation outcomes. The case represents a pedagogical innovation in AI education developed within the Erasmus+ Pathfinder Project (2024–2026), a European initiative supporting ethically grounded, competence-based AI curricula.

The research is descriptive and interpretive, examining how three frameworks: Design Thinking, EntreComp, and UNESCO AI Competency were translated into pedagogical practice. It follows design-based research (DBR) principles (Reeves, 2006; Wang & Hannafin, 2005), emphasizing iterative development, contextualization, and reflective practice. In this approach, the learning environment itself becomes an object of inquiry, bridging theory and practice in real-world settings.

The study is grounded in constructivist and sociocultural learning theories, viewing learning as an active, collaborative, and tool-mediated process (Vygotsky, 1978). Knowledge is co-constructed through interaction with peers and cultural artifacts, including generative AI systems, which function as mediating tools for exploration and reflection. From this perspective, AI acts not as a teacher replacement but as a co-participant in the learning process (Holmes et al., 2022), scaffolding higher-order thinking and ethical reasoning when embedded in collaborative learning activities.

The design is also informed by transformative learning theory (Mezirow, 1997), which emphasizes critical reflection and perspective change. Combined with human-centered design thinking, this orientation supports ethical imagination—the capacity to envision socially responsible applications of AI (Cranton & Taylor, 2012). Accordingly, the course aimed not only to build competence but to foster critical awareness, empathy, and ethical agency, aligning with UNESCO's call for human-centered and values-driven AI education.

3.2 Data Sources and Materials

The study draws on document-based qualitative data that captures the pedagogical logic, design process, and instructional implementation of the course. The course plan outlines learning objectives, weekly topics, and alignment with the Design Thinking, EntreComp, and UNESCO AI frameworks. The lesson materials (PowerPoint presentations) detail the content progression, group activities, and embedded competence goals.

No student assignments, reflections, or identifiable data were analyzed. The materials were restricted to instructor-generated and publicly accessible sources to comply with ethical standards for educational research at LAB University of Applied Sciences. This focus allowed for a detailed reconstruction of how the course operationalized theoretical frameworks and implemented interdisciplinary AI education in practice.

3.3 Data Analysis

The data analysis was designed to reconstruct and interpret the pedagogical logic of the course. Rather than seeking to measure outcomes, the analysis aimed to understand how the course design embodied theoretical frameworks and operationalized its ethical and entrepreneurial goals within a real educational context. Consistent with the conceptual case study and design-based research orientation of this project, the analysis adopted a qualitative, interpretive, and framework-driven approach.

4. Results: Course Design and Implementation

4.1 Course Context and Rationale

The course AI in Business: Ethics, Applications, and Entrepreneurship was developed and implemented at LAB University of Applied Sciences in Finland as part of the Erasmus+ Pathfinder Project (2024–2026). The Pathfinder project aims to strengthen AI literacy and entrepreneurial competence across European higher education institutions by developing innovative, ethically grounded pedagogical models. Within this initiative, the course represented a pilot implementation exploring how interdisciplinary students could engage with artificial intelligence through a human-centered, ethically responsible, and entrepreneurial lens.

The course was offered within LAB's Department of Business and Hospitality Management, yet intentionally structured to attract participation from other faculties, including Technology, Design, and Healthcare. The target learners were primarily bachelor's-level students in International Business, though several participants came from other degree programs, contributing diverse perspectives on how AI can be applied in different sectors.

Delivered fully online, the course carries 5 ECTS credits and runs from September to December 2025. The digital format was chosen to support accessibility for students from multiple campuses and to reflect the realities of remote, AI-enhanced work environments. The course includes 10 online 3h sessions in Zoom and online learning environment in Moodle.

4.2 Course Structure and Framework Alignment

The course is designed as a 10-session learning journey. Each phase is explicitly aligned with the Design Thinking phases, UNESCO AI Competency Framework's and EntreComp Framework's competence areas.

This triple-framework alignment provides both pedagogical coherence and developmental progression. It guides students from initial awareness of AI's societal roles to active, ethical engagement with AI-based business innovation. The structure ensures that technical understanding, ethical reasoning, and entrepreneurial application are integrated rather than treated as separate subjects.

The course unfolds progressively: beginning with conceptual understanding and empathy, moving toward creative ideation and prototyping, and concluding with testing, reflection, and ethical evaluation.

Table 1: Integration of Design Thinking, EntreComp, and UNESCO AI Competences Across the Course

Week	Session Title	UNESCO Dimension	Design Thinking	EntreComp
1	Course Kickoff	Overview of all	Empathize	Spotting opportunities, working with others
2	Human Agency and Accountability	Human-centered mindset	Empathize	Ethical and sustainable thinking

Week	Session Title	UNESCO Dimension	Design Thinking	EntreComp
3	Citizenship in the Era of AI	Human-centered mindset	Define	Valuing ideas, mobilizing resources
4	Embodied Ethics and Responsible Use	Ethics of AI	Define	Coping with ambiguity, uncertainty & risk
5	Ethics by Design	Ethics of AI	Ideate	Creativity
6	AI Techniques and Applications	AI techniques & applications	Ideate / Prototype	Planning and management
7	Problem Scoping	AI techniques & applications	Ideate / Prototype	Vision
8	Architecture Design	AI system design	Prototype	Taking initiative
9	Iteration and Feedback Loops	AI system design + Ethics	Test	Learning through experience
10	Seminar: Final Presentations and Reflection	All dimensions		Learning through experiences

This alignment creates a structured yet flexible learning flow, ensuring that each phase built upon the previous one both conceptually and practically.

4.3 Learning Activities and Group Work

Group-based learning forms the core pedagogical approach of the course. During the first session, students were introduced to the overall aims of the course and engaged in an exploratory brainstorming exercise to identify areas where AI could generate social or business value. From this activity, students self-organized into thematic groups according to interest areas such as healthcare, cybersecurity, sustainability, education, and creative industries.

Each group remains intact throughout the semester, collaborating synchronously in breakout sessions and asynchronously via Moodle forums and shared digital workspaces. The instructor's role evolved from lecturer to facilitator and coach, providing guidance, ethical framing, and formative feedback rather than prescriptive answers. Short input segments introduced conceptual material: AI applications in business, ethical frameworks, and innovation models, followed by extended periods of team-based exploration and dialogue.

4.4 Integration of Generative AI Tools

A distinctive feature of the course is the intentional integration of generative AI tools as reflective co-creators, rather than as sources of ready-made answers. The pedagogical aim is to cultivate AI literacy and ethical awareness by positioning large language models as dialogical partners in the learning process.

From the first session, students were introduced to the ethical and epistemic limitations of generative AI. The instructors facilitated a discussion on algorithmic bias, hallucination, and amplification of stereotypes, emphasizing the importance of critical thinking and bias awareness in AI-supported work. Students were encouraged to treat AI-generated content as provisional material for reflection and improvement, not as final output.

To support structured application of AI tools, two custom chatbots were implemented within the Moodle environment. Value Proposition Canvas Chatbot is designed to help students articulate customer segments, value propositions, and problem-solution fit for their AI-based business ideas. Business Model Canvas Chatbot is guiding teams through elements such as key partners, activities, and revenue models, helping them conceptualize how AI could generate and deliver value ethically and sustainably.

Students were asked to use the chatbots and critically assess the relevance and accuracy of chatbot outputs, identify and discuss biases or unrealistic assumptions embedded in AI responses, and propose human-centred improvements to ensure inclusivity, fairness, and contextual fit. This reflective engagement was deepened through guided group discussions following each AI-supported task. Students compared AI-generated ideas with their own analyses, debated ethical implications, and evaluated how human judgment complements algorithmic output.

4.5 Digital Learning Infrastructure (Moodle)

The course is delivered entirely online, supported by Moodle as the central digital learning hub. Each week, instructors upload session recordings, presentation slides, readings, and links to external tools, including the generative AI chatbots. This ensures that students could revisit materials, engage at their own pace, and build continuity between live sessions and independent study.

Moodle also hosts asynchronous assignments designed to scaffold learning between synchronous meetings. These include uploads of intermediary outputs created during group work and discussions in the break out rooms. While these submissions are not graded, they serve as formative checkpoints, encouraging students to iterate and maintain steady progress rather than deferring work until the end of the course.

5. Discussion and Conclusion

5.1 Reinterpreting the Course Design Through Theory

The course was grounded in constructivist, sociocultural, and transformative learning theories. Learning was conceptualized as an active, social, and reflective process, where knowledge was co-constructed through dialogue, collaboration, and mediated interaction with AI tools. In practice, students engaged in cycles of exploration and reflection that reflected Vygotsky's (1978) concept of mediated learning, where tools, in this case generative AI systems, served as cognitive scaffolds that extended learners' reasoning and creative capacities beyond individual levels.

The constructivist principle of learning by doing was embedded in the design thinking process, where students actively applied knowledge through iterative group work and project-based inquiry. This approach enabled them to negotiate meaning, refine ideas, and build shared understanding. From a transformative learning perspective (Mezirow, 1997), the course encouraged students to question common assumptions about AI, particularly the idea of AI as a neutral or purely technical system. This fostered ethical awareness and supported shifts in perspective.

5.2 Integration of Frameworks: Lessons Learned

The integration of Design Thinking, the EntreComp Framework, and the UNESCO AI Competency Framework provided a coherent, multi-dimensional foundation for learning. Design Thinking offered a flexible structure for progressing from problem identification to solution development. EntreComp provided a shared language for entrepreneurial competences, framing creativity and ethical awareness as core skills. The UNESCO framework anchored these pedagogical elements in a broader ethical and societal context, ensuring that innovation was aligned with principles of sustainability and human dignity.

Although the integration required deliberate curricular alignment, it proved pedagogically valuable. Students experienced learning as a continuous progression from conceptual understanding to practical application and ethical reflection. This illustrates the potential of multi-framework approaches to support responsible AI education within business and entrepreneurship contexts.

5.3 Generative AI as a Learning Mediator

The course reconceptualized generative AI as a learning mediator that facilitated interaction between human reasoning and computational suggestion. In line with sociocultural and constructivist pedagogical approaches, AI tools were positioned as mediating artifacts that shaped thinking and collaboration, rather than merely automating tasks.

Through guided reflection, students learned to identify bias, overgeneralization, and contextual limitations in AI outputs, fostering meta-awareness of how algorithms structure information and meaning. The course demonstrated that, when integrated through pedagogical design, generative AI can support and expand learners' cognitive and creative capacities.

5.4 Limitations and Future Directions

This study centers on the design and implementation phase of the course, with a comprehensive evaluation of student learning outcomes scheduled to take place following the course's conclusion in December 2025. Consequently, the findings presented are conceptual and formative in nature, intended to illustrate the pedagogical processes rather than to assess their impact.

Planned future research will involve multiple components. First, a detailed analysis of student reflections and project outputs will be conducted in 2026 to examine learning experiences and knowledge application. Second, comparative studies across Pathfinder partner institutions will explore the scalability and contextual adaptability of the course design.

Collectively, these future research activities aim to extend the project's contribution from an initial pilot toward a theoretically grounded and empirically validated model for ethical AI and entrepreneurship education within higher education.

5.5 Conclusions

The course contributes to three intersecting domains of educational innovation. First, within the domain of AI in education, it offers a model for the responsible and reflective integration of artificial intelligence into learning environments. Second, in the field of entrepreneurship education, it embeds ethical and sustainable thinking as core components of innovation learning. Third, in terms of pedagogical design, it demonstrates how multiple educational frameworks can be effectively aligned within a scalable, competence-based course structure.

The course exemplifies a human-centered AI learning ecosystem that enables students to engage with technology critically and creatively, while maintaining a strong ethical orientation. It underscores the potential of AI literacy, when grounded in constructivist and transformative pedagogies, to bridge the gap between technological advancement and social responsibility.

Ethics declaration: The research did not involve human subjects in the form of interviews, surveys, or identifiable student data. Instead, it drew exclusively on document-based materials, including course plans, teaching artefacts, and instructor observations, produced during the development and delivery of the course.

AI declaration: The AI was employed to assist the author in structuring sections and refining academic language for clarity and coherence and proofreading. Final editorial responsibility and intellectual authorship remain fully with the human author.

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Investigating Factors Influencing the Utilization of ChatGPT Among Students in Higher Accounting Education: Expanding the Technology Acceptance Model

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Abstract: The study investigated the factors influencing the behavioural intention to utilize ChatGPT among accounting students in higher education. Drawing on the technology adoption model, the research explores how self-efficacy and perceived risk affect their intention to adopt ChatGPT as a learning aid. The study adopted a simple random sampling technique and gathered data from 200 accounting students from Ghanaian universities. The data gathered was measured using PLS-SEM technique. The study found that the most crucial factor influencing the behavior intention toward ChatGPT among accounting students is perceived usefulness. The study also found that attitude is also very significant factor affecting the behavioural intention to adopt ChatGPT. Perceived usefulness and perceived ease of use were found to have positive relationships on student's attitude toward ChatGPT adoption. The study also found that whereas self-efficacy showed a positive effect on attitude, perceived risk showed a negative effect on attitude toward ChatGPT adoption. The findings underscore the direct influence of self-efficacy and perceived risk in AI adoption and suggest that educational policies should prioritize training programs and promote accountability frameworks around AI tools.

Keywords: ChatGPT, Students, Accounting education, TAM

1. Introduction

Artificial Intelligence has become widely used in education to support academic tasks instead of substituting human tasks. AI intelligence technologies consist of tools such as ChatGPT, Gemini and Copilot (Mustofa et al., 2025). However, the study focuses on ChatGPT adoption by students since it is the most widely accepted and recognized generative AI among educators and students. ChatGPT was built by OpenAI, a business enterprise and developed from large scale language applications including natural language processing (NLP), big data analytics and speech recognition technology. ChatGPT has the ability to generate responses comparable to human user, understand and answer users' questions in a natural and conversational way. In the context of education, it can assist teachers and students to ask complex questions and receive detailed and immediate responses (Menon and Shilpa, 2023; Sundkvist and Kulset, 2024), offers personalized learning support, more interactive and engaging learning experience (Menon and Shilpa, 2023).

Technology in education has evolved with ChatGPT gaining increasing academic interest in higher education in both developed and developing countries. In developing countries like Ghana, ChatGPT can enable academic institutions to democratize access to knowledge, support teachers and students, provide cost-effective learning resources and prepare learners for a digital, AI-driven workforce. However, the potential benefits of ChatGPT is yet to be realized by academic institutions in developing countries. To achieve these benefits, there must be maximum utilization of the technology. The acceptance of ChatGPT among students are crucial for the successful execution of the technology in academic institutions. However, knowledge and understanding relating to drivers affecting students' utilization of ChatGPT are very scarce. Then again, majority of studies have overlooked the role of self-efficacy and perceived risk in the utilization of ChatGPT among students.

Al-Hattami (2025) has found that when users have self-efficacy, it can boost their confidence to accept and engage with e-learning platforms. Then again, perceived risk consisting of technology risk and security risk can have negative impacts on users behavioural intention (Chatterjee et al., 2022). Ferri et al. (2021) have stated that even though perceived risk is significant, only a limited number of studies have integrated the variable into TAM to explain users' adoption decisions.

The aim of this study is to investigate the impact of cognitive factors (perceived usefulness and perceived ease of use and psychological factors (self-efficacy and perceived risk) on the behavioural intention to use ChatGPT by accounting students in higher education.

TAM was the theoretical framework that underlined the study. The reason for utilizing TAM is because of its wide acceptability by prior studies in unravelling factors driving students' acceptance of both existing and new technology. The framework posits that perceived usefulness (PU) and perceived ease of use (PEOU) are fundamental predictors of users' behavioural intention to use ChatGPT. Other studies have proposed that incorporating external variables such perceived risk (PR) and self-efficacy might increase the explanatory power of technology acceptance in higher education. To validate the planned framework, a questionnaire was developed and distributed. A total of 200 valid responses were gathered to authenticate the study's hypothesis.

The study's contribution is as follows: The study builds and extends traditional TAM by examining self-efficacy and perceived risk in the ChatGPT context used in accounting education. It also contributes to theory by exploring how self-efficacy by accounting students affects behavioural intention to use ChatGPT for learning purposes. Also, exploring the impact of perceived risks can inform university policies on acceptable AI use, ensure consistency and fairness.

The research is outlined as follows: Part 2 includes the explanation on TAM theory and subsequently the research hypotheses. Part 3 includes the materials and methods and part 4 includes the data analysis with results in part 5. Part 6 includes the theoretical and managerial contributions and the final part includes the conclusion.

2. Literature Review

Technology Acceptance Model (TAM)

TAM is the theory that underpinned this study. TAM is a well-known individual-level framework that has been adopted by many research to establish relationship between user beliefs, attitudes and intentions (Ly and Ly, 2022). TAM emphasizes PU and PEOU as core determinants. The theory indicates that at the individual level, PU and PEOU drives user AT and both PU and AT drive BI toward technology adoption (Dahri et al., 2024). Due to its lucidity in describing the users' attitude toward digital technology adoption, it has been extensively involved in diversified fields (Xu, Khan and Shahzad, 2024). Prior studies such as Shao et al. (2024) and Ferri et al. (2021) have emphasized that integrating perceived risk and self-efficacy extends the TAM by showing how risk consideration and perceived confidence also shape user attitude. Shao et al. (2024) have indicated that numerous empirical studies have shown that users with high self-efficacy, perceives the technology as useful and simple to apply. Also, Ferri et al. (2021) have also emphasized that perceived risk is a direct determinant of intention and has an adverse effect on intention. .

3. Research Hypothesis

Perceived Usefulness (PU)

In the context of this study, perceived usefulness (PU) denotes the degree to which a student beliefs that using ChatGPT can improve his academic performance (Davis, Bagozzi and Warshaw, 1989). In TAM, PU is one of the most crucial predictors of user's BI (Davis, Bagozzi and Warshaw, 1989). Some scholars have suggested students may perceived ChatGPT in higher accounting education as useful when it promotes the exchange of ideas, provides personalized feedback, continuous learning support, real-time problem-solving (Baig and Yadegaridehkordi, 2024), provides supplementary learning materials (Ortiz-Bonnin and Blahopoulou, 2025). Similarly, other studies indicated positive experiences with ChatGPT such as a reliable responses and efficient task completion contributes to users' belief of its usefulness. Hence, studies such as Dahri et al. (2024) have found that when users perceive ChatGPT as useful, it might influence the attitude of students in higher accounting education to accept. Then again, Shahzad et al. (2024) have found that PU has a significant impact on the behavioural intention of students toward ChatGPT. However, Sukendro et al. (2020) found no relationship between PU and AT among students to use e-learning. Thus, the study hypothesizes that:

H1: PU can positively influence students' AT toward ChatGPT in higher accounting education

H2: PU can positively influence students' BI toward ChatGPT in higher accounting education

Perceived Ease of Use (PEOU)

In the context of this study, perceived ease of use (PEOU) denotes the degree to which the students beliefs that using the technology is ease to use, ease to learn, user-friendly, intuitive and accessible (Davis, Bagozzi and Warshaw, 1989). It is a core determinant of TAM and play a crucial role in technology acceptance (Davis, Bagozzi and Warshaw, 1989). According to Shahzad, Xu and Javed (2024), ChatGPT may be perceived as ease to use in higher education by students if it is characterized intuitiveness user-friendliness and accessibility. Some prior

studies have found a positive and strong impact between PEOU and AT in higher education (Sukendro *et al.*, 2020).This demonstrates the higher the PEOU, the higher the students' behavioural intention would be toward ChatGPT usage in higher accounting education. Also, studies conducted by Amaning (2024) in higher education in Ghana that the inaccessibility of virtual accounting education negatively affected the easiness and success of the system among students/ Also, studies such as Shahzad, Xu and Javed (2024) found that PEOU significantly affect students' BI to use technology among students in higher education in China. Thus, the study hypothesizes that:

H3: PEOU can positively influence AT toward ChatGPT in higher accounting education

Self-Efficacy (SE)

SE which was advanced by Bandura (1997) states that behavior is facilitated by the strength of an individual's self-efficacy beliefs. Self-efficacy is explained in this study as a students' evaluation of his or her competence to perform desirable behaviours in specific contexts. It has been emphasized that SE can enable users to effectively organize and implement strategies to have a positive user experience when using ChatGPT (Yao and Wang, 2024). It can enhance easiness, flexibility in learning and foster a positive attitude toward the usage of ChatGPT (Xu, Khan and Shahzad, 2024). Some scholars have emphasized that SE can affect behavioural intention to use and actual use behavior of students (Hatlevik, 2017). Al-Hattami and Almaqtari (2023) have emphasized that when a student has high level of SE, he or she engages with digital technologies in a creative and innovative ways. Then again, (Yao and Wang, 2024) a study conducted among pre-service teachers found that SE can affect their intention toward AI in education. In contrast, Tang, Che-Han and Oanh (2014) found no effect between SE and BI to use e-learning. They claim that in mandatory academic settings, SE may not become invaluable in the usage of e-learning among students in higher educational environment. Thus, the study hypothesizes that:

H4: SE can positively influence students' AT toward ChatGPT in higher accounting education

Perceived risk (PR)

PR refers to an individual's belief about the potential consequences of an event given the extent of uncertainty associated with a specific behavior (Wissal et al., 2021). This means that when students belief that when ChatGPT may become risky to their academic performance and encounter losses, they may refrain their usage. Some studies have emphasized that students may perceive ChatGPT as risky when there are information inaccuracies, security and integrity issues (Ortiz-Bonnin and Blahopoulou, 2025). It may also be perceived as dangerous if the overreliance on ChatGPT would minimize their critical thinking, problem-solving and creative skills (Abbas, Jam and Khan, 2024; Ortiz-Bonnin and Blahopoulou, 2025). Based on these reasons, some prior studies have attempted to link the relationship between PR and AT. In academic context, Ortiz-Bonnin and Blahopoulou (2025) have found that PR has a negative and significant impact on BI to use ChatGPT. Also, Sarosa (2022) have found that security problem was the major PR indicator affecting high school students BI toward using online learning. Thus, the study hypothesizes that:

H5: PR can negatively influence students' AT toward ChatGPT in higher accounting education

Attitude (AT)

In the context of this study, AT can be emphasized as either a positive or negative feelings of the student toward using ChatGPT. It includes behavioural, cognitive and affective elements. Both TAM and the theory of planned behavior consider AT to be a crucial construct that can determine the user's behavioural intention to accept a technology. Masa'deh et al. (2024) used TAM to describe the antecedents affecting the usage of ChatGPT among Jordanian university students and found that AT has a positive influence on BI. Then again, a study conducted by (Hussein, 2017) found that AT is a significant predictor influencing the BI to use e-learning by students. Thus, the study hypothesis that:

H6: AT can positively influence students' AT toward ChatGPT in higher accounting education.

4. Materials and Method

Participants

The population of the study consisted of all accounting students enrolled in bachelors and master's degree at a Ghanaian university. A simple random sampling method was utilized to select the study's samples. The study which spanned for three (3) months from February 2025 to April 2025 provided the researchers with two

hundred and twenty (224) responses. However, two hundred (200) valid responses were validated for further analysis.

Research instrument

The study employed an online questionnaire developed using Google Forms. A content validity was carried out by two academic experts to confirm the validity and accuracy of the measuring items. We further performed a pilot study with twenty-five students engaged in ChatGPT usage and were later dropped after modification of the study. The measuring items consisted of 19 questions which were modified from prior studies. The questionnaire items for PU and PEOU were modified from (Shahzad, Xu and Javed, 2024), SE was modified from (Yao and Wang, 2024), PR was modified from (Kenesei et al., 2025), AT and BI was modified from (Masa'deh et al., 2024). We adopted a five (5)-point Likert scale to measure survey items from 1 (strongly disagree) to 5 (strongly agree).

5. Data Analysis

Measurement Assessment

Construct Reliability

The study employed SmartPLS version 3.0 to measure the construct reliability and validity. Table 1 shows the statistical measures relating to items with constructs including composite reliability (CR) and cronbach alpha (CA). It can be observed in Table 1 that all items loadings range between 0.828 and 0.946. The results how that item loading are acceptable since they are higher than 0.70. The construct reliability was measured using both CA and CR. The CA ranged between 0.802 and 0.883 and the CR ranged from 0.882 and 0.929. According to (Hair, Howard and Nitzl, 2020), a construct reliability is accepted when their CA or CR values falls between 0.70 and 0.95 and hence the construct validity of the study was established.

Convergent Validity (CV)

The study also measured the CV of the constructs using average variance extracted (AVE) AVE determines the average difference shared between the construct and its individual indicators and its value should be 0.50 or above (Hair, Howard and Nitzl, 2020). Table 1 shows establishment of convergent validity since AVEs falls between 0.714 and 0.813.

Table 1: Construct reliability and validity

Construct	CA	CR	AVE
AT	0.802	0.882	0.714
BI	0.860	0.915	0.782
PEOU	0.883	0.927	0.810
PR	0.871	0.913	0.777
PU	0.874	0.914	0.726
SE	0.885	0.929	0.813

Discriminant Validity (DV)

The study also measured the DV using Fornell-Larcker (FL) and heterotrait-monotrait ratio (HTMT). Fornell-Larcker (FL) preliminary assessed to test the discriminant validity of the constructs. Fornell and Larcker (1981) emphasize DV is established when each construct AVE is greater than the squared inter-construct association. Table 2 shows that DV was established since the construct AVE was higher than the squared inter-construct correlation. The HTMT can be explained as the average value of the item associations across constructs in relation to the average value of the item correlation measuring the same construct (Hair et al., 2019). Henseler, Ringle and Sarstedt (2015) suggest that DV is established when HTMT is below 0.90. Table 3 depicts that discriminant validity is also established through HTMT.

Table 2: Fornell-Larcker

	AT	BI	PEOU	PR	PU	SE
AT	0.845					
BI	0.683	0.884				
PEOU	0.593	0.677	0.900			
PR	-0.093	-0.084	0.007	0.882		
PU	0.560	0.695	0.571	-0.027	0.852	
SE	0.601	0.739	0.674	0.029	0.629	0.901

Table 3: HTMT

	AT	BI	PEOU	PR	PU	SE
AT						
BI	0.808					
PEOU	0.696	0.773				
PR	0.095	0.090	0.041			
PU	0.650	0.793	0.645	0.048		
SE	0.692	0.839	0.757	0.043	0.711	

Structural Assessment

After the measurement assessment, the SmartPLS version 3.0 was utilized to examine the path relationship of the structural model. Table 4 and Figure 1 show the path relationship and structural model. The findings show that PU has the highest positive effect on BI ($\beta = 0.455, \rho = 0.00$). The study also found that AT has a very high positive effect on BI ($\beta = 0.429, \rho = 0.00$). The study also found that PEOU has a positive effect on AT ($\beta = 0.282, \rho = 0.001$). The study also found that SE has a positive effect on AT ($\beta = 0.271, \rho = 0.001$). The study found that PU has a positive effect on AT ($\beta = 0.225, \rho = 0.001$). The study found that PR has small and negatively effect on AT ($\beta = -0.097, \rho = 0.074$).

Table 4: Hypothesis testing

Hypothesis	Path	Original Sample (O)	Standard Deviation (STDEV)	T Statistics	P Values
H1	PU -> AT	0.225	0.067	3.341	0.000
H2	PU -> BI	0.455	0.066	6.927	0.000
H3	PEOU -> AT	0.282	0.087	3.253	0.001
H4	SE -> AT	0.271	0.088	3.080	0.001
H5	PR -> AT	-0.097	0.067	1.446	0.074
H6	AT -> BI	0.429	0.072	5.957	0.000

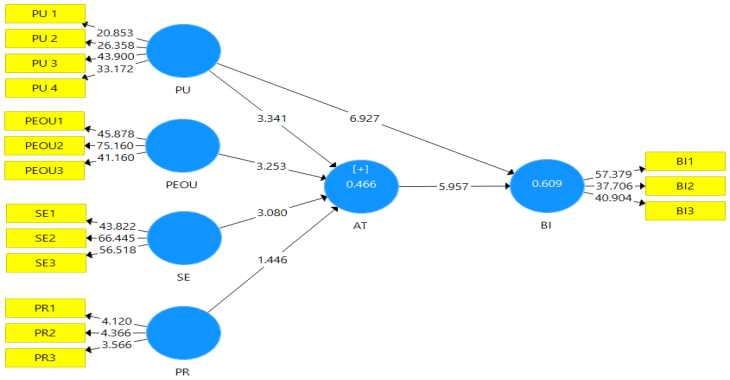

Figure 1: Structural diagram

6. Discussion

The study utilized TAM to evaluate the factors influencing students' utilization of ChatGPT in higher accounting education. The following factors were assessed in this study: attitude and behavioural intention as well as perceived usefulness, perceived ease of use, self-efficacy and perceived risk among students. The study discovered that PU positively impact students' AT toward utilizing ChatGPT in higher accounting education. The findings corroborate with prior studies such as (Sukendro et al., 2020; Dahri et al., 2024; Shahzad, Xu and Javed, 2024). The study also found that PU has the highest positive effect on students' behavioural intention toward utilizing ChatGPT in higher accounting education. This means that the students expect ChatGPT to provide exchange accurate accounting information, provide personalized feedback, adaptive content delivery, and continuous learning support to have a positive feeling and subsequently adopt the technology.

The study found that perceived ease of use (PEOU) has positive effect among students to use ChatGPT. The findings agrees with prior studies such as Shahzad, Xu and Javed (2024). It is plausible that when ChatGPT is user-friendly, easy to learn, good user interface and intuitive, it might increase their positive feeling. We also align with studies such Amaning (2024) that if the students do not feel that ChatGPT is incompatible and inaccessible, they may abort it due to uneasiness. However, if ChatGPT is compatible and easily accessible by students remotely, they may be encouraged to have positive attitude towards it.

The study found that SE has positive effect on AT among students to use ChatGPT in higher accounting education. The study's findings align with prior studies such as (Yao and Wang, 2024) which found a positive effect between self-efficacy and attitude. The findings demonstrate that SE can improve the adaptability of students toward digital learning tools. This also implies that SE can improve the easiness and flexibility in learning which can foster a positive attitude to use ChatGPT. Also, SE can also enable the students to have a positive AT and apply the technology in a creative and innovative manner and thus align with findings of prior studies such as (Al-Hattami and Almaqtari, 2023).

The study found that PR has a small and negative effect on students' AT to use ChatGPT. The findings align with Ortiz-Bonnin and Blahopoulou (2025). This implies that when ChatGPT leads to information inaccuracies, privacy and security issues, students may have a negative feeling concerning its usage. Their attitude toward ChatGPT may also be impeded if there is a high likelihood that the usage of digital learning platform can expose them to various ethical issues such as plagiarism, non-transparency, information bias and virus and malware attacks.

The study found that AT has a high positive effect on students' BI to use ChatGPT. The study's finding aligns with the results of Hussein (2017) which found AT as a predictor affecting the behavioural intention to use e-learning by students. Also, a positive AT shows that other important determinant influence the students' AT to use ChatGPT than PR.

7. Theoretical and Managerial Implication

The study contributes to present knowledge by adopting TAM to examine the factor affecting the utilization of ChatGPT in higher accounting education. The study found that PU, PEOU, SE and PR explained 46.6% of the variation in AT and both PU and AT explained 60.9% of the variations in BI to use ChatGPT. The findings shows that TAM can be very effective in the explaining the application of ChatGPT in higher accounting education in the context of developing countries. The study's findings show that SE and PR can be recognized as an antecedent of AT and BI to adopt ChatGPT among accounting students. The study also reaffirms the main assumption in the TAM confirming that PU and PEOU are crucial antecedents affecting AT and BI to use technology. The findings of the study strengthens the theoretical knowledge that cognitive beliefs and psychological beliefs are both critical in explaining ChatGPT among students in higher accounting education

The study has some managerial implications. The study found that when students have high self-efficacy, the goal of integrating ChatGPT into accounting curriculum can be achieved by educators. Also, the findings show that ChatGPT must be implemented systematically to allow mastery by students and to use ChatGPT ethically. Also, AI literacy courses and mentoring sessions must be organized so that less tech-savvy students have confidence to use the technology ethically and appropriately. Then again, administrators and educators can adopt student feedback on ChatGPT to improve teaching outcomes. Universities must establish clear guidelines on ethical AI use to mitigate risks such as cyber security issues and plagiarism. They must also provide training and accountability frameworks around AI tools.

8. Limitations and Future Studies

First, the study was carried out among students in the accounting profession and future studies could replicate the studies among students in other academic disciplines in similar setting to prove or disprove the findings. Moreover, the study was conducted in Ghana and the findings might not apply to participants in the setting of other developing countries. Hence, future studies are recommended to replicate the study in other context. Secondly, data was gathered utilizing a self-administered questionnaire allowing participants to report their own perceptions and experiences. Moreover, 53.4% and 39.1% of the variance in AT and BI were unaccounted for by the independent constructs in the study. Thus, future studies should measure the framework with addition elements such as ethics, subjective norm and trust that could affect both AT and BI. Future studies.

Ethical declaration: Ethical clearance was not required. However, informed consent was sought from the participants involved in the research study.

AI declaration: AI tools were not used for the creation of the paper.

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Organizational and Social Impact of AI-Driven Fake Review Detection in e-Commerce

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Abstract: The rapid growth of e-commerce and mobile transactions has fueled an increase in fraudulent activities with fake online reviews posing a major threat to businesses and consumers. Such reviews, often generated by seller, third parties, or bots, distort reputations, mislead consumer decisions, and erode trust. To address this, organizations are adopting AI-driven detection systems that offer scalability and efficiency while also raising challenges around bias, transparency, and ethical oversight. Drawing on insights from a doctoral dissertation focused on real-time detection of fake reviews using AI, this article examines how these systems shape platform governance, seller behavior, and consumer perceptions of fairness and trust. It highlights implications for risk management, compliance, and regulation, while also assessing social consequences such as false positives, opacity, and perceived bias. The paper recommends strengthening platform governance, ensuring fair treatment of sellers, and enhancing internal risk management at the organizational level, while at the social level, emphasizing consumer trust-building, fairness and legitimacy, and embedding ethical safeguards to protect privacy, accountability, and literacy. Finally, this paper calls for a responsible, human-centric approach to AI deployment that balances automation needs with ethical oversight, enhances consumer confidence, improves platform integrity, and promotes organizational efficiency.

Keywords: Fake online reviews, AI-Driven fake review detection, e-Commerce platform governance, Algorithmic bias and transparency, Consumer trust in digital marketplaces, Ethical AI deployment

1. Introduction

The rapid expansion of e-commerce has transformed the retail landscape by offering consumers convenient access to a vast array of products and services. At the same time, digital platforms are increasingly turning to artificial intelligence (AI) to manage scale, optimize operations, and improve user trust. The integration of artificial intelligence (AI) into digital platforms has profoundly transformed organizational structures, platform governance, and user interaction. Far beyond automating backend operations, AI now influences how content is moderated, how trust is managed, and how decisions are made across industries (Brendel et al., 2021). Organizations are increasingly adopting frameworks like reciprocal symmetry - a principle that calls for balancing technological advancement with human values to guide ethical AI deployment (Carnero, 2017, Srđević, 2025). This shift has led to cultural and structural changes within companies, requiring ethical leadership, transparency in communication, and alignment of AI initiatives with corporate social values (Carnero, 2017, Aakula et al., 2024).

AI's adoption also necessitates strategic investments in infrastructure, talent, and governance. Barriers such as inadequate systems, lack of skilled professionals, and high implementation costs continue to challenge organizations (Brendel et al., 2021). However, studies show that successful integration can foster employee engagement, enhance decision-making processes, and build resilient digital cultures. This necessitates that organizations develop a value system based on established governance guidelines that prioritize ethical AI practices and have oversight mechanisms that prevent biases from being developed and perpetuated. (Aakula et al., 2024).

However, this growth in e-commerce has also given rise to a pressing challenge: the proliferation of fake online reviews. Fraudulent reviews—whether overly positive, maliciously negative, or autogenerated by bots—distort consumer perceptions, mislead purchasing decisions, and erode trust in digital marketplaces. These deceptive practices can result in significant financial losses for consumers, damage to brand reputation, reduced sales performance, and increased operational costs for businesses (Paul & Nikolaev, 2021).

Fake reviews undermine the credibility and integrity of e-commerce platforms, making the detection and removal of such content a strategic necessity. Traditional rule-based or manual moderation systems often fail to distinguish between genuinely critical reviews and those engineered to manipulate, making the task both complex and resource-intensive. As Paul and Nikolaev (2021) note, conventional methods struggle to differentiate malicious content from legitimate user feedback. In this context, artificial intelligence (AI) emerges as a necessary and powerful tool. AI systems can process large volumes of data, detect patterns, and adaptively flag suspicious content in real time. Cao (2021) highlights AI's role in fraud detection through automation, pattern recognition, and continuous learning to address evolving fraudulent behaviors.

Failure to address fake reviews has far-reaching implications. For businesses, this includes loss of consumer trust, reputational harm, reduced marketing effectiveness, regulatory scrutiny, and declining competitive advantage (Mînăstireanu & Meșniță, 2019). For consumers, it leads to misguided purchases, returns, financial loss, and a growing sense of distrust toward online platforms (Jha et al., 2020).

This study seeks to address this problem through two research questions:

RQ1*: How can AI-based methods identify and remove fake online reviews in real time to improve trust, brand reputation, and business outcomes?*

RQ2*: What factors influence organizations to adopt AI for fake review detection, and what challenges and strategic considerations shape their implementation decisions?*

By exploring these questions, the study aims to evaluate the effectiveness and organizational implications of AI in combating fake reviews and sustaining e-commerce integrity.

2. Literature Review

The rise of e-commerce has enhanced the importance of user-generated content, with online reviews serving as a primary source of consumer decision-making (Vidanagama et al., 2019). Yet the proliferation of fake reviews whether overly positive, maliciously negative, or bot-generated poses a significant threat to digital marketplaces. Such deceptive practices distort consumer perceptions, misguide purchasing decisions, and erode trust in platforms (Christopher & Rahulnath, 2016). For organizations, fake reviews can result in reputational damage, reduced sales performance, regulatory scrutiny, and higher operational costs, while for consumers they contribute to financial loss and dissatisfaction (Crawford et al., 2015). Detecting and mitigating fake reviews is therefore not only a technical challenge but also a strategic necessity for sustaining platform integrity and competitiveness.

Another critical strand of literature focuses on trust and reputation systems, especially in e-commerce platforms where user-generated content heavily influences purchase decisions (Pavlou & Dimoka, 2006). Trust in AI systems is critical for acceptance and is multifaceted - spanning accuracy, transparency, ethical handling of data, and user empowerment (Oyekunle et al., 2024). Consumers tend to trust platforms more when AI-generated insights are presented with precision and clarity, enhancing the perceived reliability of information (Kim et al., 2021). Moreover, algorithmic transparency plays a key role in maintaining long-term engagement and minimizing resistance to automated systems (Choung et al., 2023).

In response to concerns about AI opacity and biased decision making, recent advancements in explainable AI (XAI), such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model Agnostic Explanations) aim to make AI decisions more interpretable (Perdigao et al., 2025, Desai et al. 2024). These tools offer visibility into how AI models evaluate data, helping users understand why a piece of content is flagged. This is particularly important for review moderation systems, where false positives can alienate consumers and create reputational risks for platforms. Still, XAI alone may not be sufficient without complementary efforts in digital literacy and consumer education (Swart, 2021).

There is a growing recognition in both academic and industry literature that moderation technologies shape not just platform safety but also user behavior and commercial dynamics. Consumers who perceive AI moderation as arbitrary or opaque may disengage from platforms altogether (Brendel et al., 2021, Marti et al., 2024). Similarly, sellers impacted by inaccurate flagging may lose trust in the system, which can ultimately harm brand equity and platform integrity. These concerns are echoed in the domain of misinformation detection and social media moderation, where scholars stress the need for human-in-the-loop systems and appeal mechanisms to maintain perceived fairness (Perdigao et al., 2025, Srđević, 2025).

Ethical and policy dimensions are central to discussions about AI deployment in digital environments. Literature points to challenges involving data privacy, bias mitigation, and regulatory compliance (Srđević, 2025). Frameworks such as the EU's General Data Protection Regulation (GDPR) and proposed AI Act aim to standardize accountability and promote ethical AI across sectors ((Maddula, 2018). However, these frameworks often lag the pace of AI innovation, making organizational self-regulation and ethical leadership even more important (Srđević, 2025).

This study contributes to this evolving body of knowledge by examining the organizational and social consequences of AI-driven fake review detection in e-commerce. Drawing from a doctoral dissertation that studied how machine learning models could be used to identify fraudulent reviews and understand the factors

impacting AI adoption, this research shifts the focus beyond technical accuracy to explore how AI moderation impacts platform governance, seller behavior, user trust, and ethical compliance. It positions fake review detection not just as a fraud prevention mechanism, but as a window into broader questions of responsible AI deployment, algorithmic legitimacy, and stakeholder engagement in digital commerce.

3. Methodology

3.1 Qualitative Research

A qualitative research approach was adopted to gain in-depth insights into the factors influencing the detection of fake online reviews using AI-based Fake Review Detection (FDR) systems. Given the limited prior research in this area, grounded theory was chosen to develop conceptual understanding and generate theory relevant to the research questions (Muzari et al., 2022). The study aims to enhance current understanding of the risks fake reviews pose to consumers and organizations, and the role AI can play in mitigating these risks.

Data was collected through one-on-one semi-structured interviews conducted via Zoom, each lasting up to 60 minutes. A total of 12 participants were interviewed, and this sample size was deemed sufficient upon reaching saturation. Interviews explored participants' experiences, motivations, and perspectives on AI and fake review detection.

Participants represented a range of industries—technology (58%), finance (17%), education, consulting, and healthcare (8% each)—and included professionals from large enterprises and startups. Roles spanned management, director, and C-suite levels, with backgrounds in AI, cybersecurity, and IT. The cohort was well-educated: 25% held doctorates, 50% had master's degrees, and 25% held bachelor's degrees.

The age distribution included individuals from 25 to over 65 years old, offering both early-career and seasoned viewpoints: 25–34 (17%), 35–44 (17%), 45–54 (33%), 55–64 (25%), and 65+ (8%). Gender diversity was limited, with 11 men and one woman.

Participants' AI experience ranged from intermediate (58%) to advanced (33%) and expert (8%), with most using AI tools on a weekly or daily basis. This diversity in demographic, professional, and experiential backgrounds provided rich perspectives on the organizational and technological dimensions of AI-driven fake review detection.

Table 1: Demographic Information and Interview times (in minutes)

Participant	Gender	Age	Education	Industry	AI Experience	AI Use	Interview Time
P1	Male	35-44	Masters	Technology	Intermediate	Weekly	59 mins
P2	Male	55-64	Masters	Technology	Intermediate	Monthly	51 mins
P3	Female	55-64	Doctorate	Education	Intermediate	Monthly	49 mins
P4	Male	35-44	Masters	Finance	Intermediate	Weekly	44 mins
P5	Male	45-54	Bachelors	Consulting	Advanced	Weekly	57 mins
P6	Male	55-64	Masters	Technology	Intermediate	Daily	59 mins
P7	Male	45-54	Bachelors	Finance	Intermediate	Monthly	41 mins
P8	Male	25-34	Masters	Technology	Expert	Daily	57 mins
P9	Male	25-34	Bachelors	Technology	Advanced	Daily	68 mins
P10	Male	45-54	Masters	Technology	Advanced	Weekly	51 mins
P11	Male	45-54	Doctorate	Healthcare	Intermediate	Weekly	36 mins
P12	Male	65+	Doctorate	Technology	Expert	Daily	27 mins

3.2 Data Collection and Alignment with Research Objectives

To explore the broader implications of AI-based fake review detection, this study used a semi-structured interview guide grounded in two core research questions. The guide was designed to elicit insights into how AI alters traditional risk management—such as compliance, accountability, and regulatory alignment—as well as the social consequences of AI enforcement, including trust erosion, bias, and ethical concerns.

For **Research Question 1** (How can AI-based fake review detection methods identify, detect, and remove fake reviews in real time?), the interview focused on technical and operational aspects. Questions were aimed at uncovering real-world applications, system effectiveness, and the trade-offs between automation and accuracy.

For **Research Question 2** (What factors influence organizational adoption of AI for fake review detection?), the interview explored strategic, ethical, and implementation challenges. Topics included algorithmic transparency, user privacy, organizational readiness, and stakeholder trust—key factors in evaluating the governance and legitimacy of AI deployment.

This structured yet flexible format allowed participants to share perspectives across industries and roles, ensuring a nuanced understanding of how AI systems are applied, perceived, and governed in e-commerce contexts.

4. Findings

This study's findings are organized into two key dimensions reflecting the broader implications of AI-based fake review detection: **Organizational Impact** and **Social Impact**.

4.1 Organizational Impact

At the organizational level, participants identified three primary areas affected by AI adoption: **platform governance**, **seller impact**, and **internal risk management**.

4.1.1 Platform-Level governance

The integration of AI systems into existing infrastructures presents significant operational challenges. Participants cited high implementation costs, lack of technical expertise, and limited organizational readiness as major barriers. Successful deployment requires long-term vision, financial resources, and a culture supportive of AI adoption.

AI systems must also evolve continuously through adaptive learning to counter increasingly sophisticated fraudulent tactics. Participants emphasized that failure to keep pace with these developments' risks undermining platform integrity, brand reputation, and consumer loyalty.

A recurring theme was the necessity of **human oversight** to complement algorithmic review moderation. Human reviewers provide contextual understanding such as cultural nuances that AI systems often miss. However, excessive human intervention can slow down real-time operations. Striking the right balance between automation and human judgment was seen as crucial to effective governance.

4.1.2 Impact on sellers

Participants noted that trust in AI systems hinges on their measurable performance. There was strong consensus on the need for standardized accuracy metrics such as false positive/negative rates, sensitivity, and specificity to assess system reliability. Poor accuracy not only harms seller reputation but also erodes consumer trust.

Balanced and representative datasets were highlighted as essential for ensuring fair and accurate detection. In practice, however, achieving dataset diversity remains a challenge, particularly across product categories, languages, and review styles.

Concerns about algorithmic fairness were also raised. Participants expressed apprehension about potential biases that could allow AI systems to be gamed by sellers or inadvertently penalize honest businesses—posing risks to both equity and trust.

4.1.3 Internal risk management

Participants agreed that regulatory frameworks have not kept pace with the adoption of AI. There is a clear need for comprehensive, enforceable guidelines to clarify business responsibility, define consumer protections, and support compliance.

The global nature of fake reviews was another challenge - while businesses may remove reviews from their own sites, they cannot control content on external platforms or social media. Several participants suggested that stricter penalties for hosting or spreading fake reviews could accelerate organizational adoption of AI-based solutions.

4.2 Social Impact

AI-driven fake review detection systems have far reaching social implications, particularly concerning consumer trust, perceptions of fairness, and broader ethical concerns surrounding data use and automated decision-making.

4.2.1 Consumer trust and user experience

Participants emphasized that transparency is essential for building consumer trust in AI systems. While participants acknowledged that fake review detection can enhance user experience by improving content quality, they also noted that misclassifying genuine reviews as fraudulent can have the opposite effect, eroding trust not only in the system but in the platform itself. Instances of false flags were seen to contribute to brand alienation and consumer dissatisfaction.

Participants highlighted the need for clear redressal mechanisms to guide users whose reviews are flagged or removed. Providing users with the ability to appeal or request human review was seen as critical for restoring confidence and preserving platform legitimacy. Consumer education and proactive communication about how AI is used and what safeguards exist were also considered vital for fostering trust.

4.2.2 Perceived fairness and algorithmic legitimacy

Perceptions of fairness were strongly linked to system explainability and transparency. Participants stressed that users must be able to understand why a review was flagged, and how to respond. A lack of visibility into algorithmic processes undermines confidence and fuels skepticism.

Several participants raised concerns about bias in review moderation, particularly in relation to cultural nuances, linguistic variation, and region-specific expressions. These subtleties are often missed by AI models, leading to misinterpretations that challenge the legitimacy of moderation outcomes. Additionally, the potential for algorithmic manipulation by sellers—such as gaming the system to suppress legitimate negative reviews—was seen as a threat to both fairness and platform integrity.

4.2.3 Ethical considerations

Ethical concerns emerged as a central theme in the study. Participants pointed to algorithmic fairness, data privacy, and bias mitigation as key areas requiring attention. A lack of transparency in how user data is collected and used, coupled with the absence of user consent, raised concerns about perceived censorship and consumer rights violations.

Participants also cautioned that AI systems may inadvertently favor larger companies with greater resources to invest in advanced tools, putting smaller businesses at a disadvantage and distorting market fairness. The inclusion of human oversight and the involvement of independent third-party audits were seen as effective strategies to ensure ethical accountability and enhance public confidence.

Rather than deleting reviews outright, some participants advocated for a risk-tiered classification system, allowing potentially fake reviews to be flagged for further validation rather than immediately removed—an approach viewed as more balanced and fairer to all stakeholders.

5. Discussion

This study set out to explore the broader organizational and social implications of using AI-based systems to detect and manage fake reviews in e-commerce. The findings reveal that AI is more than just a fraud detection tool; it is a transformative force shaping platform governance, user behavior, organizational strategy, and digital trust ecosystems.

At the organizational level, the adoption of AI alters traditional structures of risk management and accountability. Participants emphasized the importance of aligning AI systems with internal compliance protocols, technological capabilities, and strategic priorities. High implementation costs, data challenges, and organizational inertia emerged as common barriers. However, businesses that adapt effectively by investing in robust infrastructure, training, and oversight are better positioned to reap the benefits of AI moderation. These findings mirror similar transformations seen in social media platforms, where algorithmic content moderation has become integral to managing scale and user safety, but also raises concerns about bias, censorship, and transparency.

The study also highlights how AI detection tools shape user and seller behavior. From a consumer perspective, the presence of automated moderation may deter fraudulent activity, but it can also create anxiety when errors occur such as the flagging of genuine reviews. These errors may cause disengagement or mistrust unless users are given clear feedback and recourse mechanisms. Censorship concerns also need to be addressed to build trust. For sellers, algorithmic moderation introduces reputational risk and increases the importance of maintaining ethical marketing practices. As with misinformation detection on social platforms, perceived fairness and legitimacy are key to ensuring continued participation and compliance from all actors.

AI moderation thus enhances organizational adaptation. Companies must evolve not only technologically, but also culturally and operationally. The integration of human-in-the-loop systems, standardized accuracy metrics, and transparent communication strategies emerged as critical enablers of effective deployment. Organizations that treat AI as a participatory system—engaging stakeholders and embedding ethical safeguards—are more likely to succeed in building trust and competitive advantage.

At a societal level, the use of AI in fake review detection introduces tensions between efficiency and legitimacy. Participants voiced concerns over data privacy, algorithmic bias, and the lack of redressal options, especially for smaller businesses and linguistic user groups. These concerns echo broader debates in the field of AI governance, where the push for automation often clashes with the need for fairness, explainability, and accountability.

In sum, this study reaffirms that fake review detection is not solely a technical challenge, it is a socio-organizational one. AI has the power to enhance platform integrity and consumer trust, but only when deployed with transparency, inclusivity, and ethical oversight. The lessons drawn here resonate far beyond e-commerce, offering insights relevant to other domains of content moderation, including social media, digital advertising, and misinformation control.

6. Recommendations

Based on the study's findings and analysis, the following recommendations are proposed to guide the responsible and effective implementation of AI-driven fake review detection systems in e-commerce:

Organizational Impact

- **Strengthen platform governance:** Invest in adaptive AI systems complemented by human oversight to balance speed with contextual accuracy. Adopt standardized performance metrics using benchmarks such as false positives/negative rates and specificity to evaluate AI effectiveness and build stakeholder confidence.
- **Support sellers fairly**: Invest in diverse training data that reflect the diversity of languages, cultures, and review contexts to minimize bias and improve fairness. Prioritize transparency and explainability by clearly communicating how AI moderates reviews and why content is flagged or removed so sellers understand moderation outcomes and build trust.
- **Enhance internal risk management**: Develop clear AI governance frameworks, establish regulatory standards for AI transparency, data privacy, and algorithmic accountability in consumer-facing platforms. Collaborate across platforms and social media providers to address fake reviews across digital ecosystems.

Social Impact

- **Build consumer trust:** Educate users on AI moderation by explaining how reviews are evaluated and what steps to take if their feedback is incorrectly flagged. Implement appeal and redressal mechanisms that allow consumers and sellers to contest decisions and request human review. A hybrid model with human-in-the-loop that balances automation with human oversight can address contextual nuance and enhance the system's adaptability over time and improve both accuracy and legitimacy.
- **Ensure fairness and legitimacy:** Develop explainable AI capabilities so users and sellers understand decisions. Require platforms to notify users when content moderation is AI-driven and what recourse is available. Guard against cultural or linguistic bias through continuous dataset refinement and third-party audits to validate fairness, accuracy, and compliance with ethical standards.
- **Embed ethical safeguards:** Protect data privacy and obtain explicit user consent while upholding fairness and transparency in AI-driven moderation. Commit to transparent marketing strategies and avoid exploiting algorithmic loopholes. Hold organizations accountable through independent oversight and third-party audits. Promote digital literacy initiatives to empower consumers to

recognize fake reviews and understand the role of AI in content moderation and shaping their online experiences.

These recommendations aim to foster a responsible AI ecosystem that balances innovation with ethical integrity -enhancing consumer trust, protecting platform reputation, and supporting sustainable digital commerce.

7. Conclusion

The proliferation of fake online reviews presents a serious threat to the credibility and integrity of e-commerce platforms. These deceptive practices distort consumer perceptions, mislead decision-making, and erode trust in digital marketplaces. This study set out to explore the organizational and social implications of using AI-based systems to detect and manage fake online reviews in e-commerce.

Through qualitative analysis this study has shown that artificial intelligence offers powerful, scalable tools to detect and mitigate such fraudulent content. However, its deployment is not without complexity. AI systems influence not only the technical landscape of fraud prevention but also fundamentally alters traditional risk management practices, compels new forms of platform governance, and significantly influences seller behavior and user experience. While AI increases operational efficiency and enables real-time content moderation, it also introduces risks around fairness, transparency, explainability, and trust.

These findings underscore the double-edged nature of AI in e-commerce. On one hand, AI provides scalable, efficient tools for moderating content and protecting consumers. On the other, it can alienate users, unintentionally marginalize smaller businesses, and create new forms of bias and opacity if not carefully governed. These tensions mirror similar challenges in adjacent domains such as misinformation or fake news detection and social media moderation, where the speed of automation often clashes with the demand for procedural legitimacy and ethical oversight. The tension between efficiency and legitimacy is especially acute in environments where trust is both a consumer expectation and a competitive advantage.

Considering these dynamics, the study calls for a responsible, human-centered approach to AI deployment. At the organizational level, platforms must embed ethical safeguards, integrate automation with contextual human judgment, involve diverse stakeholders, and maintain transparency in how moderation systems are designed, implemented, and evaluated. At the social level, consumer trust must be built by providing clear explanations, offering appeal and redress mechanisms, and hybrid oversight, while ensuring fairness through explainable AI, third-party audits and continuous bias mitigation. Embedding ethical safeguards – protecting privacy, securing consent, and promoting digital literacy will be essential to align automation with fairness and accountability.

As fake reviews continue to evolve in sophistication, so too must the tools used to detect them. Yet technical advancement alone is insufficient. The future of AI in e-commerce will depend on how well it is integrated into the social, organizational, and ethical frameworks that sustain trust in digital ecosystems. By addressing both technological capability and social responsibility, AI can fulfill its promise—not just as a tool for detection, but as a foundation for more trustworthy and equitable online commerce.

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

AI Declaration: During the preparation of this article, the author used OpenAI to improve the paper's readability. After using this tool, the author reviewed and edited the content as needed.

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AI-Based Chatbots in Customer Communication: A Comparative Study of Germany and China

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Abstract: This study analyzes the implementation, usage, and acceptance of AI-supported chatbots in customer communication in Germany and China. Based on a systematic literature review and seven expert interviews with representatives of international technology companies, the research investigates both technological and cultural contextual factors influencing chatbot adoption. The study highlights how varying regulatory frameworks, infrastructure readiness, and cultural attitudes shape the deployment and effectiveness of AI-driven communication tools in different markets. Findings indicate that in Germany, stringent data protection laws, regulatory complexity, and cultural hesitations around privacy and automation present major obstacles to chatbot integration. In contrast, China's innovation-friendly regulatory environment, extensive government support, and high technology affinity foster rapid deployment and wide user acceptance of AI-based solutions. Moreover, differences in organizational priorities emerge, with Chinese companies emphasizing speed, platform integration, and functionality, while German firms focus on data security, compliance, and personalized, trust-building customer interactions. The study further explores variations in user experience and communication design, underscoring the importance of culturally adapted interfaces and context-sensitive implementation strategies. Derived from these insights, the paper offers strategic recommendations for businesses to successfully implement AI chatbots in diverse regulatory and cultural landscapes. Additionally, it outlines directions for future research, particularly regarding the development of agentic AI, multimodal interaction capabilities, and sustainable deployment models that consider ethical, infrastructural, and environmental aspects.

Keywords: AI, Customer communication, Chatbot adoption, Germany, China, Cultural factors

1. Introduction

Advancing digitalisation and rapid developments in artificial intelligence (AI) have permanently transformed communication processes between companies and customers worldwide. AI-based chatbots, in particular, have emerged as a key tool in customer-oriented service and communication management. These systems offer significant potential in terms of automation, efficiency, and continuous availability of interaction channels (cf. Helmold, 2024).

Despite their growing presence and rising public acceptance, both technological and cultural challenges affect their successful implementation. Notably, there are clear differences between Germany and China regarding legal frameworks, corporate strategies, and social expectations surrounding digital customer services.

The global rise of AI technologies—especially the adoption of chatbots—raises critical questions concerning data protection, user acceptance, and innovation capacity. While China is marked by a high level of technological openness, strong governmental support, and regulatory flexibility, Germany tends to prioritise rights-based governance, data protection, and a culturally cautious approach to innovation. Results from both empirical studies and expert interviews reveal a complex reality of chatbot implementation in these two countries.

The aim of this paper is to examine the use, effectiveness, and determining factors of AI-based chatbots in customer communication in Germany and China. The central research question is:

- How do technological and cultural differences influence the adoption and effectiveness of chatbots in an international context?

In addition to a systematic literature review (2017–2024), the analysis draws primarily on qualitative data from seven expert interviews conducted in 2025.

2. Theoretical Foundations

2.1 Definition and Technological Basis

Chatbots are dialogue-oriented AI systems designed to process and interpret natural (written or spoken) language, responding intelligently using advanced Natural Language Processing (NLP) and Machine Learning

(ML) techniques (cf. Helmold, 2024; Mainzer, 2023). Their use in customer service enables substantial automation of routine queries, while also improving availability and personalisation.

Experts highlight that the underlying architecture—ranging from simple rule-based systems to neural Large Language Model (LLM)-based applications such as GPT and ERNIE—significantly affects chatbot performance and flexibility (cf. Sun et al., 2019; own interviews). The integration of Retrieval-Augmented Generation (RAG) is increasingly seen as a key innovation in enabling context-sensitive and individualised customer interaction.

Yet, existing studies highlight tensions between efficiency gains and trust-building functions. For example, Cornelius (2019) emphasizes automation and cost reduction as primary benefits, whereas Schuster & Wecke (2023) argue that customer trust and personalization remain decisive for sustainable adoption. This indicates that technical sophistication alone does not guarantee acceptance; instead, the embedding of chatbots into broader socio-technical systems is critical.

2.2 State of Development: Germany versus China

China's technological leadership in AI is driven by innovation-friendly policies, substantial government investment, and a highly adaptable population (cf. Sun et al., 2019). Chatbots are rapidly becoming embedded in daily life, aided by their integration into dominant platforms like WeChat, Taobao, and JD.com, and supported by cloud infrastructure provided by companies such as Alibaba and Tencent (cf. own interviews; Cornelius, 2019).

In contrast, the pace of implementation in Germany remains cautious. Here, data protection, legal certainty, and regulatory compliance—particularly due to the General Data Protection Regulation (GDPR)—take priority (cf. Mainzer, 2023; IT-P GmbH, 2024). Companies tend to rely on local providers or private cloud environments for hosting and data management, and frequently invest in complex compliance processes, resulting in longer implementation timelines (cf. own interviews). However, it would be misleading to frame Germany merely as "lagging behind." Haefner & Sternberg (2020) emphasize that German firms actively invest in **privacy-preserving architectures**, which may yield long-term competitive advantages in trust-sensitive industries. Thus, rather than a simple "fast vs. slow" dichotomy, the contrast reflects **different innovation logics**: speed and market dominance in China versus compliance-driven, risk-averse innovation in Germany.

2.3 Cultural Differences in Customer Communication

Qualitative interviews suggest that culture plays a pivotal in shaping user expectations with respect to communication style, trust-building, and functionality. Generally, German customers are inclined to favour interactions that are formal, privacy-conscious, and reliable. Conversely, Chinese users tend to prioritise efficiency, speed, and continuous innovation. Chinese enterprises often consider technological openness and the adoption of state-of-the-art features—such as multimodal dialogue systems or integrated AI tools—as decisive competitive differentiators (see own interviews; Schuster & Wecke, 2023). These culturally embedded preferences are directly reflected in the design, tone, and functionality of chatbot systems tailored to each market.

While the influence of culture on chatbot design is widely acknowledged in the literature, it is frequently addressed only at a superficial level. Certain studies contend that German users exhibit a preference for formality and sensitivity toward data privacy, whereas Chinese users place greater value on efficiency and the adoption of novel features (Kero et al., 2023; Schuster & Wecke, 2023). Nonetheless, such generalisations risk perpetuating stereotypes. Recent cross-cultural research on artificial intelligence (Raval et al., 2024) cautions against oversimplified categorizations and underscores the dynamic and context-dependent nature of user expectations.

Moreover, Zeng (2020) demonstrates that technology adoption in China is intricately linked to state-driven narratives of progress and modernity, while in Germany, public scepticism is closely associated with wider debates surrounding ethics and surveillance. These findings indicate that cultural attitudes should not be reduced to static "traits", but rather examined within the broader context of political discourse, historical experience, and institutional trust.v

2.4 Research gap

Although the literature provides valuable insights into technological, regulatory, and cultural aspects of chatbot adoption, two key gaps remain:

- Lack of integrative cross-country analyses. Most studies treat Germany and China separately, without systematically comparing how regulatory and cultural contexts interact.
- Limited empirical grounding. Many accounts rely on secondary data or policy analysis, but only few integrate primary qualitative insights from industry practitioners.

This study addresses these gaps by combining a structured literature review with expert interviews to provide a more nuanced, empirically grounded comparison of chatbot adoption in Germany and China.

3. Methodology

A qualitative, exploratory research design was applied to investigate the implementation and perception of AI-based chatbots in Germany and China. The primary data source consisted of seven semi-structured expert interviews with representatives of international technology companies. Anonymity, transparency, and traceability were ensured throughout the research process.

Experts were selected using purposive sampling to ensure diversity in perspectives. The selection criteria included: (1) at least three years of professional experience in AI-supported communication systems, (2) active involvement in the deployment of chatbots in either the German or Chinese market, and (3) representation from different organizational roles (e.g., product managers, AI developers, digital transformation leads). This approach ensured that participants provided both strategic and technical perspectives. Interviews were conducted between January and March 2025, each lasting between 45 and 75 minutes. After the seventh interview, thematic saturation was reached, as no new relevant categories emerged.

The interview guide was developed in accordance with international research standards and focused on technical, organisational, and cultural aspects of chatbot deployment. The data was analysed inductively using qualitative content analysis following Mayring (2015), ensuring thematic clarity and interpretive depth. The coding process combined inductive category development (emerging from the data) with deductive elements derived from the literature review.

To strengthen the robustness of the findings, the empirical insights were triangulated with results from a structured literature review covering studies published between 2017 and 2024. This methodological approach allowed for a comprehensive synthesis of theory and practice in the context of AI-based customer communication. By combining theoretical and empirical evidence, the methodology supports a nuanced understanding of how contextual factors shape AI-based customer communication, while avoiding oversimplified cultural generalizations.

4. Results and Analysis

4.1 Use and Perception of AI Chatbots

Business practices in both Germany and China show that chatbots are primarily used to automate standard enquiries, reduce pressure on support hotlines, and improve service quality. However, the extent of implementation differs significantly between the two countries.

In China, integration is occurring rapidly, with advanced features such as multimodal capabilities and image-based use cases becoming increasingly common. In Germany, by contrast, companies typically adopt a more cautious, step-by-step approach. According to the interviews, employee acceptance increases notably when chatbot deployment is accompanied by internal communication, training, and the integration of user feedback.

Most organisations implement chatbots to automate frequently asked questions, technical support, and ensure 24/7 availability. Some companies have introduced more advanced functions, including proprietary interfaces, AI-based image recognition, and integration with HR systems.

The success of chatbot initiatives largely depends on a combination of technical innovation and strategic change management. Effective strategies include employee training, simplified interfaces, and the use of advanced AI models such as RAG. Communication campaigns, internal briefings, and the demonstration of quick, practical benefits are especially important for acceptance.

In China, linking chatbots to popular platforms such as Doubao has proven highly effective in promoting user engagement—an approach that has not yet gained traction in Western markets.

4.2 Challenges and Success Factors

In Germany, the main challenges in implementing AI chatbots are strict data protection regulations (particularly the GDPR), widespread scepticism towards AI, and—at times—limited digital skills among users. As a result, technical localisation plays a crucial role. Key measures include GDPR-compliant hosting (preferably within Germany), adaptation of training data to regional contexts, and linguistic fine-tuning to meet user expectations.

From a strategic perspective, effective change management and clearly communicated benefits are essential to overcome acceptance barriers. Internal campaigns, early stakeholder involvement, and transparency in the use of AI technologies can contribute to higher levels of trust and usability.

In contrast, China benefits from a regulatory environment that is less restrictive and more innovation-oriented. Positive societal narratives around AI and widespread digital adoption enable quicker integration and broader acceptance. Interview participants highlighted that the high level of digitisation and seamless integration of chatbots into everyday apps and services have normalised their use among consumers and employees alike (cf. Sun et al., 2019; own interviews).

Success in both countries hinges on aligning technological deployment with local user expectations, compliance requirements, and organisational readiness.

4.3 Influence of Cultural Differences and Adaptation Strategies

The interview data clearly indicate that cultural differences have a direct impact on how chatbots should be designed, formulated, and implemented. Companies that tailor their systems to regional expectations—such as linguistic nuance, communication style, and interaction preferences—can significantly increase user acceptance.

Key adaptation strategies include:

- Technical localisation, such as data hosting in compliance with local regulations (e.g., GDPR-compliant infrastructure in Germany).
- Linguistic and communicative adjustments, including tone of voice, politeness conventions, and terminology tailored to the respective market.
- Customised training data, based on culturally specific behavioural patterns and communication norms.

In East Asia, for instance, chatbots often rely on highly polite and formal expressions, while in Germany, a more neutral but privacy-sensitive tone is preferred. These nuances are not merely stylistic, but central to building trust and perceived relevance.

Overall, the effectiveness of chatbot deployment increases when systems are aligned with local communication cultures, legal standards, and user expectations.

4.4 Synopsis and Country Comparison

A compilation of key differences in a comparative matrix highlights the considerable divergences in terms of data protection, pace of innovation, regulatory complexity, and willingness to accept change (see Table 1).

Table 1: Results table Germany vs. China

aspect	Germany	China
Data protection	High requirements due to GDPR, data logs, only certified providers allowed	Lower requirements, less restrictive data storage
Regulation	Complex, difficult implementation	Fast registration and market launch possible
Technical integration	Limited use (e.g., no ChatGPT), restricted to local providers	Own LLMs such as DeepSeek, e.g. Alibaba solutions
Cultural attitude	Skepticism, reluctance among customers	Openness, technology as a matter of course
Infrastructure	Local cloud providers (e.g., Open Telekom Cloud) preferred	Major providers such as AWS China, Huawei models
Project dynamics	Long-term preparation necessary	Faster implementation

5. Discussion

The findings of this study confirm that the adoption of AI-based chatbots is shaped by a complex interplay of technological infrastructures, regulatory frameworks, and cultural narratives. However, the comparative perspective on Germany and China allows for several deeper insights that go beyond existing accounts.

First, the results corroborate prior research that highlights China's rapid adoption of AI tools, supported by state investment and integration into dominant platforms (Sun et al., 2019; Hussain et al., 2024). Yet, the interviews nuance this picture by showing that speed is not only a product of favorable regulation but also of organizational priorities—Chinese firms frequently emphasize first-mover advantages and competitive functionality. This aligns with Zeng's (2020) observation that technological openness in China is intertwined with broader political narratives of progress.

In contrast, German adoption is often framed in the literature as "slow" or "reluctant" (Mainzer, 2023; IT-P GmbH, 2024). Our findings challenge this oversimplification. While strict GDPR requirements and cultural skepticism indeed slow implementation, interviews reveal that German companies leverage this cautiousness as a strategic asset, focusing on trust, data protection, and long-term compliance. This resonates with Haefner & Sternberg's (2020) argument that digitalization in Germany is less about speed than about resilience and credibility. Thus, rather than lagging behind, German firms appear to be cultivating a distinct compliance-driven innovation model.

Second, cultural differences in customer communication must be treated with greater nuance. Previous studies often reduce German communication preferences to "formality" and Chinese ones to "efficiency" (Kero et al., 2023). Our empirical data suggests that such dichotomies are too narrow. For example, German users value reliability and privacy not only as cultural "traits" but as responses to historically rooted concerns over surveillance and data misuse. Similarly, Chinese users' openness is not simply cultural enthusiasm but reflects institutional trust in digital platforms and strong alignment between corporate innovation and state-led modernization strategies (Raval et al., 2024). This supports the call to move beyond cultural stereotypes and analyze how institutional and historical contexts shape communication norms.

Third, the comparative perspective highlights that technological barriers are less decisive than regulatory and cultural ones. Both Germany and China have access to advanced AI models, whether locally developed (QWEN, ERNIE) or internationally inspired (ChatGPT). What differentiates the two contexts is the degree of regulatory permissiveness and the framing of AI in public discourse. While China promotes AI as a driver of collective progress, Germany emphasizes rights protection and ethical oversight. These divergent framings significantly influence user acceptance, corporate strategies, and design choices.

Finally, the results have implications for theory and practice. Theoretically, the study advances the literature by positioning chatbot adoption not merely as a technological diffusion process, but as a context-dependent negotiation between compliance, innovation, and user trust. Practically, the findings suggest that multinational companies must adopt differentiated implementation strategies: in Germany, emphasizing transparency, data security, and user trust; in China, leveraging speed, platform integration, and technological novelty.

Overall, this discussion reframes the Germany–China contrast not as a binary of "fast vs. slow," but as two distinct innovation pathways shaped by regulatory logics, cultural narratives, and strategic priorities.

6. Limitations and Implications for Further

Despite the insightful results, this study is subject to several limitations. First, the analysis is based on only seven interviews, which means that the results cannot be considered representative of all international companies. Second, the responses largely reflect a specific industry perspective, limiting their generalisability. Third, linguistic misunderstandings or cultural nuances in the interviewees' statements may have influenced the interpretation.

In addition, the interviews were evaluated qualitatively and inductively, which allows room for interpretation. Despite careful analysis, a certain degree of subjectivity in coding and topic formation cannot be ruled out. Country-specific differences were described from the perspective of individual companies and were not triangulated by independent sources. Future studies could arrive at more robust conclusions by using larger samples, standardised survey instruments, or supplementary quantitative data. Future research should aim to conduct quantitative investigations and expanded, industry-specific comparative studies to ensure the

transferability of findings. Of particular interest are future developments in the field of agentic AI, the expansion to include multimodal interfaces, and the integration of energetic and ethical sustainability criteria.

The future of AI-supported customer communication will be strongly influenced by agentic AI, hyper-personalisation, and the embodiment of AI. Interview participants increasingly see chatbots not only as communication tools, but as autonomous actors that can take on individual tasks and make decisions. The transition to multifunctional, intelligent chatbot teams and integration into new platforms and legally relevant interfaces marks the next evolutionary step. Particularly noteworthy is the trend towards emotional and behaviour-based customer engagement, with high potential in markets such as China and innovative sectors such as fashion and e-commerce.

The interviewees' candid comments make it clear that, in addition to functional and strategic issues, technological fundamentals and system infrastructure are also important in AI communication. Particular emphasis is placed on the trend towards multimodality (text, image, video) and the associated need to better understand data sources, processing, and models such as visual language models (VLMs). Another aspect is technological feasibility: the high energy requirements of AI systems could become a bottleneck—especially if energy supply or the legal framework cannot keep pace. This view of systemic framework conditions shows that successful AI implementation is not just a software problem, but also encompasses infrastructure, ethics, and resource issues.

7. Conclusion and Recommendations for Action

This study has examined the adoption of AI-based chatbots in Germany and China through a systematic literature review and seven expert interviews. The comparative analysis highlights that chatbot implementation cannot be explained solely by technological availability. Instead, it is decisively shaped by regulatory regimes, organizational priorities, and cultural narratives that determine how users and companies perceive the value of automation.

Theoretically, the study contributes to the literature by reframing Germany–China differences not as a simple binary of “fast vs. slow adoption,” but as two distinct innovation pathways. In China, chatbot integration is accelerated by state-driven digital strategies, consumer openness, and platform-based ecosystems. In Germany, adoption follows a compliance-driven logic, emphasizing trust, security, and ethical legitimacy. This comparative lens helps explain why technological capabilities are insufficient to predict adoption without considering their institutional embedding.

Practically, the findings underscore the importance of context-sensitive implementation strategies. Multinational companies that attempt to deploy chatbots with a one-size-fits-all approach risk cultural misalignment and regulatory conflict. Instead, the study recommends differentiated strategies:

- Germany: Build trust through GDPR-compliant infrastructures, transparent data use, and participatory change management involving employees and works councils.
- China: Leverage openness to innovation by emphasizing speed, integration with dominant platforms, and experimentation with multimodal functionalities.
- Cross-market: Continuously monitor emerging developments such as agentic AI and multimodal systems, while aligning them with local regulatory requirements and ethical expectations.

Looking ahead, the evolution of agentic AI, hyper-personalization, and multimodal communication will likely transform chatbots from support tools into autonomous actors within customer interaction. However, their deployment must address not only technical feasibility but also ethical, infrastructural, and sustainability concerns. Future research should therefore adopt a broader comparative scope, integrating quantitative studies, industry-specific analyses, and cross-cultural perspectives to deepen understanding of chatbot adoption in global contexts.

In conclusion, AI-based chatbots represent more than a technological innovation: they embody competing visions of digital transformation. For companies, success will depend on recognizing these contextual differences and developing strategies that balance efficiency, compliance, and user trust.

Ethics declaration: This study involved qualitative research based on expert interviews with representatives of international technology companies. All participants were fully informed about the purpose of the study, the voluntary nature of their participation, and the confidentiality of their responses. Informed consent was obtained from all interviewees. No sensitive personal data were collected, and data were anonymized to

ensure privacy and compliance with applicable data protection regulations, including the General Data Protection Regulation (GDPR).

As the study did not involve sensitive personal data or vulnerable groups, no formal ethical clearance from an ethics committee was required. The research was conducted in accordance with accepted ethical standards for academic research involving human participants.

AI declaration: This paper was prepared with the assistance of an AI language model. The AI tool was used to support language refinement and to help structure sections of the manuscript. All content, analysis, and conclusions presented in this paper are the original work of the authors. The material generated by the AI was carefully reviewed, edited, and integrated by the authors to ensure accuracy, coherence, and compliance with academic standards.

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From Disruption to Innovation: Integrating Active Learning in AI-Resilient Assessment Design

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Abstract: Artificial Intelligence (AI) and generative learning technologies are transforming the landscape of higher education. With tools capable of producing essays/reports, solving complex problems, and simulating critical thought, traditional assessment practices are becoming increasingly vulnerable. The rapid, widespread, and easy accessibility of generative AI raises concerns about academic dishonesty, plagiarism, and the erosion of original thought. This disruption calls for a reimagining of assessment models that are not only robust in the face of AI but also pedagogically sound. Active Learning Strategies (ALS) offer a pathway forward. Rooted in constructivist and experiential learning theories, ALS emphasizes student participation, collaboration, and real-world application. By shifting from passive learning methods to active learning engagement, these strategies promote higher-order thinking and personal investment in learning, qualities that AI cannot easily replicate. This paper aims to analyze how ALS can underpin AI-resilient assessment design, drawing insights from a scoping literature review, an applied case study from the UNESCO-ESCS Chair in Portugal and results from inquiries to students.

Keywords: Active learning strategies, Artificial intelligence, AI-resilient assessment practices, Education, UNESCO-ESCS chair

1. Introduction

Artificial Intelligence (AI) and generating is transforming the landscape of higher education. With tools capable of producing essays, solving complex problems, and simulating critical thought, traditional assessment practices are becoming increasingly vulnerable (Howell, 2021). The widespread accessibility of generative AI raises concerns about academic dishonesty, plagiarism, and the erosion of original thought. This disruption calls for a reimagining of assessment models that are not only robust in the face of AI but also pedagogically sound.

Active Learning Strategies (ALS) offer a pathway forward. Rooted in constructivist and experiential learning theories, ALS emphasizes student participation, collaboration, and real-world application (Howell, 2021; Van Alten, 2019). By shifting from passive reception to active engagement, these strategies promote higher-order thinking and personal investment in learning, qualities that AI cannot easily replicate. This paper examines how ALS can underpin AI-resilient assessment design, drawing insights from scholarly literature and an applied case study from the UNESCO Chair in Portugal (UNESCO, 2025).

2. Literature Review

2.1 From Disruption to Innovation: Active Learning in AI-Resilient Assessment Design

The rapid advancement and widespread adoption of Artificial Intelligence (AI) tools such as ChatGPT have introduced profound disruptions to higher education, particularly in the field of assessment. These technologies pose a dual challenge: they offer pedagogical opportunities for personalization and support, but also raise significant concerns regarding academic integrity (Howell, 2021; Van Alten, 2019). As AI-generated content becomes increasingly sophisticated and difficult to detect, the boundaries between original student work and machine assistance are blurred, demanding a rethinking of assessment models across institutions.

2.2 AI and the Challenge to Academic Integrity

The arrival of generative AI has magnified concerns about cheating, plagiarism, and e-cheating. Students can now easily produce essays, problem solutions or reflections with minimal effort and without a true demonstration of understanding. Cotton, Cotton, and Shipway (2023) describe this issue as a growing threat to academic integrity in their paper “Chatting and Cheating”, underlining the urgency for new responses. Dawson

(2020) similarly argues for the defense of assessment security in a digital world, calling attention to the need for structural and pedagogical innovation to address emerging risks, including sophisticated forms of contract cheating (Howell, 2021).

These challenges force educators and institutions to reconsider not only how students are assessed, but also what should be assessed. In a context where AI can simulate surface-level outputs, the need for assessments that demand genuine understanding, critical thinking, and contextual application becomes essential (Howell, 2021).

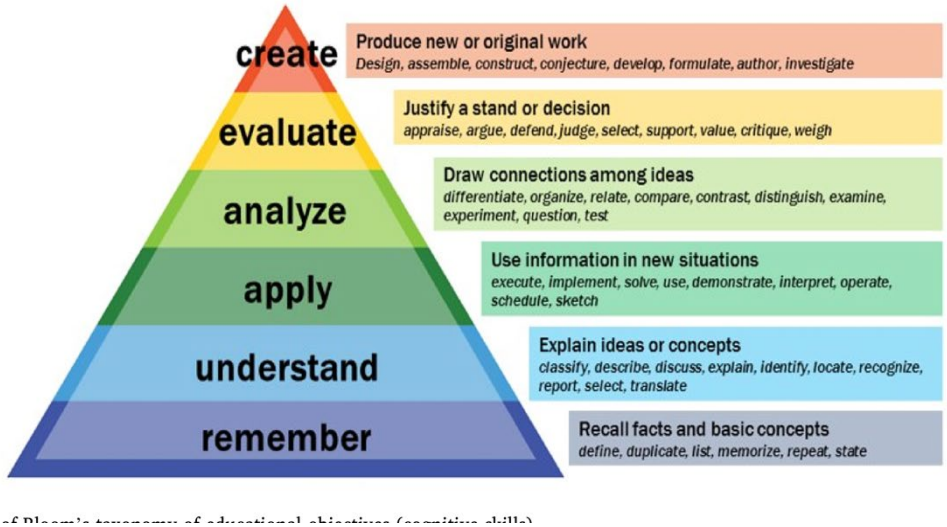

Figure 1: Adapted from Bloom's taxonomy of educational objectives Source: Vanderbilt University Center for Teaching, released under a Creative Commons Attribution Licence and adapted from Howell, 2021

2.3 Active Learning as a Pedagogical and Ethical Response

Howell (2021) presents an educational model for sustainable development in higher education that integrates active learning, reflective exercises, and the active methods of participation from students. That means the students in this methodology have active participation in the learning process, promoting autonomy, critical thinking, brainstorming, and collaborative participation. "The professor is a facilitator in this process in order to promote knowledge construction. When applied to assessment, these practices not only enhance learning outcomes but also create contexts that are difficult for artificial intelligence systems to replicate, thereby reducing the risks of plagiarism and superficial responses"(Howell, 2021).

Active learning (AL) emerged as an important pedagogical model that engages students directly in the learning process, active learning promotes deep learning, critical engagement, and reflective thinking (Howel, 2021). Mata et al., (2023) confirms the potential of these methods to create self-knowledge from students in the classroom and empower students as active participants rather than passive recipients of information. Indeed, Freeman et al., (2014), confirm that active learning significantly improves student performance across science, engineering, and mathematics.

According to Howell (2021) "the skills fostered by active learning such as problem-solving, collaboration, metacognitive reflection, and contextual analysis are far more difficult to replicate through generative AI". When students are required to co-construct knowledge, debate ethical dilemmas, or design context-specific projects, the role of AI as a shortcut becomes limited.

2.4 Designing Assessments that Resist to AI Misuse

Rather than focusing only on detection and control, educators are increasingly called to redesign assessment tasks that are resilient by design and nature. This means constructing tasks that require authentic application, personalization, and critical response that undermine the utility of AI-generated outputs AI according to Howell, (2021); Mata and Dos-Santos (2025) and Mata and Dos-Santos (2024).

On the other hand, authentic assessment has been widely recognized as a powerful mechanism for both skill development and academic integrity. Sotiriadou et al., (2019) highlights the role of authentic, real-world tasks

in fostering employability and reducing misconduct. These tasks ask students to apply knowledge in novel, often collaborative ways thus making AI-generated answers either irrelevant or easily detectable.

The literature identify other essential principles for AI-resilient assessment design include, namely: 1) Reimagining assessment purposes and in this case Bearman et al. (2020) advocate for a shift away from content reproduction and towards demonstrations of complex learning, including personal reflection, creativity, and integrated knowledge; 2) Formative assessment and feedback according to Nicol and Macfarlane-Dick (2006) "self-regulated learning and ongoing formative feedback are essential to learning ownership". This continual process of feedback and revision builds trust and discourages reliance on external, automated tools; 3) Finally, together, these approaches position active learning not just as a pedagogy, but as a design strategy to embed integrity and engagement within assessment practices in an AI-mediated world (Mata et al., 2025).

2.5 Towards a Culture of Critical Digital Citizenship

Incorporating active learning into assessment design also supports broader goals beyond classroom performance. As Selwyn (2019) and Buckingham (2020) suggest, the educational response to AI must go hand in hand with fostering media literacy, digital ethics, and civic responsibility. Students must be prepared not only to collaborate with AI but to critically evaluate its role and impact.

This perspective aligns with the mission of the UNESCO Chair "Communication, Media Information Literacy and Citizenship" (UNESCO-ESCS, 2025), which serves as the empirical foundation for the case study in this article. By bridging assessment innovation and media literacy, the Chair exemplifies how educational institutions can cultivate critical, empowered citizens prepared for complex digital futures (UNESCO-ESCS, 2025).

The disruption posed by AI in higher education is not only technological, but it is also epistemological and mainly ethical. Active learning offers a concrete, research-informed path toward assessment models that both mitigate the risks of AI misuse and promote meaningful learning. Through authentic, formative, and participatory tasks, educators can design assessments that prioritize critical engagement over reproduction, reinforcing academic integrity and preparing students to thrive in a world where working with AI is more valuable than being replaced by it (Howell, (2021).

3. Methodology

This paper presents various methods and techniques. First, we present a scoping review based on the SCOPUS database, followed by an initial selection of 178 papers. Second, a case study was conducted based on results the UNESCO - ESCS Chair "Communication, Media Information Literacy and Citizenship" at the School of Communication and Media Studies (ESCS) in Portugal. The case study was based on an open interview with a participant in a Chair, namely a researcher from ESCS and UNESCO-ESCS Chair. Finally, students from the bachelor's degrees in journalism and Audiovisual and Multimedia from ESCS were inquired about the use of AI in evaluation in their classes.

4. Results

The scoping literature review was based on information and data performed from May to June 2025. The search includes just scientific papers on SCOPUS database in English language, mainly involving full papers in journals and peer-reviewed articles in AI in education, assessment design and ALS to avoid the plagiarism. Content analysis was used, and we identified the main components of AI-resilient assessment, including authenticity, adaptability, and interdisciplinarity.

Second, a *case study* was conducted on the UNESCO Chair "Communication, Media Information Literacy and Citizenship" at the School of Communication and Media Studies (ESCS) in Portugal based on the one participant interview and developed activities by the UNESCO-ESCS Chair. The results presented are based on her/his Working Group experience/participation and on her personal view as a participant. Also, we include information and data about the UNESCO- ESCS Chair based on Bonacho (2025), namely, the main goals of the chair and their applicability at ESCS among students, academic staff and the practical results obtained until now.

4.1 Synthesis: Designing AI-Resilient Assessments

Both literature and case study underscore the importance of moving beyond static assessments. AI-resilient assessments are characterized by their focus on processing over product, collaboration over isolation, and critical inquiry over memorization. Examples include iterative writing projects, oral defenses, group

presentations, and reflective journals. These methods promote originality, accountability, and ethical engagement.

4.2 Case Study: Designing AI-Resilient Methods and Assessments in SDGs in Escola Superior de Comunicação Social in Lisbon - Polytechnic University of Lisbon

At the Escola Superior de Comunicação Social (ESCS), since the academic year of 2022-2023, the Sustainable Development Goals (SDGs) have been mandatory integrated into the curricula of all courses across the institution's undergraduate and postgraduate programs. The programs encompassed by this initiative include Journalism, Audiovisual and Multimedia, Advertising and Marketing, and Public Relations and Organisational Communication/Management at both the Bachelor's and Master's levels.

Within each course, the SDG-related content is adapted to align with the specific curricular structure, ensuring, on the one hand, the implementation of active learning methodologies. This involves students directly applying the relevant SDGs, targets, and indicators to a specific thematic area of the course as part of their academic performance and development. These projects are supported through continuous in-class supervision in groups by faculty members, as well as additional tutorial support outside the classroom.

At the conclusion of the projects, students, mainly working in groups, present their work to their peers and instructors, responding to questions regarding their findings and methodologies. Prior to presentation, all reports submitted by students undergo plagiarism detection by the faculty. In cases where plagiarism is identified, students are required to redo the assessment.

4.3 Insights from the UNESCO-ESCS Chair Case Study

The UNESCO Chair integrates ALS through collaborative projects, digital storytelling, media critique, and civic engagement initiatives. These practices promote active citizenship, media literacy, and ethical awareness. The emphasis on real-world challenges, such as misinformation and climate change, connects academic learning with societal needs, creating authentic and context-rich assessment environments (Bonacho, 2025; and UNESCO-ESCS, 2025). Students engage in activities like analyzing misinformation campaigns, creating community-based interventions, and participating in peer-reviewed reflective blogs. These tasks require critical engagement and personal expression, making them difficult for AI to replicate or automate.

4.4 Results from the Interview of UNESCO – ESCS Participant

According to Bonacho (2025) (Appendix 1), "The Chair aims to integrate research and education into society in order to develop fundamental skills for critically communicating and understanding the world, while resisting polarization and stereotypes." Polarization is also a consequence of the dominant presence of the mainstream media in Portugal partially dominated by "'partisan' journalism" (Álvares & Damásio, 2013; Santana-Pereira, 2016). On the other hand, nowadays due to the failure of the media business model in Portugal, a large part of editorial teams is composed of interns and agency journalism as a cost-reduction strategy to avoid failure (Fonseca et al., 2016). That reduces investigative journalism and the pursuit of truth.

The results from the open interview/activities of the UNESCO-ESCS by a participant of she refer "In the current context of increasing civic disengagement, particularly among young people, from political participation and local democratic processes, it becomes imperative to rethink the role of higher education institutions as agents of civic education and community engagement. Higher education, especially academic chairs with pedagogical and scientific responsibilities, plays a key role in fostering a more robust, inclusive, and informed democratic culture.

With the aim of reinforcing this mission, a Citizenship Week was designed and implemented under the coordination of a university chair focused on community engagement. According to the participant "Its objective was to bring students closer to local political realities, promote critical thinking, and encourage constructive debate around municipal elections—frequently overlooked or undervalued by younger audiences, despite their direct relevance to everyday governance and community life."

The participant indeed describes all the previous activities of the UNESCO – ESCS Chair that becoming effective and approved in 2025.

The activities developed included "*An week included a diverse set of activities across educational, cultural, and political dimensions, structured around five main pillars:*

1. Thematic Reading Club session, dedicated to literary and essayistic works on citizenship, democracy, and political participation, aiming to foster accessible and interdisciplinary reflection.
2. Informative Session on the Functioning of Municipalities and Local Electoral Processes, especially targeted at students, in order to combat widespread lack of knowledge about local governance.
3. Public Interviews with Local Government Representatives, allowing for direct dialogue between students and local decision-makers, and enhancing understanding of proximity-based governance.
4. Interview and Debate with an Portuguese Political Commentator, focused on critically analyzing political participation in Portugal and the role of civic education—bridging academic discourse and political experience.
5. Documentary Exhibition, showcasing visual and informational materials on the history of local governance, electoral campaigns, and practices of active citizenship in both local and national contexts.

These initiatives aimed not only to inform but to educate, by creating a space for experiential learning, real-world engagement, and the development of argumentative and critical skills. Ultimately, it sought to consolidate the notion that higher education must go beyond the transmission of technical-scientific knowledge and also embrace a transformative civic function committed to social cohesion, democratic participation, and the sustainable development of communities.

4.5 Results from Inquiries in Classroom to Students from ESCS

Students at ESCS also were inquired during the last semester of 2024-2025 during the lectures about the use of AI in various courses in ESCS, their potential and the practical usage in academic duties, mainly in evaluation support. The inquiries were done in the form of brainstorming, including a focus group methodology, but in an "informal environment". The number of participants was 25 in Journalism and 23 in Audiovisual and Multimedia. The gender distribution was 53 females and 47% males. The average age of the students is 22 years old, with a median age of 21 years old, representing approximately 55%. The use of AI by students differs significantly between the two degrees. Most of the students 89% are from the Metropolitan region of Lisbon, and the remaining 11% are from the Azores Islands/the Algarve Region, and the Porto Region.

The use of AI by students differs significantly between the two degrees. About the frequency of the use of AI the journalism students refer mainly to short research in ChatGPT /Grok about the last news or some punctual research about specific new /or to synthesize all the information about one specific new, most of the time, as a result od special interest from student and not in academic environment/evaluation goals. They refer to the utility of the impossibility of total use in the elaboration of a comprehensive evaluation, as the software tool utilized blocks the use of AI (Identific, 2025). Most of the Journalism students report that AI is used primarily as a complementary tool during assessment moments, as most course evaluations incorporate active learning strategies, including case studies, individually presented reports, and practical assessments. The same applies to students in the Audiovisual and Multimedia (AM) degree program. The majority of the evaluation has a practical component, which involves filming, design, digital skills and practical models of evaluation, where AI was not possible to use as a complete tool. The students of AM usually use AI not to search for the required news, but more on a digital and graphical design focus as a tool in AM.

4.6 Discussion

The literature confirms that ALS are essential to addressing the challenges posed by using generative Artificial Intelligence in higher education. These strategies foster deeper learning, case studies, critical thinking, and greater student autonomy, namely by promoting their competencies that are difficult for AI tools to replicate. The reviewed research further highlights the effectiveness of flipped classrooms, project-based learning, and collaborative approaches in enhancing student engagement and content retention (Freeman et al., 2014; Prince, 2004). As highlighted in Howell's (2021) model of sustainable education, active learning and reflective practices provide not only pedagogical benefits but also a framework for designing resilient assessments in higher education.

Moreover, the studies underscore the importance of rethinking assessment models by prioritizing authenticity, personalization, and reflective thinking. This aligns with Howell's (2021) "emphasis on embedding reflection and student agency into assessment design, ensuring that learning outcomes are grounded in autonomy and deeper engagement rather than rote reproduction". Assessments that include peer review, self-reflection, real-world problem solving, and collaborative projects demonstrate greater resilience to AI misuse, as they require contextualized knowledge application and personal expression (Sotiriadou et al., 2019; Bearman et al., 2020).

The literature also refers that merely detecting the use of AI is insufficient; assessment tasks must be designed in ways that inherently challenge machine-generated responses. Therefore, the integration of ALS should be understood not only as a pedagogical approach but also as an ethical and design strategy to safeguard academic integrity (Dawson, 2020; Nicol & Macfarlane-Dick, 2006).

Finally, the literature highlights the need to align assessment design with long-term learning goals by developing transferable skills such as critical thinking, self-regulation, digital literacy, and active citizenship (Selwyn, 2019; Buckingham, 2020). In this sense, ALS not only reinforce meaningful learning but also equip students to act responsibly in an increasingly AI-mediated world. This perspective further supports Howell's (2021) argument "that sustainability-oriented pedagogies must cultivate transferable skills such as autonomy, critical thinking, and ethical responsibility, which are essential in an AI-mediated academic environment".

5. Conclusion

The rise of AI presents both challenges and opportunities for higher education. While traditional assessments are increasingly vulnerable to AI-generated content, Active Learning Strategies offer a robust framework for innovation. At the same time ALS reveals high potential to eliminate the AI plagiarism from the academic evaluation process because by embedding authenticity, collaboration, and reflection into assessment design, educators can foster learning environments that resist AI misuse and promote deeper, more meaningful student engagement. Institutions must support this transformation by investing in staff development, investment in research and development, promoting excellency, rethinking learning spaces, and promoting a culture of academic integrity. The future of assessment lies not in resisting AI, but in reimagining pedagogy to transcend it.

Acknowledgement

This work is funded by national funds through FCT – Fundação para a Ciência e a Tecnologia, I.P., under the support UID/05105: REMIT – Research on Economics, Management and Information Technologies, Portucalense University

Ethics Declaration: The research presented in this paper did not require ethical approval, as it did not involve human participants, animals, or sensitive data requiring consent or review by an ethics committee.

AI Declaration: The authors affirm that an AI tool (ChatGPT, developed by OpenAI) was used only to improve the clarity and fluency of the English language in the manuscript. The content, analysis, and conclusions of the paper were entirely developed by the authors. No AI-generated content was used in the conceptual or analytical development of the research.

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Appendix 1

Results from *UNESCO Chair "Communication, Media Information Literacy and Citizenship" presented by the Coordinator (Bonacho, 2025) and By UNESCO – ESCS, (2025).*

According to Bonacho, (2025) "T*he UNESCO Chair "Communication, Media Information Literacy and Citizenship" is an initiative aimed at addressing the challenges of the 21st century, a time marked by an unprecedented digitization of communication. While the benefits of digital media are undeniable, their uncritical use has led to misinformation, fake news, hatred, and intolerance. These phenomena threaten the sustainability of tolerant, inclusive, and democratic societies, where full citizenship is both a right and a duty. In this context, media education and citizenship development are essential. They allow for the construction of a diversified coalition of autonomous individuals who recognize, analyse and resist harmful forms of expression and communication. The Chair aims to integrate research and education into society to develop fundamental skills for communicating and understanding the world critically, while resisting polarization and stereotypes. The teaching and research carried out at ESCS support this chair and are at the centre of international cooperation. This includes notably the countries of the South and Lusophone, encouraging academic alliances and promoting knowledge sharing. The Chair shares the principles of UNESCO, promoting communication for inclusive, multicultural, and democratic societies. It aims to bridge the gap between academia and civil society, to develop media education, to defend freedom of expression, to fight against hate speech and misinformation, while promoting responsible critical thinking and preventing violent extremism. In addition, it aims to develop actions and projects for sustainable societies, while strengthening knowledge for climate action".(Bonacho, 2025).*

The Mission of the Chair

Communication is as much a compromise as it is the recognition of the other, both at the root of democratic societies. The XXI century is marked by the unprecedented digitalization of communication, and though the benefits of digital media are undeniable, their indiscriminate and uncritical use brought disinformation, misinformation, fake news, hatred and intolerance menacing the sustainability of tolerant, inclusive and democratic societies where full citizenship is both a right and a duty. In this context, media and information literacy and citizenship cultivation are crucial, building a diverse coalition of empowered people who recognize, analyse, and resist harmful forms of expression and communication. The chair proposal is a process of research and education integration in society to develop the fundamental skills to communicate and critically understand the world, resisting polarization and stereotyping while shortening the participatory gap that hinders engaged and well-informed citizens. (Bonacho, 2025).

Values

It sets up a critical process that empowers and engages people as global citizens, with media literacy at the heart of strategies while envisaging a culture of communication that is open, inclusive, critical and based upon respect for human rights and democracy, contributing to human development and understanding of the world.

It will work for inclusive and accessible education and promote lifelong learning opportunities for all by addressing education, general or specialized and for all ages, as an essential component of media literacy. More educated people are more informed, more aware of critical thinking and less likely to be led by disinformation and misinformation or engage in hate speeches and misogyny (Bonacho, 2025).

The actions, projects and cooperation will promote freedom of expression and the right to information, as well as combat discrimination, hate speech and gender harassment, through pursuing research projects on these and actively engage in new projects within the network of the Chair (Bonacho, 2025).

Particular attention will be paid to media literacy in digital media environments as they affirm to be a game changer on disinformation, misinformation and fake news propagation, particularly perpetrated by authoritarian and extremist movements, menacing democracy and freedom of expression, while at the same time remaining in certain regions of the world an opportunity for free information and debate (Bonacho, 2025).

It will foster knowledge and skills development in the digital and multimedia environment by preparing and supporting citizens to face the constantly changing digitization of society giving them skills grounded on creativity, critical thinking, intercultural dialogue competencies, media use abilities, and participation and interaction opportunities (Bonacho, 2025).

Objectives

- *To promote communication for inclusive, multicultural, equal and democratic societies, ensuring education and long-life learning through the creation of open and accessible digital resources and mobility exchanges among the Chair partner's networks.*
- *To develop media and information literacy by promoting freedom of speech, countering hate speech and disinformation whilst fostering critical thought and enhancing the bridge between the academy and civil society through knowledge transfer (digital and other) and cooperation activities on the domains of the Chair.*
- *To promote active citizenship and civic engagement by working for and with the communities and civil society organizations by developing actions and projects towards sustainable societies and enhancing knowledge for climate action (Bonacho, 2025).*

IT Governance, Audit and Risks Management in Banks: A Narrative Literature Review and Future Research Agenda

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Abstract: The increasing digitalization of the banking sector has significantly reshaped institutional control mechanisms and governance structures, particularly in the realm of Information Technology (IT). This narrative literature review examines the evolving role of IT audit and governance in banks, with a specific focus on how these mechanisms contribute to risk management and regulatory compliance. Drawing upon a corpus of 26 peer-reviewed studies spanning from the early 2000s to 2025, this paper offers an integrated framework to understand the complex interrelations between IT governance, internal auditing, emerging technologies, and institutional oversight. Our literature review situates IT audit practices within broader organizational, cultural, and regulatory contexts. It explores how frameworks such as COBIT and COSO serve not only as technical guides but also as institutional artifacts that shape organizational behavior, strategic decision-making, and normative compliance. The review reveals that the role of IT audit has expanded from a purely technical function to a strategic enabler of trust, transparency, and accountability within financial institutions. Furthermore, audit committees and specialized board-level IT committees are shown to play a critical role in translating technological risks into governance priorities, thereby fostering a culture of proactive risk mitigation. Our analysis addresses the competencies of IT auditors, emphasizing the increasing demand for specialized skills in cybersecurity, data governance, and AI-integrated systems. The findings suggest that organizations with robust IT governance structures and trained audit personnel are better equipped to address technological disruptions and regulatory pressures. Moreover, the integration of Artificial Intelligence (AI) into audit processes is identified as both a transformative opportunity and a governance challenge. This paper contributes to the literature by providing a picture that connects technical auditing practices with broader sociotechnical systems. It identifies critical gaps in current audit practices, highlights the importance of organizational culture and ethics in IT governance, and proposes avenues for future research, particularly on the intersection of AI, audit methodologies, and institutional compliance.

Keywords: IT governance, Risk management, Banks, COBIT, AI

1. Introduction

The ongoing digitalization of the banking sector is reshaping operational models redefining the control systems within financial institutions. The conjunction of regulatory pressure, the diffusion of new technologies and the presence of cyber threats has led to the necessity of reinforcing IT governance to ensure security, reliability and compliance. In this landscape, IT governance takes shape in an ensemble of processes, structures and decision-making mechanisms with the purpose of generating value for the organization, while supporting the achievement of the entity's objectives maintaining acceptable levels of risk.

In particular, the introduction of Artificial Intelligence into the organizational processes poses new challenges for control design and testing. For this reason, it is essential to identify AI-integrated applications and define assessment models to guarantee this new technological dimension is properly governed. Among the latter, we deem relevant to explore the contribution of the COBIT (Control Objectives for Information and related Technology) framework in supporting digital risk management and regulatory compliance.

The research question driving our investigation is:

RQ1:What is the significance of information technology audit in reinforcing risk management and regulatory : compliance in banking?

To answer this question, we performed a narrative literature review on the role of IT audit and governance in the banking sector. Findings are based both on literature review and researchers' expertise by direct involvement in the field. The review looks at how IT audit connects with risk management and regulatory compliance, gathering insights from various studies since the early 2000s up to now. The paper digs into concepts like IT governance, internal controls, auditor independence, and compliance, creating a big-picture view that blends different research approaches.

2. A Narrative Literature Review on the Role of IT Audit and Governance in the Banking Sector

Narrative literature review is an approach used to answer broad questions and to evaluate literature from a vast point of view, including studies with heterogeneous methodologies, as stated by Baumeister e Leary (1997). A distinctive aspect of this type of review is the ability to offer a comprehensive landscape on the topic, not limiting to an exposition of results but defining as well the theoretical background of the analyzed studies, and providing a fitting way to examine the argument using a qualitative method, since the subject of this research is IT governance and IT audit, thus the predominant analysis is not quantitative. Snyder (2019) refers to narrative review as semi-systematic review and delineates the concept of meta-narratives, affirming that "the review seeks to identify and understand all potentially relevant research traditions that have implications for the studied topic and to synthesize these using meta-narratives instead of by measuring effect size" (p. 335).

Following the guidance of Baumeister and Leary (1997) and Snyder (2019), the present work uses a narrative literature review to delve into IT audit in the banking sector, between risk management and regulatory compliance, examining research to reconstruct the landscape and apply it on the case study analyzed in the last chapter. This review was conducted using academic databases like Scopus and Google Scholar, researching "IT audit" and "IT governance" as "Article title", "Abstract", "Keywords" and making use of keywords such as "information technology", "COBIT", "information system security", "cybersecurity", "Internal Control", "Internal Audit", "external audit", "auditor independence", "compliance", "risk management", "audit reports", and selecting subject areas as "Business, Management and Accounting" and "Economics, Econometrics and Finance". Lastly, although the temporal range was set from 2010 to 2025, it was then extended to include relevant contributions of the early 2000s, to incorporate foundational studies. The result of the research was equal to 178 documents: the selection of the studies was based on the discussion of the topic and the relevance of the main themes for the current research and their publication in scientific or academic journals. The exclusion criterion was built on their relevance to this investigation: articles not focusing on the financial sector and more precisely on banking were excluded or, if included, they were especially pertinent and suitable to analyze widely IT governance.

In our aim the reviewed literature should underscore the increasing significance of Information Technology (IT) audit within the landscape of risk management and regulatory compliance in the banking sector. Over the past decades, the rapid evolution of digital technologies has transformed traditional financial oversight, necessitating robust frameworks for governance, internal controls, and risk mitigation. Central to this transformation are frameworks like COBIT (1996, 2012) and COSO (1992, 2013, 2017), which integrate IT governance with broader organizational objectives. This body of research explores how IT audit functions as both a mechanism for ensuring regulatory adherence and a strategic tool for managing emerging risks inherent in digital infrastructure.

Out of all the documents retrieved, 26 articles were selected and used for the writing of this paper. Our findings unfold around the following themes:

- Evolution of IT audit and governance in Banking
- IT controls implemented into audit procedures
- Application of IT governance frameworks to strengthen internal controls
- The competence of IT auditors and the role of innovative technologies such as AI

3. Findings

3.1 Evolution of IT Audit and Governance in Banking

Several organizations maintain an internal audit function that encompasses responsibilities related to IT audit and IT governance. But what is "internal audit"? This practice has been defined as follows by the Institute of Internal Auditors (IIA):

"Internal auditing is an independent, objective assurance and consulting activity designed to add value and improve an organization's operations. It helps an organization accomplish its objectives by bringing a systematic, disciplined approach to evaluate and improve the effectiveness of risk management, control, and governance processes" (Institute of Internal Auditors, n.d.).

Among other risks, it analyses technology risk and focuses on the ICT system of an enterprise, in which the performers of the procedures, the IT auditors, must be independent and objective, and must review the effectiveness of the ensemble of risk management, governance, internal controls and information system, by performing tests and investigation.

The development of Information Technology made the introduction of IT audit necessary to manage governance in institutions subject to normative requirements and risk management processes. As early as the 2000s, Moeller (2010) defined concepts that nowadays are habitual notions, treating the topic of IT audit spanning from technological evolution of processes and internal control implications, passing through information systems security, business continuity and data recovery, towards the compliance of new legislation, that at the time was the Sarbanes-Oxley Act of 2002. His discussion includes both IT general controls and IT automatic controls, reviewing various frameworks to perform the audit, such as COBIT, and underlining the newfound role of the auditor in an embryonal digital transformation environment. Merhout and Havelka (2008), not only underline the crucial role of IT audit in IT governance but also propose a relationship between auditors and managers aimed at perceiving audit practices as a value-added activity for the firm, bettering documentation and internal operations for starters, and improving overall strategic planification, risk management and governance.

To define the link between governance, risk management and IT audit, a recent research study underlined the evolution of the audit committee: from a body with supervisory and monitoring functions from the financial point of view to a risk management authority in the IT and cyber field. Chen et al. (2022) uncovered that IT experts in the audit committee lower significantly the probability of data breaches and better the enterprise's capacity to mitigate technology risk; the audit committee strengthens operational resilience and already in 2014 there was evidence of the fact that these committees had responsibilities for cyber risk management (NACD, 2014). A survey showed that only 37% of firms in the world include IT experts on the board of directors, limiting the cyber risk management (EY, 2020).

To avoid the dilution of the audit committee, causing the ineffectiveness of the body, many authors advise the creation of ad hoc technology committees at the board level, showing improvements in internal control and security of the firm overall, comprehending the disadvantage of cyberattacks just by its institution (Chen et al., 2022). Furthermore, IT committees can share their knowledge with the board of directors, instructing on complex themes and contributing to the development of a strategic approach on digital risk management, reducing the gap of expertise among managers of traditional approach and new ICT challenges (Hartmann & Carmenate, 2021).

Another research (Higgs et al., 2016) reveals that the presence of a technology committee increases the likelihood that the company will report data breaches and, more importantly, it discloses that market response proves to be better if the firm includes a technology committee, unveiling the influence and impact of this structure from a reputational standpoint. De facto this work also contributes to the signaling theory, as the presence of the committee signals to the market that IT governance is robust and enhances stakeholder confidence.

3.2 IT Controls Implemented Into Audit Procedures

While the establishment of specialized board committees illustrates the growing awareness of IT risks and cybersecurity challenges, regulatory compliance frameworks introduce requirements to ensure that IT controls are implemented into audit procedures. These findings are integrated with the obligations imposed by the Sarbanes-Oxley Act 404(b), that redefined audit on internal controls: regulatory compliance requires a precise evaluation of the period-end financial reporting process by the auditors. The so-called financial close process includes both manual and automatic controls, among other the most relevant are the IT general controls (ITGC) and the IT application controls (ITAC): a study reveals that many deficiencies occur when external auditors verify them and this limits the efficiency of the controls in ensuring security of the firm and integrity of financial data: this is the rationale for the introduction of the IT audit in the other general audit practices (Janvrin et al., 2019). The study performed by Janvrin et al. (2019) underlines the necessity to test the information technology systems in a sound manner, in fact the Public Company Accounting Oversight Board (PCAOB) (a nonprofit corporation created by the Sarbanes–Oxley Act of 2002 to oversee the audits of US-listed public companies) noted how auditors limit their activity to the entity level controls and the walkthrough tests, only a preliminary analysis to consolidate the understanding of how the firm assesses ICT risks. The same study suggests that the approach of the external auditors in integrated audits is guided by their over-reliance on internal controls information, not performing substantive testing; while, when executing financial statements

audits, they tend to use stricter techniques to give assurance on the data. This is the first reason for the increase in the competencies of both internal and external IT auditors: in fact, other researches (Hadden & Hermanson, 2003; Hadden, Hermanson & DeZoort, 2003) using a survey found the presence of the audit committee when in the board of directors there where individuals with auditing experience and acquaintance with the COBIT model, assigning the duty of IT controls to this particular committee but also highlighting its expertise on the subject. The role of board-level IT committees shows to be fundamental also in the management of data breaches, IT attacks and on increasing stakeholders' trust in the enterprise processes (Hartmann & Carmenate, 2021).

3.3 Application of IT Governance Frameworks to Strengthen Internal Controls

In recent years, many studies have underlined the importance of integrating technical competences and IT governance structures in the internal audit functions, and in general inside the organizations' governance structures, to the end of responding more effectively to IT risks. A study performed in 2025 on the adoption of IT governance frameworks by clients subject to external audit, revealed that it is positively correlated with a higher efficiency of the audit. This is connected to a better integrity of data, better risk management and advanced transparency on IT processes: the findings show clearly that regulators should incentivize the adoption of frameworks like COBIT to lower the risk of material errors and approach a progressively higher compliance with financial reporting requirements (Roustom et al., 2025). The results of this study are consistent with prior findings affirming that IT governance lowers control risk and helps define an effective audit strategy and is central to the topic of this thesis, since it implies an appropriate integration of IT risks and therefore IT controls, suggesting a more robust control environment and better risk management.

Although the study by Roustom et al. (2025) provides recent evidence of the benefits of IT governance adoption, these findings are consistent with earlier research: Huang et al. (2011), proposed a quantitative evaluation model of IT general controls, based on the integration of the principles of the Enterprise Risk Management and COBIT's best practices, already introduced in chapter 2. Their work shows that activity-level IT controls are critical for ensuring the reliability of the financial reporting systems. Some examples of these controls are data management, system security and end-user application controls. The validation of this theoretical model is enforced by a case study on a Big Four auditing firm, included in Huang et al.'s (2011) research, which demonstrates how structured risk-based IT control frameworks contribute to strengthening the internal control environment. Taken together, these articles confirm that well-designed ITGC and, more generally, solid IT governance are essential to enhance risk management practices and in accomplishing higher audit quality and regulatory compliance.

This thesis is also confirmed by Rubino et al. (2014) that emphasize the role of COBIT in reinforcing internal controls over financial reporting, integrating this framework with the COSO framework to identify, document and monitor ITGCs and ITACs. The analysis performed uses the relationship between COBIT domains and the five integrated COSO components, highlighting how this framework helps comply with regulatory requirements and supports risk management in financial reporting processes. Building upon their earlier work, Rubino et al. (2017) expanded their vision, including cultural and organizational components, and shifted their attention from a compliance-focused view to an integrated outlook: the result of the study supports the introduction of IT governance frameworks, especially COBIT, to minimize risk for the whole ITC infrastructure of the organization. They also point out that implementing IT controls has a direct impact on planning, development and support of ICT systems, in particular IT general controls contribute actively to the identification of roles and responsibilities in the organizational structure and IT application controls assure completeness and accuracy of data, influencing internal and external reporting. Because it is complex to analyze ITGC and ITAC, the authors decided to investigate the controls based on three IT dimensions: organizational controls, process controls and soft variables controls. The former category defines policies and procedures, roles and responsibilities, and the general corporate organization. The second category regulates the internal documentation and informational flows, contributing to better the quality of the data and providing clarity, efficiency and integrity, this being one of the main objectives of the COBIT framework. The latter category concentrates on organizational culture, integrity and the management's values, monitoring any update of the code of conduct and promoting ethical behavior towards the employees. These three types of controls are strictly interconnected: IT organizational controls define the rules and procedures, that alone are not enough to ensure the well-functioning of the firm, then IT process controls assure the information reliability and supervision of the way in which it is used, on the other side IT soft variables controls step in upstream, given that the definition of the controls of the other categories can be performed only when the values and the culture of the organization are clear.

The following image summarizes the aforementioned concepts:

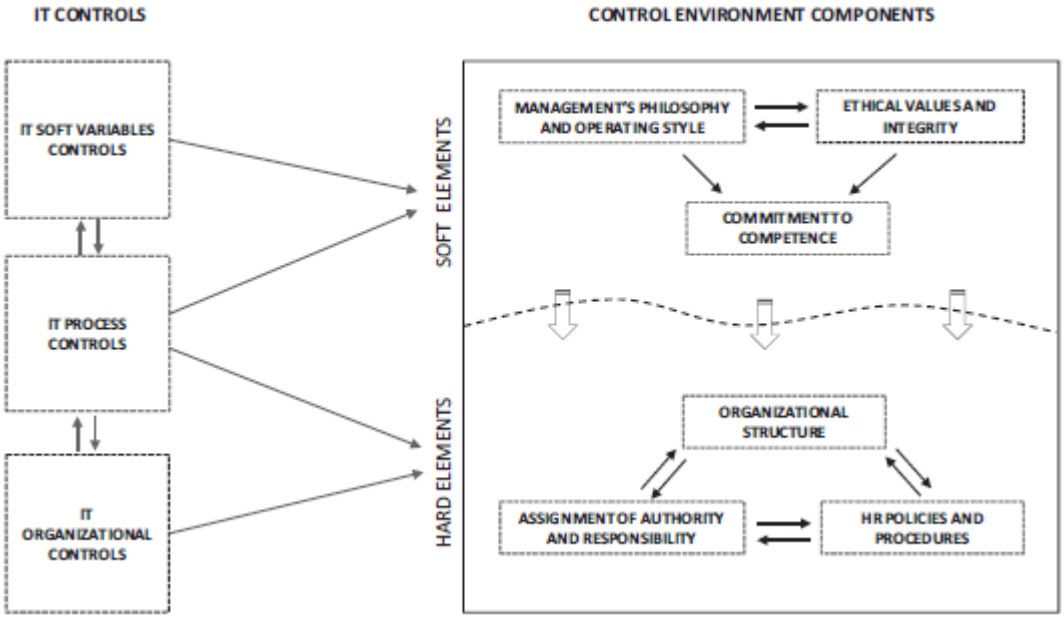

Figure 1: The role of IT controls in the control environment components

Another research (Nuijten et al., 2023) exploring the role of IT auditors compared with general auditors, both in the internal audit function, reveals that IT auditors perceive IT risks more than general auditors, and this difference of opinion is more pronounced in the so-called yellow risks, of moderate and medium gravity, than in red and green risks, respectively severe and light. This shows that the expertise of IT professionals provides more precise judgement and less biases based on personal propension of risk, and therefore it constitutes an optimal reason to introduce IT frameworks and specialized personnel inside the organization.

3.4 The Competence of IT Auditors and the Role of Innovative Technologies Such as AI

External auditors distinguish themselves from internal auditors because "…. the standards, requirements, or other audit criteria used in external audits are declined outside the organization being audited" (Gantz, 2014). The same applies to IT external auditors, specialists in information technologies.

In 2015, a study on Italian banks (D'Onza et al., 2015) underlined that the senior management expected better IT security, to prevent data breaches and system vulnerabilities, strategic support on process design and risk minimization, through the identification of emerging risks, above all in cybersecurity. The model on which the research was based arises from the classification of IT audit in three categories: IT governance, IT management and IT technical, with a specific focus on the first two areas to study the relationship between managers and IT auditors. IT governance was evaluated using the five domains defined by COBIT: strategic alignment, value delivery, resource management, risk management and performance evaluation, while IT management was assessed through the Global Technology Auditing Standard No. 17 of the Institute of Internal Auditors (IIA) and Moeller's classification (2010) defining the following seven areas: IT acquisition and development, change management, operations and maintenance, disaster recovery and business continuity, IT outsourcing, IT security, IT control over financial reporting – aligning with the compliance requirements for Italian listed banks to Law 262/2005, the equivalent of the Sarbanes-Oxley Act in Italy. This discussion serves as further groundwork to understand the role of IT auditors in the banking sector, with their weaknesses and chances for improvement.

On the topic of auditors' expertise, an article by Haislip et al. (2016) highlighted that firms with material weakness in IT controls are more likely to change their external auditor in favor of more experienced ones: this signals to the market that the management aspires to strengthen the IT governance framework, based on external knowledge. Another finding of this study is the fact that the transition to the more capable auditor

improved the company's IT performance within one year, demonstrating the fundamentality of IT knowledge in audit practices, not only for IT controls but for the entirety of internal controls, showing regulators that IT training improves financial reporting outcomes and it becomes the bridge to cover the gap between regulatory expectations and the actual efficacy of controls in organization. Finally, IT audit is shown as a key factor in regulatory compliance but also in governance and prevention of IT risks: the role of IT auditors does not stop at compliance but influences directly audit methodologies and control frameworks to mitigate this category of risks.

However, the results of a more recent study (Mahlangu & Moosa, 2023) on IT knowledge and competences of internal auditors show that their proficiency at the moment is low and the conclusion of this discussion underlines that an insufficient understanding of these procedures can lead to inability to detect IT risks, among other operational risks: this is where the role of IT auditors from external accounting firms lies. External auditors find a deficiency whenever the risk management plan lacks strategy for a specific risk and there is no control arranged to oversee it, or the control is not effective. As underlined by Spears et al. (2013), the institution of new policies and practices often results in symbolic compliance, not supported by real changes in the firm aimed at appearing sound at the external auditors' eye; the real assurance can be given when the IT risk is controlled and managed substantively and effectively.

Finally, the role of innovative technologies, such as artificial intelligence in the context of IT audit and internal control, has recently been investigated by some studies. On one hand, Tanriverdi & Taskin (2023) have performed a systematic literature review and found that some technologies, machine learning, mining and predictive analysis overall, have been implemented significantly in IT audit processes. On the other hand, Almaqtari (2024) carried out an empirical study that resulted in showing that the integration of AI in auditing processes is pandered by the IT governance structure: without an appropriate IT governance framework the adoption of advanced technologies could be critical because the organization would be exposed to major risks, while if put in place adequately becomes a enabling factor for an innovation compliant with the firm's processes.

4. Conclusions

Our narrative approach captures the broad and heterogeneous landscape of research, emphasizing the importance of theoretical integration and qualitative analysis in understanding the dynamics of IT governance and audit practices. The evolving role of audit committees from supervisory bodies to proactive risk managers in IT and cybersecurity further underscores the integration of IT and risk management strategies in contemporary organizational governance.

The findings also reveal that effective IT audit practices are rooted in adherence to standards and principles, ensuring independence, professional competence, and comprehensive evaluation of internal controls.

The central role of IT governance frameworks in managing risks, enhancing internal controls, and supporting digital transformation within organizations, particularly in the banking sector. The literature emphasizes that well-designed IT controls and frameworks like COBIT and COSO contribute significantly to regulatory compliance, risk mitigation, and audit quality.

Finally, our review highlights the importance of specialized IT auditors whose expertise allows for more precise risk assessment, especially in contexts involving moderate risks, and their role in strengthening governance and internal controls through advanced technologies like AI and machine learning.

These insights underline the interconnectedness of IT governance, risk management, and audit practices in fostering organizational resilience, regulatory compliance, and strategic innovation, making them highly relevant for discussions among social scientists focused on management and accounting in the digital age.

4.1 Future Research Avenues Related to the Implementation of Artificial Intelligence (AI) and Other new Technologies

Based on the narrative review, several avenues for future research related to the implementation of Artificial Intelligence (AI) and other new technologies within organizations can be identified:

Impact of AI on Risk Management and Internal Controls Future studies could explore how AI technologies influence the effectiveness of internal controls and risk mitigation strategies. Investigating whether AI integration leads to measurable improvements in detecting, preventing, and managing operational and financial risks would deepen understanding of AI's strategic value.

Role of AI in Enhancing IT Governance Frameworks Research could examine how AI tools support the implementation and evolution of IT governance frameworks like COBIT or COSO. This includes assessing whether AI automates compliance processes, enhances decision-making, or facilitates real-time monitoring of controls, thereby strengthening overall governance structures.

Adoption Barriers and Facilitators for AI Technologies further inquiry can focus on organizational, cultural, and regulatory factors that influence the adoption of AI in audit and risk management functions. Understanding the facilitators and barriers can inform best practices and policy recommendations for effective AI integration.

Impact on Auditor Expertise and Decision-Making future research could analyze how AI affects the decision-making processes of IT and internal auditors, especially concerning their perception of risks and controls. Exploring whether AI leads to biases or improves objectivity due to enhanced data analysis capabilities would be valuable.

AI and competency development in audit teams investigations could target the evolving skills requirements for auditors in the era of AI, identifying necessary competencies, training needs, and the influence of AI on professional judgment and independence.

Finally, ethical and regulatory challenges of AI in Audit and Governance future work could explore ethical considerations, regulatory compliance issues, and the legal implications of deploying AI in critical organizational functions, promoting the development of responsible AI frameworks aligned with governance standards.

These research directions will significantly contribute to understanding the transformative potential of AI technologies within management and accounting contexts, supporting more resilient, transparent, and efficient organizations.

Ethics statement: Ethical clearance was not required for the research

AI statement: AI tools were used to check the English language for the proofread

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The Legal Framework of Artificial Intelligence in the European Union: Regulation, Liability, and Sectoral Challenges

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Abstract: This paper provides a systematic analysis of the emerging legal profiles in the artificial intelligence ecosystem, structured along three interdependent conceptual axes. Firstly, it examines the multi-level regulatory framework taking shape in the European Union. The EU Regulation 2024/1689 is critically explored in its risk-based approach, with particular attention to the categories of high-risk AI systems. The synergies and tensions with the legal framework governing data circulation in the Union are analyzed, with a profound influence in terms of compliance on data-driven technologies. This includes the EU Regulation 2016/679, which directly addresses crucial issues such as automated decisions and profiling; the EU Regulation 2022/868 on data altruism mechanisms and the reuse of public data; the EU Regulation 2023/2854, which introduces rules related to accessing data generated, among others, by IoT and industrial devices, as well as the EU Regulation 2025/327. Secondly, the complex issue of AI liability is evaluated, in the dual dimension of and safety. Particular attention will be paid to the now dismissed EU regulatory proposals. A specific focus will deal with the possible applicability of the product liability discipline. Finally, several sectoral criticalities are identified through case studies in healthcare and transport domains, evaluating for each the difficult balance between potential benefits and risks from algorithmic biases and systemic discrimination. The methodology combines dogmatic analysis, legal comparison, and concrete case studies, contributing to the debate on harmonization between technological innovation, protection of fundamental rights and sustainable legal governance models in the AI era.

Key words: AI civil liability, EU AI regulation, High-Risk AI systems, Algorithmic discrimination, Healthcare AI, Autonomous transport, Financial services AI, Product liability directive, Data governance act, Regulatory fragmentation

1. AI Regulation, Digital Market, and Data Protection/Governance

The transformation of the technological scenario, accelerated since the beginning of the new millennium, has been driven by digital and computational sciences, robotics, and bioengineering, fields relying on algorithms and machine learning within the wider framework of Artificial Intelligence. These advances have enabled sophisticated models capable of self-learning and autonomous decision-making, exploiting the vast amounts of data circulating in the ICT market. Human–machine interaction has thus become a central issue in scientific and philosophical inquiry across domains such as transport, healthcare, social relations, and the IoT (Finocchiaro, 2024).

Beyond questions of safety and reliability, ethical dimensions are increasingly considered both as frameworks guiding technological design and as standards governing the behaviour of AI systems. These aspects reshape the modalities of social and economic interaction.

The wide availability of data—an economic driver and catalyst of digitalisation—has led the EU legislator to establish rules aimed at ensuring AI safety and reliability, while promoting competitiveness and cooperation among Member States (Nitzberg and Zysman, 2022). The AI Act (Regulation (EU) 2024/1869) provides a framework to foster innovation while safeguarding liberty, privacy, security, health, environmental protection, democracy, and the rule of law, in line with the Charter of Fundamental Rights.

EU regulation has evolved from the protection of personal data under Regulation (EU) 2016/679 (GDPR) and non-personal data under Regulation (EU) 2018/1807, towards valuing interoperable data within a broader data-sharing strategy (European Commission, 2020). This shift underpins the Data Governance Act (Regulation (EU) 2022/868) and the Data Act (Regulation (EU) 2023/2854), both central to the Union's data governance architecture. The Council of Europe's 2024 Framework Convention (n.225) on AI and Human Rights, Democracy and the Rule of Law reinforces principles of transparency, trustworthiness, accountability, privacy, and democratic values.

Further initiatives include the 2022 Digital Services Package (Digital Services Act and Digital Markets Act), intended to protect users' fundamental rights and ensure a level playing field for innovation, growth, and competitiveness.

Nonetheless, concerns arise over the coherence between new sectoral rules and existing national legal categories. Tensions are especially visible in the redefinition of the legal status of personal data, contractual obligations linked to networked products, and civil liability for damages caused by AI systems—issues still subject to active debate (Di Gregorio, 2022).

1.1 The Circulation of Data: From Data Protection to Data Economy

As data drives economic activity and is increasingly shaped by artificial intelligence, the EU adopted the Data Governance Act (2022) to establish European data spaces and promote a forward-looking digital economy. Building on the GDPR's focus on protection, the DGA enhances innovation by enabling large-scale data sharing while ensuring safe circulation through rules on re-use of public data, data intermediation services, and voluntary registration of altruistic entities.

Together with the Data Act, which frames data both as a protected asset and as an economic resource, this legislation creates obligations for holders to ensure fair and transparent access. The framework fosters innovation and competitiveness by optimising production processes and enabling AI-based solutions across IoT devices, transport, healthcare, and virtual assistants, while safeguarding trade secrets and reducing contractual imbalances.

Overall, the EU's data strategy seeks to balance innovation with protection, empowering individuals and businesses and supporting the delivery of high-quality, personalised products and services through data-driven AI.

1.2 The AI Act within the Framework of the EU Single Market for Data

Within the digital market, the AI Act (Regulation (EU) 2024/1869) provides a central regulatory framework for a rapidly expanding sector. Building on earlier scepticism but now recognising AI's economic potential, the Act adopts a risk-based approach inspired by product safety law and aims to promote human-centric, trustworthy AI.

It differentiates obligations according to system risk level, prohibiting certain practices and imposing stricter requirements on high-risk systems while maintaining lighter duties for others. Its scope also covers non-EU providers, reflecting a rationale distinct from the GDPR. Risk assessment is supported by Fundamental Rights and Conformity Assessments, often linked to harmonised standards, with sanctions and liability in cases of non-compliance.

For high-risk systems, the Act requires robust data governance covering training, validation, and testing to prevent bias, especially in sensitive areas such as healthcare and credit scoring, while reaffirming the primacy of the GDPR. Obligations extend to general-purpose and generative AI, which must meet transparency and documentation duties, with models of systemic impact subject to enhanced oversight, including incident reporting and cybersecurity safeguards.

Together, algorithms, data, and computing power form the foundation of the AI ecosystem. The AI Act, alongside EU data regulation, embodies the Union's strategic vision of a digital society, positioning Europe as a global leader in trustworthy AI governance.

2. Navigating the Maze of AI Liability: The European Approach to AI Liability and the Risk of Fragmentation

Since the early 2000s, scientific advances in technology have raised complex liability issues concerning robotics and Artificial Intelligence (AI), yet the European legislator has not provided a comprehensive regulatory framework, leaving rules fragmented among Member States and derived from national legal systems; this section reviews successive European legislative proposals on AI liability, explains their withdrawal or failure, and considers the current reform of producer liability. The Commission has long recognised liability as central to Europe's AI strategy (European Commission, 2018). A reform should simplify liability by clarifying responsibility to users, reduce litigation costs (Bertolini, 2020), create recourse mechanisms across the value chain, limit overlapping regimes, and achieve harmonisation to prevent market fragmentation (Palmerini and Bertolini, 2016). However, EU rules operate within a wider framework left to Member States (Expert Group on Liability and New Technologies, 2019), reflecting a policy choice to avoid deep harmonisation; unlike regulation-based proposals, Commission texts were directives, culminating in the 2025 withdrawal of the directive on AI civil liability (European Parliament Legislative Train, 2025). A uniform approach remains crucial to sustain the 'Brussels Effect' (Bradford, 2020), as partial interventions risk disciplinary and market fragmentation (Bertolini

and Riccaboni, 2020), thereby weakenig user protection and limiting technological dissemination. In the absence of harmonisation, some Member States have adopted sectoral rules: Germany amended its Road Traffic Act (Straßenverkehrsgesetz) for autonomous vehicles, Estonia debated specific legislation, and Italy's Draft Bill on AI (2024) includes 'sectoral provisions'. Such bottom-up rules contrast with the Commission's technological neutrality, risk creating entrenched path-dependencies (Podsiadla, 2013), and may generate irreversible legal and market fragmentation, with differing by-design product requirements shaping the very architecture of AI technologies.

2.1 Technological Neutrality and Expanding Liability: From Producers to Operators

The European product liability regime, reinforced by recent reform, remains central to AI liability. Although the Commission in 2018 deemed Directive 85/374/EEC "consistent with EU consumer protection legislation, relevant and future-proof" (Commission Staff Working Document, 2018), persistent shortcomings justified reform. Yet the legislator has resisted revising the principle of technological neutrality, which insists on functional equivalence and treats AI no differently from human helpers, thereby neglecting issues specific to self-learning systems and excluding other actors such as the "operator" envisaged in the European Parliament's 2020 proposal. Victims of technological harm should not be disadvantaged compared to victims of human conduct, but legislators are not obliged to provide superior remedies (Castronovo, 1981). Nonetheless, innovative approaches—expanding strict liability, easing causation, introducing automatic indemnity, or lowering evidentiary burdens—are essential to protect victims effectively.

The 2020 Parliament proposal (European Parliament, 2020) introduced strict liability for operators, defined as those controlling AI risks, whether frontend (direct users) or backend (shaping features and providing data). It applied to high-risk AI, coupled with mandatory insurance and joint liability, while other cases followed fault-based rules with reversed burden of proof. Producers had to cooperate by disclosing information. Despite its innovation, the proposal struggled with distinguishing liability types, coordinating EU and national rules, and resolving causal uncertainty (Gabrielli and Ruffolo, 2019). Accidents with automated vehicles illustrated the difficulty of attributing fault when human and machine factors overlap. By broadening responsibility to multiple operators, the scheme sought simplification but still required identifying risk within each sphere of control. The absence of a designated liable party, unlike consumer sales guarantees (Barcellona, 2009), left compensation uncertain.

The 2024 reform of the Product Liability Directive (COM (2022) 495 final; European Parliament legislative resolution, 2024) confirmed technological neutrality, retained the Directive's structure, and extended "product" to software, digital files, and AI systems (Art. 4(1)). Compensation now covers defects attributable to manufacturers, component makers, importers, non-EU suppliers, modifiers, or platform operators (Art. 7–8). Injured parties must still prove defect, damage, and causation (Art. 10(1)), though presumptions and disclosure obligations ease this burden. Defects are defined by consumer expectations but also by post-market learning (Art. 7(2)(b)) and interaction with connected systems (Art. 7(2)(c)). Courts may order disclosure from producers (Art. 9), subject to trade secrets, though critics highlight delays, costs, and information overload (Ben-Shahar and Schneider, 2010; Kahneman, 2012). Article 10 introduces rebuttable presumptions of defect or causation, codifying doctrines such as *res ipsa loquitur* (Martorano, 1966).

Despite these developments, structural weaknesses persist: the outdated concept of "defect," exclusion of compensation for the defective product itself, vague notions such as "technical complexity," and reliance on disclosure that risks inconsistency and high costs. Ultimately, both the Parliament's 2020 proposal and the 2024 reform fall short of adapting liability law to the opacity and autonomy of AI. The former faltered due to causal indeterminacy; the latter modernised producer liability but preserved fragmentation, limiting the framework's effectiveness in addressing the risks of technological innovation (Di Gregorio, 2024).

2.2 Between Technological Neutrality and Legal Fragmentation: Rethinking AI Liability

The Proposal for a Directive on Liability and Artificial Intelligence (COM(2022) 496 final) was conceived to complete the EU framework for damages caused by AI, especially high-risk systems, but stalled in the legislative process. As an autonomous text complementing the Product Liability Directive, it addressed negligent civil liability, extending some provisions to non-high-risk systems. Based on technological neutrality and the AI Act's risk-based categories (Regulation (EU) 2024/1689) (Wagner, 2023), it recognised the inadequacy of national rules given AI's opacity, but rejected strict liability in favour of fault-based procedures, perpetuating disparities. High-risk AI was defined via Annex III or additional criteria, yet interpretative uncertainty persisted (Faccioli, 2024).

The Directive imposed disclosure obligations on providers or deployers, creating a presumption of fault but not causation, criticised for excessive costs, delays, and obstruction. Article 4 further presumed causation between fault and malfunction, mandatory for high-risk AI and discretionary otherwise, reversing the traditional relation between fault and causation and complicating human–machine contexts such as autonomous vehicle accidents (Bertolini, 2025). Fault, redefined as breach of technical standards, risked conflicting with national doctrines such as medical liability. Thus, the text clashed with entrenched traditions, failed to resolve causal opacity, and reinforced fragmentation through overreliance on technological neutrality, definitional ambiguities, evidentiary burdens, and poor coordination with national laws.

Its failure illustrates the tension between horizontal and sectoral regulation. Attempts at general rules, intended to secure the "Brussels Effect" (Resta, 2022), collided with legal diversity. Categories like "high-risk" proved too indeterminate, undermining certainty. A more sector-specific method is needed, regulating professional fields and acknowledging AI's heterogeneity.

Despite a decade of debate, results remain limited. Product liability, intended as a safety net, is weakened by litigation barriers and the outdated notion of "defect." The European Parliament's strict liability proposal sought to internalise risks but collapsed under definitional uncertainty and causation issues. Legislators abandoned it, favouring the producer liability reform, which preserved structural weaknesses, and procedural rules modelled on German law that interfere with doctrines of causation and fault (Scognamiglio, 2023).

The Draft ultimately failed because excessive generality and pursuit of neutrality generated cascading problems: uncertainty in classifying "high-risk" AI, risks of fragmentation, burdensome disclosure, and tensions with national civil liability. Horizontal rules for all AI proved excessive, altering the substantive balance of causation and fault. Future regulation must address professional sectors directly, with tailored liability regimes.

In the end, the EU legislator preserved an outdated system: product liability still excludes compensation for the defective product itself and remains tied to the elusive concept of defect. The procedural innovations add little clarity, leaving courts ill-equipped to address AI opacity. Abandoning reform entrenched fragmentation and path dependency, ensuring persistent uncertainty and insufficient victim protection (Lasmar Almada, 2024).

3. Algorithmic Non-Discrimination and Vulnerable Persons

According to the World Health Organization, about 15 per cent of the world's population has some form of vulnerability (disabled and elderly people) that limits the freedom to enjoy public relations, to live in an urban environment and to exercise the fundamental rights.

Article 3 of the UN Convention officially introduces disability into the sphere of human rights, with the aim of to eliminating obstacles to the enjoyment of fundamental rights (Art. 5) (Marra, 2011), of removing discrimination while promoting inclusion also through the digitalization of services.

Furthermore, at the European level, the general prohibition of discrimination is contained in Article 19 TFEU, which is a fundamental document of the European Union's anti-discrimination framework and empowers the institutions to carry out acts to encourage member states' policies to prevent inequality.

The protection of the rights of persons with disabilities against discriminatory acts is then enshrined in the Charter of Fundamental Rights of the European Union, which, in Article 21, prohibits discrimination also based on 'disability' and provides in Article 26 for the 'inclusion' of persons with disabilities in the social and employment fabric, promoting their self-determination. In the broader international framework, the rights of disabled people have acquired a position among the fundamental rights with the proclamation, in the 2006 UN Convention on the Rights of Persons with Disabilities (UNCRPD). At the same time the Strategy on the Rights of Persons with Disabilities 2021-2030 aimed at improving social inclusion, the realization of wellbeing, and the recognition of the full exercise of the rights of persons with disabilities, in a perspective also accepted in the recent directives on the accessibility of products, services and websites and by the Court of Justice.

The use of new technologies, including AI systems and Internet of Things plays a fundamental role in ensuring the inclusion of fragile groups in the social context and in the urban social economic empowerment, especially in the field of transport (Al Mureden-Calabresi, 2021; Turci, 2024), healthcare, education (Di Gregorio, 2020, p. 19; Di Gregorio, 2023, p. 55).

Legal systems, including the Italian one, have identified solutions to the issues posed by ageing, fostering the wellbeing and autonomy of the elderly promoting access to public goods and services on an equal footing with other citizens, adapting goods and services for the city also to people's disability conditions using the technology

and AI system (e.g. by using robot assistants, by optimising access routes to health services through AI). The protection of vulnerable people rights by legal system constitutes also the criterion for evaluating the effectiveness of the measures adopted and based on new technologies.

At the same time, developments in technology are accompanied by new risks for the individual rights (P. Perlingieri, 2020; C. Perlingieri – Martone, 2023) making it necessary to devise strategies for compliance with the rules in force and with the drafting, where necessary, of new rules capable of exploiting the opportunities offered by scientific development, but at the same time able of limiting the risks generated by the production and marketing of instruments and Epparatuses, including the phenomenon of algorithmic discrimination, which can significantly affect vulnerable people in Smart Cities.

In this teleological context are important interventions of the European legislator, In particular, Directive 2016/2102/EU on the accessibility of public bodies' websites and mobile applications (Web Accessibility Directive, WAD), which obliges all public and private bodies in the EU to make their websites and mobile applications accessible, transposed within the Italian legal system by Legislative Decree no. 106/2018 and Directive 2019/882/EU on the requirements of accessibility of products and services in the internal market of the European Union (European Accessibility Act), which was enacted to ensure full web accessibility to the websites of PAs and private companies, so that the content can also be used by people with disabilities, implemented by d. lgs. 27.5.2022, no. 82 and intended to harmonise the internal legislation of the Member States,

With a special focus on the elderly population, the Italian legislature implemented the principles of digital accessibility with Law No. 33/2023, which establishes the criteria for the promotion of active ageing and social inclusion, including digital literacy interventions for the elderly, which are fundamental for access to the services offered to fragile people in the social context and in the Smart Cities.

Ultimately, the European and national frameworks on non-discrimination and digital inclusion show that the regulation of artificial intelligence cannot be confined to safeguarding technological innovation but must also ensure the effective protection of vulnerable persons, by preventing algorithmic exclusion and fostering a model of technological development genuinely oriented towards the respect of fundamental rights.

4. AI and Healthcare

The increasing use of next-generation digital medical devices is promoting the automation of healthcare processes and promises to make crucial phases autonomous: from workflow management and departmental coordination to diagnostics, therapy administration, and patient monitoring. This transformation is driven by the significant benefits these technologies seem to guarantee, offering tangible improvements in both the quality and quantity of services.

However, while the potential of robotics and artificial intelligence (AI) is clear, assessing the risks associated with their use is far more complex, particularly regarding the identification of parties who may be held legally liable in the event of damage (De Berardinis, 2020). The rapid diffusion of AI in healthcare raises legal issues linked to evident contraindications affecting fundamental rights such as health, liberty, dignity, and self-determination. Consequently, the law faces a challenge requiring profoundly innovative interventions to fill current gaps.

The introduction of AI – particularly machine learning systems – surpasses the limits of individual medical experience by enriching it with knowledge derived from vast clinical datasets. This computational power allows for the interpretation of increasingly heterogeneous clinical information. Within this context, the healthcare professional operates in a complex network of people, structures, and tools that cannot be entirely mastered, meaning the allocation of damage is moving away from the classical scheme based on the predictability of one’s own actions (Amore and Rossero, 2023).

The main issues in classifying liability can be summarised in two areas:

The attribution of liability is complicated by the presence and interaction of multiple actors, including producers of hardware or neural networks and the providers of the healthcare service itself through structures involving several professionals (Prifti, Stamhuis and Heine, 2022).

On the objective side, the so-called black-box effect results in the impossibility of observing the training, self-learning, and correction stages that lead to a decision. This undermines the traditional scientific method, as only the output can be inferred from static connection weights. Post-hoc explanation techniques can only provide an approximate reconstruction.

The black-box effect is an intrinsic feature of AI systems. The European Data Protection Supervisor has examined it in terms of explainable AI (XAI)—the ability of AI systems to provide clear explanations of their decisions. Striving for maximum explainability should, theoretically, allow for the development of more suitable liability criteria, moving away from pure strict liability, which would otherwise impose a *probatio diabolica* on both clinicians and injured patients.

Reducing reliance on strict liability also helps contain the risk of defensive medicine, which could discourage the adoption of AI. The EU's AI Act aims to promote the development and use of AI systems, hence the need for transparent tools. However, while explainability might be a workable solution for non-generative AI, reconstructing the decision-making processes of generative AI currently appears impossible, leaving many questions on liability standards open.

The EU Regulation aims to ensure AI systems on the market are safe and respect the Union's fundamental rights and values. It confirms a risk-based approach, introducing differentiated obligations depending on the level of risk posed (Marsico, 2024). Regulatorily, the aim is to adapt constitutional principles to AI applications, outlining a human-centric and trustworthy AI inspired by ethical purposes.

Nevertheless, the problem of allocating liability remains central when an AI system causes harm. The difficulties are exacerbated by technological peculiarities like the black-box effect. After initially considering a dedicated instrument (the withdrawn 2022 Proposal for a Directive on AI Liability), the EU legislator has so far left the matter to the general framework and to national legislation. In practice, patients can rely both on EU law protections—particularly product liability—and on ordinary civil remedies against physicians or healthcare institutions under the medical liability rules of each Member State.

5. Autonomous Horizons: Charting the Regulatory Course for AI in Aviation and Maritime Transport

The integration of Artificial Intelligence (AI) and Machine Learning (ML) promises transformative safety, efficiency, and autonomy in transport, but also raises complex legal and regulatory challenges. Aviation and maritime sectors lead this shift, with regulators such as the European Union Aviation Safety Agency (EASA, the EU body responsible for civil aviation safety) and the International Maritime Organization (IMO, the UN agency overseeing global shipping regulation) seeking frameworks that balance innovation with safety. This section examines sectoral issues, EASA's AI Roadmap, IMO's work on Maritime Autonomous Surface Ships (MASS), the impact of the forthcoming EU AI Act, and unresolved liability questions.

Aviation, already a pioneer in automation, now faces AI-driven autonomy. EASA's AI Roadmap establishes a risk-based "AI trustworthiness" framework aligned with the European Commission's *Ethics and Guidelines on Trustworthy AI* (EASA & Daedalean, 2024). It outlines a phased approach from lower-level assistance to higher autonomy. Key pillars include "Learning Assurance" (ensuring AI learns safely), "AI Explainability" (making AI decisions understandable), and "AI Safety Risk Mitigation" (identifying and reducing risks).

A persistent challenge is AI's "black box" nature (Turci, 2025), meaning that its internal decision-making processes are often opaque. This complicates accident investigations and liability attribution (Prakash, 2021). EASA therefore stresses explainability so that operators can understand AI outputs, which is vital for both safety and accountability.

In maritime transport, the IMO's Joint MSC-LEG-FAL Working Group on MASS is preparing a goal-based framework and a non-binding MASS Code (IMO, 2023). A central issue concerns the role of the ship's "master". Although ultimate responsibility remains with a human, the master may control the vessel remotely from a Remote Operations Centre (ROC) that raises jurisdictional questions under the United Nations Convention on the Law of the Sea (UNCLOS) when ROCs are located outside the vessel's flag State (Ringbom, 2019). Additional challenges stem from the International Convention on Standards of Training, Certification and Watchkeeping for Seafarers (STCW), which sets minimum global competence requirements for ship crews, alongside unresolved issues about how to define "remote operators" and how to mitigate interoperability and cybersecurity risks (IMO, 2023).

The EU AI Act (Burden & Stenberg, 2023), expected in 2025, will broadly affect mobility. Its risk classification system deems AI safety components in Annex II products as high-risk, requiring CE marking (the EU's product safety certification) and registration, but exempts aviation, motor, and agricultural vehicles that are already regulated under other regimes. This creates fragmentation: for example, an AI collision-avoidance system may be considered high-risk in industrial machinery but exempt in trucks.

Annex III also designates certain stand-alone uses of AI as high-risk, including traffic management and pollution control. Thus, AI embedded in a car's steering may be exempt, but AI managing city traffic lights could be high-risk. Manufacturers operating in both markets must therefore comply with high-risk obligations. Users of such systems (Art. 29) must also ensure oversight, data quality, and GDPR-compliant Data Protection Impact Assessments (DPIAs). Regulatory sandboxes (Arts. 53–55) provide controlled environments for testing innovative AI applications, even allowing the use of personal data beyond its original purpose when required for public safety or environmental goals.

Despite evolving frameworks, liability for AI-driven damage remains unsettled in Europe. The reformed Product Liability Directive (EU) 2024/2853 attempts to address issues posed by evolving systems (Art. 7(2)(b)–(c)) (Di Gregorio, 2024). New provisions on disclosure (Art. 9) and presumptions (Art. 10) aim to ease litigation but may instead create costly and complex proceedings (Faccioli, 2024). The withdrawn AI Liability Directive (COM(2022) 496 final) had sought to address opacity through disclosure obligations and causality presumptions, but failed due to complexity and lack of alignment across Member States. The result is continuing legal uncertainty, fragmented national approaches, and risks that victims may not be compensated. In the United States, cases involving Tesla and Uber highlight how liability may be shared between manufacturers, operators, and infrastructure providers (Prakash, 2021). Maritime law adds the specific issue of the "remote master": if an ROC in another country controls a MASS, questions arise about which jurisdiction and liability rules apply, and current conventions such as the Civil Liability Convention (CLC) and the Convention on Limitation of Liability for Maritime Claims (LLMC) cannot resolve these conflicts (Dremliuga & bin Mohd Rusli, 2020).

AI in transport offers major benefits but also novel risks. EASA and IMO are proactively shaping sectoral frameworks, while the AI Act will set horizontal standards for non-exempt systems (Turci, 2025). Yet liability gaps persist. Only sustained collaboration between regulators, industry, legal experts, and insurers can secure safe, efficient, and accountable autonomous transport.

6. Conclusion

The analysis demonstrates that the European Union has progressively developed a dense, multi-layered regulatory architecture for Artificial Intelligence, rooted in the twin objectives of safeguarding fundamental rights and fostering innovation. While the AI Act represents a milestone in consolidating a risk-based approach, significant challenges remain in the field of civil liability, where the unresolved issues of causation, fault, and compensation persist. The technological neutrality is a guiding principle that has ensured continuity with established regimes, yet it has also revealed its limitations in addressing the opacity and autonomy of AI systems.

Sectoral perspectives, particularly in healthcare, financial services, and transport, highlight that horizontal rules are insufficient to capture the specificities of complex domains where algorithmic decision-making intersects with human vulnerability and systemic risks. Likewise, the debate on non-discrimination underscores the need for inclusive technological governance to ensure that innovation does not exacerbate pre-existing inequalities.

The future trajectory of European regulation will therefore depend on its ability to balance horizontal coherence with sector-specific precision. A sustainable model of governance should integrate robust principles at Union level with tailored instruments capable of responding to the peculiarities of each field of application. Only through this dual strategy AI can evolve into a tool that promotes human dignity, equality, and social solidarity, transforming potential sources of conflict into drivers of responsible innovation and collective progress.

Author contributions: This paper is the result of joint research and reflection by the Authors. For the purposes of this paper, however, paragraphs 1 and 3 are attributed to Valentina Di Gregorio; paragraphs 2, 5, and the conclusions are attributed to Matteo Turci, and paragraph 4 is attributed to Monica Gigola.

Ethics statement: No ethical clearance was required for this research.

AI statement: AI tools have been used to check the compliance of the paper to style guidelines.

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Bridging the AI Governance Gap: Ethical and Regulatory Imperatives for Generative AI in Nigeria

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Abstract: As generative artificial intelligence (AI) technologies—such as *ChatGPT*, *DALL·E*, and other large language and image models—become increasingly mainstream, they introduce new ethical, legal, and governance challenges that are particularly urgent in developing countries. Nigeria, Africa's most populous nation and a regional technology hub, offers a compelling case study of how these technologies are being adopted in environments with minimal regulatory infrastructure and limited public awareness. This paper examines the ethical and societal implications of generative AI in Nigeria and interrogates the country's preparedness to manage these risks. Despite the creation of the National Centre for Artificial Intelligence and Robotics (NCAIR) in 2020 and the recent passage of legislation such as the Nigeria Data Protection Act (2023) and the Startup Act (2022), Nigeria lacks a unified national AI formal risk classification systems, or sector-specific ethical guidelines. These gaps are important given the widespread, unregulated use of generative AI tools in education, politics, and digital commerce. In higher education, students increasingly rely on generative AI for assignments and projects, raising concerns about academic integrity in a system already strained by infrastructural deficits. Meanwhile, in the political domain, deepfake videos and AI-generated misinformation have circulated in election periods, threatening democratic stability in a media world prone to disinformation and weak content regulation. The paper compares Nigeria's regulatory trajectory with global trends, particularly the European Union's Artificial Intelligence Act and similar initiatives in Kenya, South Africa, and Rwanda. It highlights how Nigeria's reactive approach to AI governance contrasts sharply with more proactive global models. Sectoral analysis reveals risks including digital labour displacement, cultural misrepresentation through foreign-trained models, algorithmic bias, and the erosion of public trust. Ultimately, the study calls attention to Nigeria's urgent need for a comprehensive, context-sensitive AI ethics and governance framework. Through an analysis grounded in local realities and informed by global comparisons, the paper contributes to broader conversations about equitable, responsible AI adoption in the Global South.

Keywords: Generative artificial intelligence, AI ethics, AI policy, Misinformation, Deepfakes, Global south

1. Introduction

Artificial Intelligence (AI) is powerfully transforming how our economies work, how governments operate, what happens in schools, and even how we live our lives. Among its most disruptive advances is generative AI, a category of systems capable of producing human-like text, images, audio, and video. These tools, such as ChatGPT and Gemini, operate through large language models (LLMs) and deep learning algorithms that process vast datasets to generate new content. While such systems promise innovation, they also pose serious ethical risks, particularly in countries with weak regulatory frameworks and limited digital literacy. In the Nigerian context, generative AI introduces challenges that touch on misinformation, algorithmic bias, privacy erosion, academic dishonesty, and labour market disruption (Al-kfairy et al,. 2024).

This paper argues that in countries like Nigeria, where institutional readiness is limited and regulatory instruments are fragmented, the proliferation of generative AI could make existing social and economic problems worse. Even with some early efforts like the National Centre for Artificial Intelligence and Robotics (NCAIR) and the release of the draft *National Artificial Intelligence Strategy (NAIS)* in 2024, Nigeria still struggles to articulate and enforce an ethical framework capable of responding to the speed and complexity of these technologies. Nigeria's low standing in global AI readiness reports (Oxford Insights, 2024) further shows a disconnect between digital ambition and regulatory implementation. Most discussions about AI ethics come from Europe, North America, and China, which have stronger legal systems (Fjeld et al., 2020; Jobin et al., 2019). However, less is known about AI ethics in the Global South, especially based on real-world examples. This paper helps fill that gap by looking closely at how generative AI affects ethics, laws, and society in Nigeria. Using insights from technology, ethics, and data studies, it argues for AI rules that fit Nigeria's unique social conditions, limited infrastructure, and past power imbalances. Also, by studying AI's effects on education, political communication, and the digital economy, this paper offers new information into regulating AI in a developing digital society. Its findings are useful for experts in AI ethics, digital policy, African studies, and anyone creating fair AI rules. Ultimately, this study adds to the discussion on responsible AI globally and suggests ways to build ethical AI systems that support both new ideas and social safety.

2. Literature Review

As generative AI changes how we learn, govern, and communicate, researchers and policymakers are deeply concerned about how to ethically control them. Generative AI, which Kaplan and Haenlein (2019) explain as AI's ability to understand information, learn from it, and create new, human-like output, creates specific ethical difficulties. These challenges involve people losing trust, the risk of knowledge being manipulated, and problems with figuring out who is accountable. Recent discussions have moved past theoretical debates to concentrate on practical governance methods and how institutions should be set up. This shift represents what Anamoji (2024) calls a "third wave" of AI ethics. This new approach prioritizes putting ethical principles into action, ensuring openness, and creating ways to turn ethical values into clear responsibilities.

Ethics in AI generally means the guiding values and standards used when creating and applying AI, aiming to ensure it is fair, clear, accountable, and respects human rights (Floridi et al., 2018). Yet, scholars like Zuboff (2019) and Acemoglu (2024) caution that if there aren't strong protections in place, AI could worsen existing unfairness, increase monitoring, and even put democratic stability at risk. These worries aren't only about formal laws. Cath (2018) stresses that governing AI also involves private companies taking responsibility, public discussions, and civil society groups participating in how AI systems are designed, checked, and limited. Generative AI poses distinct ethical threats. In education for instance, a major concern is its potential to undermine academic integrity; students might use tools like ChatGPT to generate coursework with minimal personal input (QAA, 2023a; Pavlik, 2023). Furthermore, research highlights the inherent biases within these models, which are often trained on data reflecting existing societal inequalities. Weidinger et al. (2021) demonstrate how this can perpetuate stereotypes or exclude certain voices. Misinformation is also a central issue. Generative AI can create fabricated or "hallucinated" facts, and because AI-generated content can appear highly credible, it increases the risk of public manipulation (Spitale, Biller-Andorno and Germani, 2023). This danger is particularly acute in regions with vulnerable democratic institutions, where synthetic content can obscure the distinction between genuine information and deception (Kreps et al., 2022). The deployment of deepfakes in political propaganda adds another layer of risk, eroding confidence in electoral processes and further weakening civic bodies (Dobber et al., 2021).

These problems are even bigger in the Global South. There, managing new technologies is often hard due to weak institutions and poor infrastructure. While most AI ethics talks come from wealthier countries, more and more research says we need to "decolonize" AI rules by focusing on the views and needs of Global South societies. Birhane (2020) argues that ethical models brought in from outside often do not fit local realities, and the values in common AI systems do not match the experiences of disadvantaged groups. In Africa, Mhlanga (2023) points out that countries with weak rules and low digital skills face greater risks. These situations mean generative AI could do more harm than good, increasing exclusion instead of promoting empowerment. Despite these critical insights, empirical studies on generative AI in African societies remain limited. Although Nigeria has established institutions like the National Centre for Artificial Intelligence and Robotics (NCAIR), these efforts have not been accompanied by comprehensive legal frameworks or public awareness initiatives (Anamoji 2024). This gap points to a broader issue in the literature: the underexplored interaction between ethical theory, regulatory design, and local sociopolitical conditions in non-Western contexts. Most existing studies focus on normative frameworks or technical risks without engaging the everyday realities of AI use in places where the state, market, and civil society operate under different constraints.

This paper builds on these discussions by offering a detailed analysis of the ethical, legal, and societal implications of generative AI in Nigeria. Rather than treating ethics as a set of universal rules, it takes a context-specific approach, examining how global models of AI governance are applied (or fail to be applied) within Nigeria's unique institutional and social environment. It also provides empirical data to a body of literature that is heavily focused on the Global North, offering information into how generative AI is already impacting education, political discussions, and the digital economy in a setting characterized by uneven infrastructure and fragmented regulations.

3. Case: Nigeria

Nigeria's experience with generative AI shows a clear struggle: it wants to embrace new technology but is not ready with the necessary rules and systems. The country has made visible efforts, like the release of the draft *National Artificial Intelligence Strategy (NAIS)* in 2024. However, its ability to predict, track, and address the ethical, legal, and social risks of generative AI is still scattered, underfunded, and often just reacting to problems. When it comes to education, the disconnect is very clear. A *TechCabal* article reported that Nigerian university

students are widely using AI, like ChatGPT, for their studies (Techcabal, 2025). They are using it to write essays, solve math problems, fix computer code, and quickly summarize readings. While students globally are doing this, Nigeria's educational institutions have not set up clear responses. Most universities still use outdated methods like paper exams and basic plagiarism checks that do not consider AI use (Abubakar et al., 2024). There are no federal rules or specific university guidelines for using AI ethically in schools, and many teachers have not learned about digital integrity in the AI era. This means academic rules are changing because of how students use AI, not because of thoughtful reforms by educators. This points to a major failure in forward-thinking governance and highlights the risks of policy inaction in a sector crucial for national progress.

The political domain presents an equally pressing challenge. In the lead-up to the 2023 general elections, manipulated videos and AI-generated audio recordings circulated widely across social media platforms, some of which falsely depicted leading candidates making inflammatory remarks (Davis, 2024). Although not all of this content was definitively identified as AI-generated, fact-checking organisations such as *Dubawa* confirmed that generative tools had been used to alter or fabricate elements in several viral posts (Nwankwo, 2024). These developments occurred in a context where over 100 million Nigerians are active online and social media remains a dominant source of political information, particularly among first-time voters and youth populations (Statista, 2024). The realism of synthetic content, combined with low levels of digital literacy and high political polarisation, makes such material extremely potent. Existing laws, including the Cybercrimes Act (2015) and the Nigeria Broadcasting Code, do not contain provisions that address the manipulation of digital content using AI. Furthermore, regulatory agencies such as the Nigerian Broadcasting Commission (NBC) lack the technical capacity to trace or verify synthetic media at scale and have faced sustained criticism for inconsistent enforcement and politicised decision-making (Arise TV, 2023). This regulatory void heightens the risk of disinformation, electoral manipulation, and declining public trust in democratic institutions. In a country where elections have historically been marred by violence, mistrust, and ethnoreligious tension, the implications of unregulated generative AI use in political discourse are particularly acute.

The digital economy reveals another layer of generative AI's uneven impact. According to *McKinsey's* 2024 report, 71% of organizations now regularly use generative AI in at least one business function (Singla et al., 2025). Platforms such as Copy.ai, Jasper, and ChatGPT have become integral to daily business functions, used to generate marketing copy, write client reports, automate customer responses, and develop pitch documents (BusinessDay, 2024). These tools promise enhanced productivity and lower operational costs, which are especially attractive in a struggling economy marked by inflation, currency instability, and rising unemployment. However, the benefits of this technological shift are not evenly distributed. Entry-level jobs in writing, transcription, customer service, and administrative support, many of which employ young Nigerians, are increasingly at risk of automation. At the same time, fintech platforms are deploying AI-powered credit scoring systems to accelerate loan approvals (Iroche, 2025). Yet these models often rely on data inputs that exclude informal workers, rural users, and individuals without established digital footprints, perpetuating patterns of financial exclusion under the appearance of innovation (Mhlanga, 2023). These trends suggest that generative AI is being integrated into the economy in ways that reproduce existing inequalities, raising ethical questions about algorithmic transparency, data bias, and the absence of regulatory protections for informal labour.

Across these three domains of education, political communication, and economic activity, a pattern of ethical vulnerability emerges. Generative AI is not a speculative or future concern in Nigeria; it is already reshaping practices, expectations, and outcomes across society. Yet its adoption is unfolding in a regulatory vacuum. Institutions lack the legal instruments, technical capacity, and policy vision to respond to the pace and complexity of these changes. Civil society, academia, and professional associations remain largely excluded from formal governance processes, leaving ethical guidance to be improvised or ignored. This produces a situation in which those with greater access to AI tools benefit disproportionately, while those with fewer resources or weaker institutional support bear the brunt of the risks. The Nigerian case does not simply illustrate a lack of readiness. It reveals how technological acceleration, when not matched by ethical infrastructure, produces systemic blind spots that can undermine democratic institutions, deepen inequality, and erode social trust. The convergence of weak regulation, institutional fragmentation, and low digital literacy creates a fertile ground for the harmful use of generative AI. This raises urgent questions not only about national capacity but also about the translatability of global ethical frameworks into contexts shaped by historical marginalisation, infrastructural disparity, and contested legitimacy. As generative AI continues to expand its reach, Nigeria's experience offers a cautionary case for other countries navigating similar constraints.

4. Global Comparisons and Policy Gaps

The ethical risks posed by generative AI are now the subject of urgent global attention. Governments, international organisations, and regional blocs are racing to develop regulatory frameworks capable of managing the disruptive potential of these technologies. While generative AI systems transcend national boundaries in their development, distribution, and usage, their governance remains decisively shaped by domestic legal institutions, regulatory capacity, and political will. Scholars often frame this governance landscape through three "Digital Empires"—the United States, the European Union (EU), and China—whose approaches highlight contrasting visions for balancing innovation, security, and ethics (Bughin et al., 2021).

The EU has advanced the most comprehensive legal regime through the *Artificial Intelligence Act* (2024), which classifies systems by risk. Generative AI falls into the high-risk category when applied in education, recruitment, or politics, requiring transparency, human oversight, and strict data governance standards (European Union, 2024). This model emphasises fundamental rights and public accountability, extending to law enforcement and welfare systems where mandatory ethical impact assessments apply. Such a framework could provide useful direction for Nigeria, where institutional oversight of AI is still dispersed across agencies with limited coordination.

In the United States, regulation has been less centralised but is moving toward intervention. The 2023 Executive Order on Safe, Secure, and Trustworthy AI required federal agencies to establish governance strategies and procurement guidelines promoting fairness (Federal Register, 2023). In 2025, the White House launched *Winning the Race: America's AI Action Plan*, structured around three pillars—innovation, infrastructure, and security (White House, 2025). The plan promotes AI-led economic growth through investments in data centres and export controls while rescinding some earlier restrictions viewed as burdensome. Sectoral rules in education, finance, and healthcare illustrate growing recognition of generative AI's risks. The U.S. model, while market-driven, depicts the role of state power in steering private innovation with strategic safeguards.

China's approach contrasts sharply, prioritising sovereignty, state control, and global influence. Its *Global AI Governance Initiative* (GAIGI), launched in 2023, promotes a "people-centred" approach that stresses sovereignty and consultation, especially with developing nations (Racicot and Simpson, 2025). Domestically, Beijing enforces binding rules on algorithms and generative content, aligning AI safety with surveillance and political stability under Communist Party priorities. Internationally, China advances its model through bodies like the International Telecommunication Union (ITU), co-hosting AI capacity-building events with African partners. Critics argue GAIGI extends China's geopolitical ambitions, aiming both at leadership in AI innovation by 2030 and at embedding authoritarian governance norms globally (Racicot and Simpson, 2025).

Moreover, multilateral actors also provide important normative frameworks. United Nations Educational, Scientific and Cultural Organization's (UNESCO) *Recommendation on the Ethics of AI* (2021) emphasises human rights, inclusion, and sustainability, and has guided several national strategies. The Organisation for Economic Co-operation and Development (OECD) has established AI principles and policy observatories to track implementation (OECD, 2019). Recent reports, such as *Governing with Artificial Intelligence: Are Governments Ready?*, stress both opportunities for efficiency and risks like bias and privacy loss (OECD/UNESCO, 2024). Also, joint OECD/UNESCO initiatives, such as the *G7 Toolkit for Public Sector AI*, offer practical guidance for embedding safeguards into government use. (OECD/UNESCO, 2024)

Comparative experiences from other African countries demonstrate that viable alternatives exist for governing AI, even in resource-constrained settings. Kenya's *National AI Strategy 2025–2030*, launched in March 2025, aligns with the AU-AI Continental Strategy by prioritising ethical governance, sectoral innovation, and capacity building (Kenya Ministry of ICT, 2025). It emphasises local data sovereignty and applies AI to agriculture, healthcare, and small and medium enterprises (SMEs), while also establishing national AI research centres and fostering public–private partnerships to strengthen its ecosystem. Similarly, South Africa's *National AI Policy Framework* (2024) prioritises human rights, particularly in healthcare, where predictive analytics are being deployed to reduce hospital readmissions (South Africa National AI Policy Framework, 2024). Rwanda has also embedded ethics into its policymaking through oversight committees and mandatory risk assessments, ensuring that AI applications in health and agriculture meet legal standards while reflecting local needs (CIPIT, 2025). Zambia's *National AI Strategy 2024–2026* commits to inclusive governance and infrastructure development in education and service delivery, while Ghana integrates data governance into its broader digital transformation agenda, stressing multi-stakeholder engagement to tackle bias, promote social inclusion, and protect privacy. These initiatives are united by political commitment, stakeholder participation, and forward-looking design, aligning with both the *African Union's Agenda 2063* and the *Sustainable Development Goals* (SDGs) (CIPIT, 2025).

Four major policy gaps emerge from this comparative analysis. First, there is no institutional framework for classifying AI systems by risk level or for authorising their deployment. Second, enforcement of existing digital laws is uneven and often politically constrained. Third, businesses and institutions are not required to conduct algorithmic audits, explainability disclosures, or fairness assessments. Fourth, there is limited civic participation in policy development, resulting in regulations that do not reflect the lived experiences or concerns of the public. These deficiencies are interlinked and mutually reinforcing. Hence, while global and regional actors are moving toward structured, enforceable, and participatory models of AI governance, Nigeria remains caught in a cycle of reactive policymaking and fragmented institutional response.

5. Conclusion and Recommendations

This paper studies how new AI, like ChatGPT, is impacting Nigeria in terms of what is right (ethics), what is legal, and how society functions. We found that even though this AI is quickly becoming common in schools, politics, and the digital economy, Nigeria is not ready. The rules and systems in place are weak, incomplete, and not properly enforced. Current Nigerian efforts, are helpful but do not fully tackle the specific challenges generative AI brings. When we compare Nigeria to places like the EU, US, China, Kenya, South Africa, Zambia, and Rwanda, who are actively putting rules in place to manage AI risks, Nigeria falls behind. It does not have a thorough national plan for AI, a system to check AI risks, or a way to audit AI programs. Also, many of the AI systems used in Nigeria come from outside and are not built to understand local languages or cultures, which creates even more ethical problems.

To address these challenges, five interconnected policy recommendations are proposed. These are grounded in the evidence presented and tailored to Nigeria's institutional realities:

- Establish an AI Ethics and Safety Commission: A dedicated and independent regulatory body should be created to monitor and assess high-risk AI applications. This commission would be responsible for issuing ethical standards, reviewing compliance, conducting impact assessments, and coordinating with relevant agencies across sectors such as education, elections, and finance.
- Strengthen Institutional Capacity and Digital Literacy: Policymakers must invest in building institutional readiness. This includes training for regulators, public officials, educators, and journalists on AI ethics, digital rights, and algorithmic accountability. University curricula should integrate AI ethics and governance modules to build awareness among future professionals.
- Localise Data and Promote Indigenous AI Development: Reducing reliance on foreign systems requires investment in local AI research ecosystems. This includes developing large-scale datasets in Nigerian languages, supporting local start-ups, and funding collaborative research that reflects Nigerian societal needs. Such efforts would enhance digital sovereignty and ensure cultural relevance.
- Protect Labour Rights in the AI Transition: The state should enforce protections for workers whose roles are susceptible to AI-driven automation. This includes fair use policies in the workplace, government-backed reskilling programmes, and new regulations that encourage human-AI collaboration instead of replacement.
- Promote AI Awareness Through Civic Engagement: Public education campaigns on the ethical use of AI should be launched in collaboration with media houses, tech hubs, and NGOs. Increasing public awareness will help citizens better understand their rights and risks in an AI-driven society.

Lastly, the ethical governance of generative AI in Nigeria is not a peripheral or secondary issue. It sits at the intersection of technological transformation, institutional fragility, and public trust. Ensuring that AI systems serve the public good will require coordinated, inclusive, and locally grounded responses. While this paper has focused on Nigeria, the findings speak to broader patterns in the Global South, where digital innovation often accelerates in the absence of regulatory preparedness. Nigeria's experience illustrates both the dangers of delayed governance and the possibilities of reform. It invites scholars, policymakers, and practitioners to reimagine AI governance in ways that are attuned to local realities, informed by critical research, and committed to social justice.

Acknowledgements

The author wishes to thank colleagues at the Reformers' Initiative for Development in Africa for their insights into technology and governance issues in Nigeria. Appreciation is also extended to academic mentors and research collaborators who provided valuable feedback during the conceptualisation of this work. Special thanks to civic tech practitioners whose work continues to inspire ongoing discourse on responsible AI in Africa.

Ethics declaration: This research did not involve any experiments with human or animal subjects. All secondary data and publicly available information referenced in this paper were sourced from reputable academic publications, policy documents, media reports, and institutional websites. The author affirms that the study was conducted with respect for intellectual integrity, cultural sensitivity, and transparency. No conflicts of interest are declared.

AI declaration: Artificial intelligence tool (Chat-GPT) was used solely for purposes of grammatical refinement and language clarity during the drafting of this paper. No AI-generated content was used for developing core arguments, analysis, or original writing. All substantive contributions—including research, critical analysis, interpretation, and referencing—are the sole work of the author. The AI tool's output was carefully reviewed, edited, and integrated only to enhance readability.

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Building Trust Through Transparent AI Governance: Embedding Ethical Oversight Into Academic Curricula Development

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Abstract: As artificial intelligence (AI) technologies become increasingly embedded in higher education, from adaptive learning platforms to algorithmic assessment tools, there is a growing imperative to examine the ethical and governance implications of such systems. While AI holds significant promise for improving efficiency and personalisation in education, its deployment also raises concerns around surveillance, algorithmic bias, data privacy, and equity. This article critically explores how transparent AI governance frameworks can be systematically integrated into academic curricula. It argues that ethical oversight and trust must be embedded not merely at the institutional policy level but within the design, delivery, and evaluation of educational programmes themselves. Drawing on interdisciplinary insights from digital governance, education policy, and data ethics, the paper develops a conceptual model for curriculum reform, articulates the ethical dimensions of AI in education, and presents illustrative case studies of institutions that have begun embedding such oversight into their teaching practices. By aligning curriculum design with emerging ethical principles, this study proposes that universities and higher education institutions can develop graduates who are not only technically proficient but ethically literate, capable of navigating and interrogating the socio-technical dimensions of AI in their future professions.

Keywords: Artificial intelligence, Higher education, Curriculum design, Data ethics, Transparent governance, Algorithmic accountability, Educational policy, Ethical pedagogy

1. Introduction

The rapid proliferation of artificial intelligence (AI) within higher education systems is transforming the fundamental dynamics of teaching, learning, and governance. AI now shapes a broad spectrum of academic functions, from automated admissions processes and AI-driven plagiarism detection to learning analytics and intelligent tutoring systems (Zawacki-Richter et al., 2019). These developments are frequently framed in terms of progress and innovation, often championed for their potential to enhance institutional efficiency, personalise student learning, and optimise resource allocation. However, such narratives frequently obscure the complex ethical, epistemological, and political implications of AI integration in educational spaces (Selwyn, 2022; Williamson, 2019).

Critical scholarship has started to challenge the techno-solutionist logic underpinning many AI deployments in education. Concerns about algorithmic bias, opaque decision-making processes, unequal access to digital infrastructure, and the commodification of student data raise urgent questions regarding justice, accountability, and institutional responsibility (Knox, 2020; Prinsloo & Slade, 2017). Furthermore, AI systems often operate within globalised commercial infrastructures, where datafied student experiences are subject to proprietary algorithms governed by external actors with limited institutional or pedagogical accountability. In this context, AI in education is not simply a technical innovation but a socio-political intervention with profound consequences for academic autonomy, student agency, and public trust.

Despite the growing literature on the ethics and governance of educational AI, there remains a significant disconnect between theoretical critique and curricular practice. While universities have increasingly adopted ethical AI policies at the institutional level, such frameworks rarely permeate the pedagogical core of academic programmes. Ethical AI principles tend to reside in high-level declarations or research ethics protocols, seldom filtering into learning outcomes, assessment structures, or instructional content (Floridi & Cowls, 2019; Williamson, 2019). This lacuna signals a deeper structural issue: ethical engagement with AI is too often marginalised or relegated to specialist disciplines, rather than being treated as a foundational element of higher education.

This article seeks to address that gap by interrogating how transparent AI governance can be embedded within the development and implementation of academic curricula. The central argument advanced here is that trust in AI systems – and the institutions that deploy them – must be cultivated through pedagogical transparency, critical inquiry, and ethical reflexivity. Curricula are not neutral repositories of knowledge; they are sites of power that shape how students conceptualise technology, authority, and social justice. Therefore, embedding AI ethics into curricula represents a necessary shift towards cultivating ethically literate graduates equipped to interrogate the socio-technical systems that will define their professional and civic lives.

The article adopts a multi-level analytical approach. It begins by establishing a theoretical and conceptual foundation that draws from critical pedagogy, curriculum theory, and digital ethics. It then maps the ethical risks associated with AI in education, highlighting the structural and epistemic challenges these technologies introduce. A comprehensive framework for curriculum reform is subsequently proposed, outlining principles and practices for embedding ethical AI governance into educational design. To illustrate these proposals, the article analyses case studies from institutions that have initiated reforms aimed at integrating AI ethics into teaching and learning. The final sections consider institutional and policy implications, offering recommendations for curriculum designers, accreditation bodies, and higher education leaders.

Overall, this paper calls for a reconfiguration of academic responsibility in the age of AI. It posits that the legitimacy and credibility of higher education depend not only on the adoption of innovative technologies but also on the cultivation of transparent, just, and democratically accountable pedagogical practices. By embedding ethical oversight into curricula, higher education institutions can reclaim a normative commitment to education as a public good – one that upholds the values of trust, transparency, and social responsibility in an increasingly datafied world.

2. Theoretical and Conceptual Foundations

A rigorous and critical exploration of AI governance in education necessitates a theoretical framework that not only interrogates power and ethics but also provides the conceptual tools to rethink curriculum design in an age of rapid technological change. This section draws from three interrelated domains – curriculum theory, digital ethics, and critical pedagogy – to formulate a multi-dimensional foundation for embedding AI governance into higher education curricula. These perspectives illuminate the socio-political dynamics that shape educational systems and provide normative guidance for aligning curriculum development with democratic values, human rights, and institutional accountability.

2.1 Curriculum Theory and the Politics of Educational Knowledge

Curriculum theory interrogates the purposes, structures, and contents of formal education, recognising that curricula are embedded within broader systems of cultural production and ideological control (Apple, 2008; Pinar, 2012). Traditional curriculum models, often informed by technocratic and neoliberal imperatives, tend to prioritise standardisation, efficiency, and market responsiveness over critical engagement and ethical inquiry (Au, 2012). Within such frameworks, the role of AI is frequently positioned as a neutral enhancer of educational delivery, abstracted from its socio-political implications.

Yet, as Bernstein (2000) notes, curricula encode specific forms of knowledge that reflect and reinforce dominant social relations. The absence of AI ethics and governance from mainstream educational programmes thus constitutes a form of epistemic exclusion – silencing critical perspectives on one of the most powerful technological transformations of the contemporary era. If curricula serve as mechanisms for social reproduction, then their redesign must become a site of contestation and transformation. Integrating AI ethics into curriculum development challenges not only what is taught but how knowledge is framed, whose voices are legitimised, and whose interests are served.

2.2 Digital Ethics, Surveillance Capitalism, and Algorithmic Governance

The rise of AI in education cannot be understood apart from the broader phenomenon of digital capitalism, where personal data becomes a primary commodity and algorithms operate as instruments of governance (Zuboff, 2019). Digital ethics emerges as a response to the normative crises generated by these transformations, offering a vocabulary for assessing the moral and political consequences of automated decision-making systems (Mittelstadt et al., 2016; Selbst et al., 2019).

In the educational domain, AI technologies are increasingly used to monitor student behaviour, predict academic performance, and personalise content delivery. These applications are frequently implemented with limited transparency or public debate, raising concerns about surveillance, consent, bias, and institutional accountability (Williamson, 2017). Ethical principles – such as fairness, explainability, non-maleficence, and data sovereignty - are often articulated in policy documents but lack operational clarity in everyday pedagogical practices.

Digital ethics thus demands more than reactive compliance with external regulations; it calls for proactive, critical, and context-sensitive engagements with the design, implementation, and consequences of AI systems. Embedding these concerns into curricula enables students to interrogate not only technical functionalities but also the value systems and power structures that underpin them.

2.3 Critical Pedagogy, Reflexivity, and Epistemic Justice

Critical pedagogy, grounded in the works of Freire (1970), Hooks (1994), and more recently scholars like Andreotti (2011), provides a transformative vision of education as a practice of freedom, justice, and democratic participation. It rejects the banking model of education – where knowledge is deposited into passive learners – and instead positions students as active agents capable of critiquing and reshaping the world around them.

In the context of AI, critical pedagogy emphasises the need for epistemic justice: the right of learners to access, produce, and challenge knowledge that affects their lives. AI technologies, when uncritically implemented, risk entrenching epistemic injustices by privileging certain data regimes, algorithmic logics, and commercial interests over lived experience, contextual knowledge, and social accountability (Fricker, 2007; Knox, 2020).

Embedding critical pedagogy into AI governance curricula involves cultivating reflexive awareness among students – encouraging them to question how technologies are constructed, whose perspectives are embedded within them, and who bears the risks of their failures. This approach shifts the educational emphasis from mere technical proficiency to critical consciousness, preparing students to participate ethically and democratically in an AI-mediated world.

2.4 Toward an Integrated Framework for Ethical Curriculum Design

These three domains - curriculum theory, digital ethics, and critical pedagogy – provide the building blocks for a holistic and ethically grounded approach to curriculum design. They challenge prevailing assumptions about neutrality, efficiency, and progress, instead advancing a normative agenda that places social justice, transparency, and human dignity at the heart of AI governance in education.

An integrated framework based on these principles calls for:

- Recognising the curriculum as a contested space where technological ideologies must be interrogated.
- Embedding ethical reasoning and digital literacy as core learning outcomes across disciplines.
- Designing assessment practices that reward critical thinking about technological impacts.
- Providing professional development for educators to navigate the ethical and pedagogical dimensions of AI.

In doing so, institutions can begin to cultivate a new generation of learners equipped not only to use AI technologies but to shape their development in ethically responsible and socially responsive ways. The following sections examine how these theoretical insights can be operationalised through curriculum reform and pedagogical innovation, addressing the structural and epistemic risks posed by AI while foregrounding principles of trust, transparency, and justice.

3. Ethical Risks and Governance Challenges in AI-Driven Education

The increasing reliance on artificial intelligence within educational systems has introduced a range of ethical risks and governance challenges that are both systemic and underexamined. While many institutions have embraced AI tools for purposes such as student monitoring, performance analytics, and personalised learning, these applications often outpace institutional capacity for critical oversight and ethical regulation. This section provides a critical analysis of the key ethical risks posed by AI in educational contexts and identifies the structural conditions that exacerbate their impact.

3.1 Algorithmic Bias and Discrimination

One of the most persistent risks associated with AI technologies is the reproduction and amplification of bias. Algorithms trained on historically biased datasets can reinforce existing inequities, particularly for students from racialised, disabled, and socioeconomically disadvantaged backgrounds (Benjamin, 2019; Noble, 2018). Predictive analytics used in academic advising, for instance, may systematically underestimate the potential of students from marginalised groups, leading to exclusionary decisions regarding access to advanced courses or scholarships.

Moreover, the opacity of proprietary algorithms used by edtech companies creates accountability gaps. Without access to the underlying data and model architecture, educational institutions and students have limited recourse to challenge or interrogate discriminatory outcomes. As Eubanks (2018) argues, such

algorithmic governance mechanisms often function as "automated inequality," embedding bias under the guise of neutral computation.

3.2 Surveillance and Datafication of Learning

Another key concern relates to the surveillance infrastructures embedded within AI-enhanced educational platforms. Learning management systems, plagiarism detection tools, and remote proctoring technologies collect vast amounts of data on student behaviour, often without meaningful consent or understanding. This expansion of datafication raises fundamental questions about autonomy, privacy, and the erosion of trust in the student-institution relationship (Williamson et al., 2020).

The normalisation of surveillance in educational settings may have chilling effects on intellectual freedom and student expression. Additionally, the repurposing of educational data for secondary uses – such as behavioural profiling or third-party marketing – increases concerns over data sovereignty and institutional complicity in digital exploitation (van Dijck et al., 2018).

3.3 Inequitable Access and the Digital Divide

Despite claims that AI can democratise education through personalisation and adaptive technologies, unequal access to digital resources remains a structural barrier. Students in underfunded institutions or regions with limited internet infrastructure often face systemic exclusion from AI-enabled learning environments. The implementation of AI tools without consideration of access differentials risks deepening existing educational inequalities (UNESCO, 2021).

In addition, many AI applications require students to have sophisticated digital literacies to engage meaningfully. The failure to support the development of these literacies further entrenches inequities, disproportionately affecting learners who are already marginalised by race, gender, disability, or class.

3.4 Institutional Inertia and Ethical Blind Spots

Even when ethical principles are articulated at the policy level, institutions often struggle to translate them into operational practices. Institutional inertia – driven by bureaucratic constraints, budgetary limitations, and commercial partnerships – frequently results in a gap between ethical aspiration and pedagogical implementation. Moreover, decision-making around AI adoption is often concentrated among senior administrators or IT professionals, with limited input from educators or students (Selwyn, 2022).

This centralisation of technological governance not only undermines democratic accountability but also reinforces a technocratic logic that prioritises efficiency over pedagogy. Without institutional mechanisms for ethical deliberation, participatory governance, and curricular integration, AI deployment remains disconnected from the values and mission of higher education.

Addressing these challenges requires a paradigm shift that centres ethical reflexivity and transparency in both policy and curriculum. The next section develops a framework for embedding these values into curriculum design, offering practical strategies for equipping students and educators to navigate the socio-technical complexities of AI-driven education.

4. Methodology and Approach

This article employs a conceptual and interpretive methodology grounded in critical analysis, documentary review, and illustrative case study synthesis. Rather than pursuing empirical generalisation, the objective is to construct a theoretically informed and practically relevant framework for embedding ethical AI governance into academic curricula. The approach reflects the growing consensus that curriculum design in the era of AI must be informed by interdisciplinary scholarship, normative principles, and institutional practice (Williamson, 2019; Floridi & Cowls, 2019).

The methodological strategy unfolds in three interconnected stages: (1) critical literature synthesis, (2) purposive case study selection and analysis, and (3) conceptual framework development.

4.1 Critical Literature Synthesis

The first stage entailed a systematic synthesis of academic and policy literature across four domains:

- Curriculum theory and educational policy (Young & Muller, 2013; Pinar, 2012).
- Digital ethics and responsible AI (Floridi & Cowls, 2019; Mittelstadt, 2016).

- AI governance and regulatory standards (European Commission, 2019; UNESCO, 2021; OECD, 2024).
- Critical pedagogy and democratic education (Freire, 1970; Giroux, 2011).

This interdisciplinary synthesis helped distil core ethical imperatives (transparency, fairness, accountability), governance dilemmas (opacity, regulatory lag), and curricular implications (integration of values, ethics-based assessments). The normative analysis drew upon international guidelines such as:

- The European Commission's Ethics Guidelines for Trustworthy AI (2019).
- UNESCO's Recommendation on the Ethics of Artificial Intelligence (2021).
- The OECD AI Principles (2024).

These documents provided essential reference points for evaluating how ethical principles can inform both curriculum content and institutional structures.

4.2 Case Study Selection and Documentary Analysis

To ground the normative analysis in real-world practice, three illustrative case studies were selected based on the following inclusion criteria:

- Demonstrated commitment to ethical AI integration within formal curricula.
- Availability of detailed curriculum documents on public domains.
- Institutional alignment with interdisciplinary and socially responsive education.

Documentary materials analysed included course syllabi, programme handbooks, institutional mission statements, and online curriculum repositories. The case studies reflect different geographical, institutional, and disciplinary contexts as highlighted in Table 1:

Table 1: Summary of Cases

Institution	Programme / Initiative	Core Features	Pedagogical Approach
University College London (UK)	MSc in Public Policy, Technology and Innovation (STEaPP) – Distance Learning	100% online PGT programme focusing on policy ethics, algorithmic accountability, digital governance.	Interdisciplinary, policy-oriented, critical inquiry.
Monash University (Australia)	ATS2292: Ethics of AI (Undergraduate course)	Mandatory ethics module in Monash Bioethics Centre; themes of bias, fairness, human-centred design.	Cross-disciplinary, case-based, values-driven.
Stanford University (USA)	CS181: Computers, Ethics, and Public Policy	Required ethics integration for CS majors; emphasis on platform governance and normative reasoning	Integrated humanities-computing model, reflexive.

These cases exemplify diverse strategies for embedding ethical reasoning, reflexive critique, and social accountability into AI-related educational programmes. The comparative analysis identified shared priorities (e.g. algorithmic fairness, civic responsibility), as well as structural and pedagogical innovations relevant to curriculum reform.

4.3 Framework Development and Normative Synthesis

The final stage involved the construction of a multi-level conceptual framework for embedding ethical AI governance into higher education curricula. This framework was iteratively developed by synthesising thematic insights from the literature and international guidelines, pedagogical strategies observed in the case studies, and theoretical perspectives from curriculum theory (Bernstein, 2000), critical digital pedagogy (Knox, 2020), and AI ethics (Mittelstadt, 2016).

The resulting framework – presented in the next section – encompasses three interrelated levels:

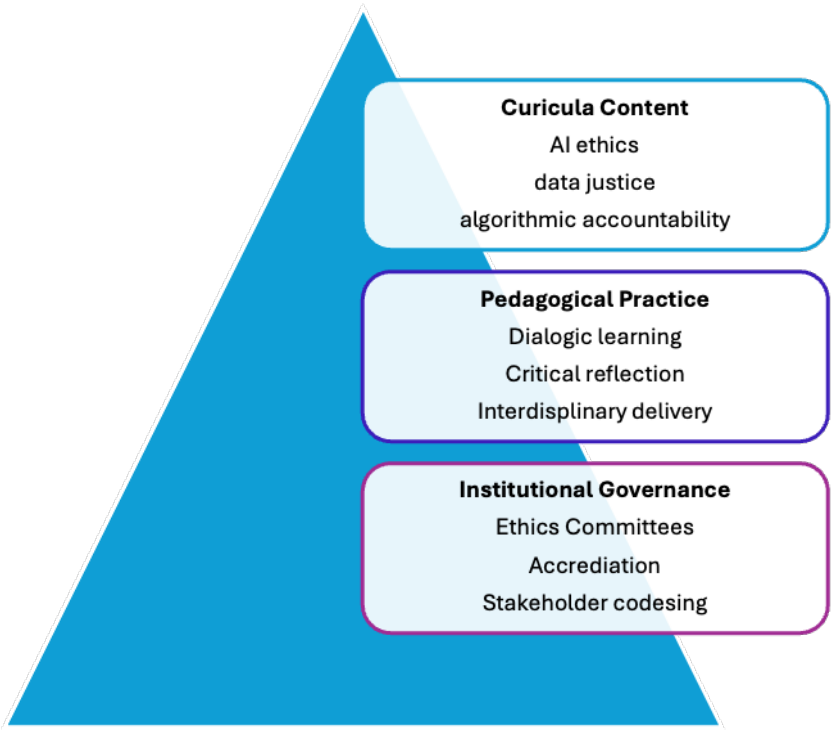
- Curricular Content: Integration of ethical principles, regulatory knowledge, and socio-technical critique into programme modules.
- Pedagogical Practice: Use of critical reflection, interdisciplinary problem-solving, and dialogic learning to foster ethical reasoning.
- Institutional Governance: Establishment of ethics boards, co-design mechanisms, and accreditation standards to reinforce ethical commitments at the systemic level.

This methodology provides the scaffolding for a normative intervention: a practical yet theoretically grounded proposal for reimagining higher education curricula in the age of AI. It privileges conceptual clarity, interpretive insight, and institutional relevance - responding to the urgent need for trust, accountability, and transparency in educational engagement with AI technologies.

5. Framework Development and Curriculum Reform

Efforts to embed ethical AI governance into higher education require far more than the retrofitting of technical syllabi with standalone ethics modules. They demand a systemic transformation of educational design, delivery, and institutional purpose. This section builds on the conceptual framework and case analysis presented earlier to articulate a robust model for curriculum reform that foregrounds trust, transparency, and accountability in the age of AI. The framework operates across three interdependent layers - curricular content, pedagogical practice, and institutional governance – each of which must be critically reconfigured if higher education is to fulfil its democratic and epistemic responsibilities in shaping AI futures.

Figure 1 presents a visual representation of a layered framework for embedding ethical AI governance into higher education curricula.



Source: Author (2025).

Figure 1: Layered Framework for Embedding Ethical AI Governance in Higher Education

The framework highlights three interdependent levels, each serving a distinct but interconnected role in fostering transparency, accountability, and ethical reflexivity. The layered structure underscores the foundational importance of curriculum design, while recognising that pedagogical strategies and institutional governance are essential for sustaining meaningful and systemic change.

It should be stressed, however, that this framework is not prescriptive but strategic. It provides a normative orientation and practical structure through which universities can diagnose gaps, build capabilities, and design ethically robust curricula responsive to the socio-technical complexity of AI. In doing so, it reasserts the public role of higher education – not as a pipeline for technical labour, but as a democratic institution tasked with preparing ethically responsible, critically informed, and socially engaged citizens.

5.1 Rethinking Curricular Content: From Technical Instrumentalism to Ethical Literacy

Contemporary AI curricula often reflect a technocratic orientation – prioritising optimisation, efficiency, and deployment over ethical reflection and public responsibility (Williamson, 2019; Knox, 2020). This instrumental approach is insufficient for addressing the profound societal challenges posed by algorithmic systems,

including surveillance, discrimination, and epistemic injustice. Ethical literacy, therefore, must become a core learning outcome – not only for computer science students, but across disciplines engaged with data and digital technologies.

A reformed curriculum should include:

- **Critical AI studies**: Modules that introduce students to the social, historical, and political dimensions of AI. Such offerings, inspired by the work of scholars like Noble (2018), Benjamin (2019), and Crawford (2021), equip learners to interrogate the embedded power relations and racialised logics within AI systems.
- **Algorithmic accountability and explainability**: Teaching students to examine the design assumptions, training datasets, and systemic risks of AI technologies. This includes practical exercises in identifying and mitigating algorithmic harms, drawing on frameworks from Binns (2018), Sandvig et al. (2014), and Mittelstadt et al. (2016).
- **Global, plural, and decolonial perspectives**: AI education must go beyond Eurocentric ethics paradigms by including epistemologies and use-cases from the Global South, Indigenous communities, and historically marginalised voices (Mohamed et al., 2020; Birhane, 2021). This enables students to appreciate the situated ethics of AI and resist normative universalism in technological development.

Importantly, these curricular elements must not be siloed in elective courses or isolated in philosophy departments. Instead, they should be embedded into core disciplinary pathways – e.g., engineering ethics as a compulsory component of machine learning modules, or critical data studies within public policy degrees. The case of Monash University illustrates this integration by mandating AI ethics training for undergraduates, thereby institutionalising ethical reasoning as a foundational competency rather than an optional enrichment.

5.2 Reimagining Pedagogical Practice: Ethical Reasoning as Transformative Learning

The pedagogy through which AI ethics is taught is just as critical as the content itself. Ethical reasoning cannot be meaningfully cultivated through didactic lectures, rote memorisation, or abstract codes of conduct. Instead, it requires a pedagogy of critical reflexivity, dialogue, and experiential engagement – an approach long championed by critical theorists such as Freire (1970), Hooks (1994), and Giroux (2011).

Ethical pedagogy should prioritise:

- **Dialogic learning**: Classrooms should function as spaces of critical dialogue, where students are encouraged to engage with ethical dilemmas through collaborative reasoning, debate, and situated reflection. Case studies involving controversial AI deployments (e.g., predictive policing, facial recognition bans, biased hiring algorithms) can serve as springboards for such dialogue.
- **Problem-based and scenario-driven approaches**: Rather than abstract ethics, students should tackle complex real-world problems that require both technical and normative reasoning. For instance, an assignment may involve auditing a content moderation algorithm for bias and then proposing mitigations based on fairness principles and legal considerations.
- **Critical self-reflection and values clarification**: Students should be supported to examine their own assumptions, professional identities, and moral frameworks. This is particularly important in technical disciplines, where students may have internalised value-neutral conceptions of design and development. Reflective essays, positionality statements, and ethical impact assessments can cultivate this awareness.

The UCL and Stanford cases both exemplify such pedagogical approaches, where students are engaged not merely as passive learners but as active moral agents - capable of scrutinising the systems they build and the social orders those systems help sustain.

Equally crucial is capacity-building among faculty. Many educators lack formal training in ethical theory, digital rights, or critical pedagogy. Universities must therefore invest in professional development programmes that support interdisciplinary team teaching, critical facilitation skills, and engagement with emerging debates in AI governance. Without this scaffolding, even well-designed curricula risk being delivered in ways that undermine their ethical ambitions.

5.3 Transforming Institutional Governance: Structural Alignment for Ethical Oversight

Curriculum and pedagogy alone cannot carry the weight of ethical transformation. Institutional governance structures must also be reconfigured to ensure that ethical commitments are institutionalised, enforced, and continuously reviewed. Ethical education in AI must be embedded not just in syllabi, but in the institutional DNA of universities.

This includes:

- **Curriculum ethics committees**: Establishing formal review bodies that assess the ethical content and implications of new and existing programmes. These committees should include interdisciplinary faculty, students, and external stakeholders to ensure legitimacy, accountability, and diverse perspectives.
- **Embedding ethics in accreditation and quality assurance**: Universities should work with national regulators and professional bodies to include ethical AI education as a core requirement for programme approval and renewal. As the OECD and UNESCO guidelines suggest, governance frameworks for trustworthy AI must include human capital development as a pillar of policy.
- **Participatory governance and stakeholder engagement**: Institutions should institutionalise co-design processes involving civil society, industry, and affected communities – especially those historically marginalised by algorithmic systems. This reflects a shift from top-down curriculum imposition to democratic knowledge production, aligning with the principles of public accountability and civic responsibility.

These bodies can also serve as bridges between academia and public discourse, helping to shape policy debates and public understanding of AI ethics.

The multi-layered conceptual framework (refer to Figure 1) underscores that ethical AI education is not merely a matter of content addition but requires systemic alignment across educational design, instructional delivery, and institutional regulation.

6. Discussion: Operationalising Ethical AI Education in Context

While the conceptual framework outlined above offers a strategic vision for embedding ethical AI governance into higher education, its practical realisation is fraught with institutional, political, and epistemological challenges. This discussion critically reflects on these tensions, exploring what it means to operationalise ethical AI curricula within diverse educational contexts shaped by uneven resources, competing imperatives, and global asymmetries in technological development.

6.1 Structural Constraints: Fragmented Governance and Institutional Inertia

A major barrier to reform lies in the fragmented and often conservative governance structures of higher education institutions. Curriculum development tends to be decentralised, slow-moving, and shaped by disciplinary silos. As such, even well-intentioned initiatives to integrate AI ethics often face resistance or dilution, especially in technically oriented faculties where ethical inquiry is seen as tangential or peripheral.

Moreover, institutional incentives remain misaligned. In many contexts, performance metrics tied to graduate employability, publication outputs, or industry funding discourage critical, values-based curriculum reform. There is often a reluctance to introduce content that could be seen as politically sensitive, ideologically divisive, or commercially disruptive. Consequently, ethical education risks being marginalised or sanitised, reduced to abstract principles rather than positioned as a foundation for critical engagement and social accountability.

This highlights the importance of institutional leadership and cross-functional governance mechanisms. Without support from senior administrators, quality assurance bodies, and academic boards, ethical AI education will remain patchy and under-resourced.

6.2 Epistemic Tensions: Whose Ethics, Whose Knowledge?

A second set of challenges arises from the epistemological assumptions embedded in dominant approaches to AI ethics. Much of the mainstream discourse reflects liberal individualist and Western moral frameworks – grounded in abstract principles like autonomy, justice, and beneficence (Floridi & Cowls, 2019). While these concepts are valuable, their universalisation often obscures cultural specificity, political context, and historical injustice.

As Mohamed et al. (2020) argue, global AI ethics must move beyond "ethics-washing" to engage with structural inequalities, colonial legacies, and systemic harms. Similarly, Birhane (2021) cautions against reductive technical fixes to ethical problems that are fundamentally social and political in nature. These raises pressing questions for curriculum designers:

- Whose ethical frameworks are being taught, and why?
- How can curricula reflect pluralistic, decolonial, and community-based approaches to AI ethics?
- What forms of knowledge and experience are being excluded in the name of technical neutrality?

Addressing these questions requires a deeper commitment to epistemic justice. It entails not only diversifying reading lists and case studies but also creating space for students to engage with contested values, lived experiences, and critical traditions from across the globe.

6.3 Resourcing and Equity: Who Has the Capacity to Reform?

The ability to implement a comprehensive ethics-focused curriculum reform is also shaped by material conditions. Well-resourced institutions – such as those included in this study (UCL, Stanford, Monash) – may have access to interdisciplinary faculty, external partnerships, and flexible governance structures. In contrast, universities in the Global South, public institutions facing austerity, or newer universities may lack the institutional bandwidth to support such reforms.

This disparity raises concerns about global equity and the reproduction of epistemic privilege. If only elite institutions can afford to "do ethics well," then ethical AI education risks becoming another site of global inequality - where critical literacy and civic agency are privileges of the few rather than rights of the many.

Thus, the framework must be adaptable and scalable. Policymakers, development agencies, and philanthropic funders have a role to play in supporting capacity-building, faculty training, and collaborative knowledge-sharing initiatives across institutions and borders.

6.4 Toward Transformative Possibilities: Ethics as Praxis

Despite these challenges, the growing visibility of AI's societal impacts presents a critical pedagogical opportunity. Students are increasingly aware of the ethical stakes of technological development – from climate surveillance to predictive policing to AI-generated misinformation. There is a rising demand for educational experiences that go beyond instrumental skills and offer critical frameworks for ethical reasoning, political engagement, and collective responsibility.

Curriculum reform can harness this momentum - but only if ethics is approached not as a static body of knowledge, but as praxis: reflective, situated, and action-oriented. This involves:

- Framing ethics as a mode of inquiry, not a checklist.
- Situating technological critique within broader questions of justice, democracy, and solidarity.
- Encouraging students to see themselves not just as future employees, but as citizens, designers, and change agents.

When embedded effectively, ethical AI education has the potential to rehumanise technological learning, reorient institutional values, and reclaim the civic mission of the university.

7. Conclusion: Ethical AI Governance as a Curriculum Imperative

As artificial intelligence continues to reshape the epistemic, economic, and political landscapes of contemporary societies, higher education institutions face a profound responsibility: to prepare students not merely to work with AI, but to critically engage with its ethical, social, and political dimensions. This paper has argued that ethical AI governance must be embedded into the core of academic curricula - not as an ancillary concern, but as a foundational imperative.

Through a multi-level framework encompassing curricular content, pedagogical practice, and institutional governance, the paper has outlined a strategy for designing ethical AI education that is theoretically grounded, practically feasible, and normatively robust. Drawing on interdisciplinary literature, international policy guidelines, and illustrative case studies from UCL, Monash, and Stanford, it has been demonstrated that systemic, cross-cutting reform is essential if higher education is to build trust, foster transparency, and contribute to a more just technological future.

The framework presented here emphasises that:

- Ethical literacy must be cultivated across disciplines and not confined to philosophy or ethics modules.
- Pedagogical methods must centre dialogue, critical reflection, and experiential engagement rather than rote compliance.
- Institutional structures must support ethics through formal governance, inclusive curriculum review processes, and alignment with accreditation standards.

However, the implementation of this agenda is not without challenge. As the discussion has shown, universities must navigate entrenched silos, resourcing disparities, competing political pressures, and deep epistemic questions about whose ethics and whose knowledge are privileged in curriculum design. These constraints cannot be ignored. Yet they do not negate the urgency or the possibility of change.

In fact, the proliferation of AI-driven harms – from algorithmic discrimination to automated misinformation – makes ethical curriculum reform more urgent than ever. In this context, higher education can no longer position itself as a neutral pipeline for technological expertise. It must instead act as a critical site of democratic formation, equipping students to ask difficult questions, recognise power asymmetries, and imagine alternatives to dominant techno-economic paradigms.

This transformation requires not only conceptual clarity and practical frameworks, but courageous institutional leadership and collective pedagogical imagination. It demands that ethics be treated not as a tick-box exercise, but as an evolving, contested, and situated form of knowledge - one that reflects the complexities of living in a world increasingly shaped by artificial intelligence.

8. Future Directions

While this paper has laid the groundwork for a theoretically and practically informed approach to embedding ethical AI governance in curricula, several areas merit further investigation:

- Empirical research on student experiences, learning outcomes, and educator perspectives in ethics-integrated programmes.
- Comparative analyses of how ethical AI education is implemented in different cultural, economic, and regulatory contexts.
- Policy research on the role of national quality assurance bodies, international standards, and funding agencies in promoting ethics integration.
- Collaborative curriculum development involving civil society, industry actors, and marginalised communities to ensure inclusive, context-responsive design.

Ultimately, building trust through transparent AI governance is not solely a technical or institutional task. It is an educational challenge – and one that higher education must meet with both intellectual rigour and moral seriousness. Indeed, the integration of transparent AI governance into academic curricula is not a peripheral concern but a strategic necessity. Failure to act risks entrenching opaque and inequitable systems that erode trust, weaken educational integrity, and leave graduates unprepared for the ethical and societal challenges of AI. Conversely, embedding governance principles into teaching and learning creates pathways for accountability, human-centred innovation, and employability, while positioning universities and higher education institutions as proactive leaders in shaping digital futures that serve the public good.

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

AI Declaration: I confirm that generative AI tools were utilised in the preparation of this manuscript. Specifically, ChatGPT-4.0 (OpenAI) and Grammarly (1.127.0.0) were employed for proofreading, summarising, and improving the clarity and coherence of the text. These tools were not used to produce original research content or interpret data. All outputs were reviewed and edited by the author to ensure accuracy and academic integrity.

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A Comparative Study of AI and Human Evaluation for Student Website Projects

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Abstract: Artificial intelligence (AI) tools based on large language models (LLMs) are increasingly being adopted across a wide range of fields, including higher education. Given the substantial workload often faced by educators, these tools offer promising potential to assist in the evaluation of student work. However, empirical research on their reliability—particularly in assessing practical, design-oriented assignments such as student-developed websites—remains limited. This study aimed to investigate the ability of various AI tools to evaluate student website projects and the consistency between the evaluations given by AI tools and human instructors (HIs) using the same criteria. Based on a literature review, a set of evaluation criteria was developed across three categories: user interface (UI), user experience (UX), and code quality. Each student project included a website prototype and the corresponding implementation code. Nine student projects were evaluated independently by seven AI tools and HI, using a Likert scale. To reduce variability, all AI tools were provided with the same evaluation prompt. The Wilcoxon signed-rank test revealed no statistically significant differences in many evaluation criteria between AI tools and HIs, suggesting general similarity in overall scoring. On the other hand, the Spearman correlation analysis revealed low consistency in how AI tools and HI evaluated specific aspects of the projects. This indicates that while the evaluation provided by AI tools and HIs may appear similar at a surface level, their underlying judgment patterns—particularly regarding certain criteria of UI/UX design and code quality—can diverge. However, ChatGPT-4.5 and ChatGPT-4o delivered particularly promising outcomes. From an educational perspective, the study results highlight the importance of treating AI tools as supportive assistants rather than autonomous evaluators—at least for now—especially in domains involving subjective or context-sensitive judgment. Identifying where AI tools' evaluations align or conflict with human judgment provides valuable insight into the appropriate use, potential, and limitations of such tools in academic evaluation.

Keywords: Website development, UI/UX design, Code quality, Artificial intelligence tools, Large language model, Automatic vs human evaluation

1. Introduction

Artificial intelligence (AI) tools powered by large language models (LLMs) are increasingly applied across various domains. These tools enhance the accuracy of healthcare diagnostics (McKinney et al., 2020), enable the generation and intelligent editing of multimedia content (Shao et al., 2024), and support the development of reliable web applications (Ghai et al., 2024).

AI tools have also shown promise in evaluating student work. Despite some limitations in the evaluation of calculus problem solutions (Gandolfi, 2025), studies have demonstrated that AI-generated evaluations closely correspond with those of human instructors (HIs) when evaluating essays (Impey et al., 2025; Liew and Tan, 2024) and introductory programming tasks (Cisneros-González et al., 2025). Although a few studies have explored the application of LLMs in evaluating user experience (Hsueh et al., 2024), the potential of these tools for the holistic evaluation of websites remains underexplored.

This study examines the evaluation of website projects from a development perspective, encompassing both website design and coding. Website design includes user interface (UI) and user experience (UX), which are guided by well-established design principles. Coding involves the application of best practices to ensure code quality.

The study aims to investigate the ability of AI tools to evaluate website projects and the consistency between the evaluations of AI tools and HIs across different stages of website development. The following research questions are posed:

RQ1: What AI tools are able to evaluate students' website projects?

RQ2: Are there significant differences in website project evaluations provided by AI tools and HIs using the same evaluation criteria?

RQ3: Is there a correlation between website project evaluations provided by AI tools and HIs using the same evaluation criteria?

Understanding where AI tools' evaluations align or diverge from human judgment helps clarify their appropriate role and limitations in academic settings.

1.1 Web Design Principles and Code Quality

In today's digital environment, most companies maintain a website to ensure online visibility and accessibility. Visually appealing websites play a crucial role in shaping users' perceptions of trust and credibility (Arizal et al., 2024). This requires thoughtful design of both the UI and UX. UI design focuses on the aesthetics of the visual elements users interact with, including website visual style and layout. A well-considered UI design enables users to navigate through the website easily, find desired items, and complete transactions with minimal effort (Kurniawan, 2025). Such an approach contributes to a positive UX (Jansson et al., 2022), which is focused on ensuring the website performs effectively from the user's perspective (Kumar et al., 2023; Novák et al., 2024).

While numerous factors can be considered in the website UI design process, the authors of the current study focused on those they identified as most essential. In UI design, *colours* help evoke emotions, direct users' attention, establish visual hierarchy within the website (Kurniawan, 2025) and enhance users' sense of trust and satisfaction (Cyr et al., 2010). Proper *contrast* guides attention toward key elements of a website (Olejnik-Krugły et al., 2021) and makes a website more attractive to users (Jongmans et al., 2022). Carefully selected *typography* ensures readability, clarifies messaging and fosters deeper user interaction (Kurniawan, 2025). G*rouping* visual elements effectively helps users process website content more efficiently (Xiao et al., 2024).

Although UX is a multidimensional construct (Jongmans et al., 2022), this study focuses specifically on *usability*. As a key component of UX design, usability refers to how effectively, efficiently, and satisfactorily users can interact with a website (Kumar et al., 2023; Novák et al., 2024). High usability ensures that users can complete their tasks with minimal effort and confusion. Usability is directly enhanced by visual design, which supports better orientation, task flow, and overall interaction quality (Jongmans et al., 2022).

Websites' design and functionality are implemented through code, using various web development technologies. Keeping a website up and running requires continuous work on the code. This highlights the importance of code quality, which in this study is explored through two essential aspects. Code *readability* refers to how clear and accessible the source code is for reading and understanding (Martinović and Rozić, 2024; Tashtoush et al., 2023). Code readability is closely related to code *maintainability* (Martinović and Rozić, 2024; Tashtoush et al., 2023). The latter ensures that further modifications to the code can be done efficiently and without affecting the overall functionality of the website (Martinović and Rozić, 2024).

1.2 AI Tools in the Evaluation of a Website

Shao et al. (2024) argue that AI tools are able to analyse pictures. While AI can help detect layout structure and object relationships in visual media (Mishra, 2023), the specific application of AI tools to evaluate compliance with established web design principles, such as colour, contrast or usability, remains largely unexplored.

AI tools are widely used in assessing code quality (Almeida et al., 2024; Shao et al., 2024; Yi et al., 2024). These studies often treated code quality as a broad construct, typically analysing it based on overall functionality or security. However, they have not explored code readability or maintainability, which would provide a deeper understanding of how AI tools' evaluations align with those of HI.

2. Methodology

2.1 Context of Study

In this study, the analysed website projects were final assignments for the university course *Web Page Creation for Advanced Users*—an 8-week, 3 ECTS Estonian-language course. Aimed at students interested in web development, the course required no prior experience and was delivered fully online, with no in-person sessions. Learning materials, including text-based tutorials with code snippets, short videos, and supplementary links, were accessible via the university's Moodle platform from the start. The course covered six core topics, including UI/UX design principles and the use of AI in web development. Students were introduced to key technologies such as HTML, CSS, JavaScript, and Vue.js. Throughout the course, students completed practical tasks graded on a pass/fail basis by the course instructor.

For the final assignment, students applied their skills to create a comprehensive website project. Teams of two or three students self-organised, selected their own topics, and first created a multi-page *website prototype* using a design platform like Figma. Another team used this prototype to develop the *actual website* using the technologies taught.

2.2 Participants and Instruments

Although 21 students participated in the course during the autumn 2024/2025 academic year, only 18 provided consent for their projects to be analysed using AI tools. The sample consisted of an equal number (9) of female and male students. Less than one-third (28%) were master's students, while the remainder were bachelor's students. The vast majority (83%) were enrolled in the Department of Computer Science. In terms of prior web development experience, 39% reported being "somewhat satisfied" and another 39% were "neither satisfied nor dissatisfied". The remainder were "somewhat dissatisfied". As the project was completed in teams, this study analyses nine website projects. The topics of the websites varied, ranging from service platforms to online stores.

To answer the first research question, the authors selected nine different AI tools based on their personal interests. Each tool was asked to self-describe its purpose of use and its ability to work with website projects. To eliminate potential biases in the responses, this part of the research was done on the same day (April 7, 2025) using the same prompt in Estonian. This language was chosen because all evaluated website projects were in Estonian. For the purposes of this article, the original prompt has been translated into English to ensure clarity and accessibility for an international audience:

> *"I would like to learn more about the [AI tool]. Please write answers to the following questions:*
>
> *What is [AI tool] primarily intended for?*
>
> *What are the general strengths and weaknesses of [AI tool]?*
>
> *Can [AI tool] be used to evaluate websites where adherence to user interface and user experience design principles (such as typography, grouping, usability) and code quality play an important role?*
>
> *Justify your answer. Limit your answer to 5–6 sentences. Write the answer in academic Estonian."*

To ensure a theoretically grounded and pedagogically meaningful evaluation, a rubric was created based on criteria identified in the literature. These covered key principles of UI design (colour, contrast, typography, and grouping), UX design (usability), and code quality (readability and maintainability). The fulfillment of each criterion was evaluated on a Likert scale from 5 ("strongly agree") to 0 ("strongly disagree"). Two HIs and various AI tools independently evaluated all nine website projects using the created rubric. Human evaluation was based on a consensus between the authors of the current study. To evaluate UI/UX design, each AI tool received webpage screenshots; to evaluate code quality, the full source code was submitted to the AI tools. A single prompt, translated into English for this article, was used consistently across all tools to ensure comparability and reduce variability. The prompt to evaluate the website prototype was as follows:

> *"I will be uploading various screenshots of the same website project (not full-stack, but only front-end). You have to evaluate the whole project based on two design approaches: user interface (UI) and user experience (UX). Each design has its own criteria:*
>
> *User Interface (UI)*
>
> *Colour*
>
> *Contrast*
>
> *Typography*
>
> *Grouping*
>
> *User Experience (UX)*
>
> *Usability*
>
> *For each project as a whole, please evaluate the fulfillment of each criterion on a Likert scale, where 5 refers to "strongly agree" and 0 refers to "strongly disagree"".*

The prompt to evaluate the code of the developed website was as follows:

> *"I will be uploading the website project's full source code (not full-stack, but only front-end). You have to evaluate how well the code of the project is written. Use the following evaluation criteria:*
>
> *Readability*

Maintainability

For each project as a whole, please evaluate the fulfillment of each criterion on a Likert scale, where 5 refers to "strongly agree" and 0 refers to "strongly disagree"".

2.3 Data Analysis

The IBM SPSS Statistics 30 software package was used for the statistical analysis. Descriptive statistics, such as the minimum, maximum, and median, were calculated. The Shapiro-Wilk test revealed that, in many cases, the data (evaluations provided by HIs and AI tools) were not normally distributed. In addition, due to the ordinal nature of the data and the small sample size, the use of non-parametric tests was justified (Gust and D'journo, 2015; Harris et al., 2008; Schober et al. 2018). Since the two datasets included the evaluations of the same website projects, the Wilcoxon signed-rank test was employed to determine whether there were significant differences between the evaluations of AI tools and HIs. The Spearman rank correlation was employed to assess the consistency between evaluations by AI tools and HIs. According to Schober et al. (2018), correlations below 0.4 should be considered "weak" and those above 0.7 should be considered "strong".

3. Results

3.1 AI Tools' Ability to Evaluate Website Projects

In this study, nine AI tools based on various LLMs were selected to investigate their ability to evaluate students' website projects. Due to space limitations, the full-text responses of the AI tools to the prompt described in section 2.2 are not included here. However, Table 1 provides a summary of the main findings.

Table 1: Summary of AI tools' self-description (as of April 7, 2025)

AI tool	Intended use	General strengths	General weaknesses	Ability to evaluate UI/UX design principles and code quality
ChatGPT -4o	Natural language processing	Context awareness, fluency, variety of knowledge	Factual accuracy, data freshness	Can be applied to website project evaluation, especially when assessing UI design compliance with general principles; can analyse code quality in general. *
ChatGPT -o1	Text-based tasks solving	Context awareness, fluency, variety of knowledge	Factual inaccuracy, nuance handling	Can provide general recommendations on UI design, but critical analysis of finer design details may be limited; to some extent, may assess code quality and semantic inconsistencies. *
ChatGPT -4.5	Intelligent text processing	Knowledge breadth, coherence, comprehension	Factual errors, nuance limits, data dependency	Lacks deep visual and interactive understanding of user interfaces, assessing design and usability indirectly through text-based recommendations; in code, can identify standard and clearly structured solutions but may lack an understanding of complex code nuances. *
Gemini 2.0 Flash	Low-latency response generation	Speed, processing power	Size limit, analytical weakness	Lacks contextual understanding and aesthetic analysis to assess UI design principles carefully; can somewhat analyse code structure and detect patterns. *
Gemini 2.0 Pro	Complex tasks with multimodal processing	Big data processing, context handling	Hallucination, bias caused by training data	Lacks subjective experience and the ability to evaluate actual user experience and visual appeal; can be used to analyse code quality in website projects by detecting errors, assessing style guideline adherence, and evaluating code complexity. *
Claude 3.7 Sonnet	Natural language understanding and generation	Knowledge breadth, context understanding, detailed answers	Outdated knowledge, novelty barrier	Can analyse both UI/UX design principles and code quality because it is trained to understand design concepts and code structures; the evaluation of code relies on the input provided, but cannot independently visit websites.
Mistral	Open-source LLM creation, customization	Flexibility, performance, low latency	Text-oriented, visual incapacity	Can offer usability improvement suggestions, but visual design principles are not its main strengths; can assist in analysing code quality. *

AI tool	Intended use	General strengths	General weaknesses	Ability to evaluate UI/UX design principles and code quality
Deep-Seek	Complex text-based tasks solving	Context understanding, problem-solving, ability of analysis	Visual assessment limitations	Can analyse UI design principles based on descriptions; can assess code quality for readability, structure, and standards compliance. *
Copilot	Natural language process assistance	Natural language generation, context awareness	Cultural insensitivity, bias caused by training data	Can evaluate website projects by analysing and providing suggestions on UI design principles; however, its ability is based on statistical analysis of texts; can evaluate code quality.

Many AI tools (marked with an asterisk in Table 1) emphasised that they are best suited for providing initial analysis and recommendations, but not for final quality assessment in technically complex projects. Based on their responses, these tools suggest being used as assistants, with the final evaluation performed by a human. DeepSeek and Copilot, which only provide feedback on text descriptions, were excluded from further analysis.

3.2 Comparison of Website Project Evaluations Provided by HI and Various AI Tools Based on Same Criteria

The authors of the current study analysed nine website projects that were evaluated by two HIs and seven AI tools using the same rubric described in section 2.2. The results for each criterion are provided in Table 2, where z- and p-values correspond to the Wilcoxon signed-rank test results. Statistically significant differences between HI and AI evaluations are highlighted in bold.

Table 2: Comparison of website project evaluations

	HIs	ChatGPT-4o	ChatGPT-o1	ChatGPT-4.5	Gemini 2.0 Flash	Gemini 2.0 Pro	Claude 3.7 Sonnet	Mistral
Colour								
Mean	4.22	3.44	3.33	4.11	4.11	3.44	3.22	3.44
SD	.972	.882	.500	1.054	.601	.726	.667	.527
Min-Max	3-5	2-4	3-4	2-5	3-5	3-5	2-4	3-4
Median	5	4	3	4	4	3	3	3
z-value		-2.646	-2.070	-.447	-.302	-1.838	-2.081	-2.070
p-value		**.008**	**.038**	.655	.763	.066	**.037**	**.038**
Contrast								
Mean	3.67	3.89	3.44	4.44	3.89	4.44	3.00	3.11
SD	.866	.928	.726	.882	.333	.527	.866	.333
Min-Max	3-5	3-5	2-4	3-5	3-4	4-5	2-4	3-4
Median	3	4	4	5	4	4	3	3
z-value		-.707	-.649	-1.890	-.707	-1.732	-1.730	-1.518
p-value		.480	.516	.059	.480	.083	.084	.129
Typography								
Mean	4.00	3.67	3.22	4.56	4.00	4.56	3.00	3.44
SD	1.118	.707	.441	.882	.500	.527	.500	.527
Min-Max	2-5	3-5	3-4	3-5	3-5	4-5	2-4	3-4
Median	4	4	3	5	4	5	3	3
z-value		-.750	-1.734	-1.890	-.175	-1.406	-2.121	-1.406
p-value		.453	.083	.059	.861	.160	**.034**	.160

	HIs	ChatGPT-4o	ChatGPT-o1	ChatGPT-4.5	Gemini 2.0 Flash	Gemini 2.0 Pro	Claude 3.7 Sonnet	Mistral
Grouping								
Mean	4.11	4.11	2.89	4.56	4.00	4.78	4.11	4.00
SD	1.054	.928	.601	1.014	.500	.441	.333	.000
Min-Max	2-5	2-5	2-4	2-5	3-5	4-5	4-5	4-4
Median	4	4	3	5	4	5	4	4
z-value		.000	-2.309	-1.633	-.302	-1.857	.000	-.333
p-value		1.000	**.021**	.102	.763	.063	1.000	.739
Usability								
Mean	4.22	3.89	3.56	4.67	4.11	4.44	3.44	4.00
SD	1.093	.782	.527	.707	.333	.527	.527	.000
Min-Max	2-5	3-5	3-4	3-5	4-5	4-5	3-4	4-4
Median	5	4	4	5	4	4	3	4
z-value		-1.342	-1.387	-2.000	-.176	-.378	-1.588	-.632
p-value		.180	.165	**.046**	.860	.705	.112	.527
Readability								
Mean	3.89	4.22	4.00	5.00	4.00	3.78	3.44	4.00
SD	.601	.441	.000	.000	.000	.972	.527	.000
Min-Max	3-5	4-5	4-4	5-5	4-4	2-5	3-4	4-4
Median	4	4	4	5	4	4	3	4
z-value		-1.342	-.577	-2.640	-.577	-.378	-1.414	-.577
p-value		.180	.564	**.008**	.564	.705	.157	.564s
Maintainability								
Mean	3.22	3.11	4.00	5.00	4.11	2.78	2.78	4.11
SD	.833	.601	.000	.000	.333	1.093	.833	1.054
Min-Max	2-4	2-4	4-4	5-5	4-5	1-4	2-4	3-5
Median	3	3	4	5	4	3	3	5
z-value		-.378	-2.070	-2.701	-2.060	-1.054	-.964	-1.725
p-value		.705	**.038**	**.007**	**.039**	.292	.340	.084

SD – standard deviation

Although the median values varied, the study found that overall evaluations by AI tools and HIs were not significantly different. However, significant differences appeared in some specific criteria. For example, ChatGPT-4o, ChatGPT-o1, Claude 3.7 Sonnet, and Mistral were more critical when evaluating the use of colour, awarding lower scores. In contrast, ChatGPT-o1, ChatGPT-4.5, and Gemini 2.0 Flash evaluated code maintainability higher than HIs did. Overall, evaluations by ChatGPT-4.5 tended to show greater differences from HI evaluations compared to the other studied AI tools.

3.3 Correlation Between Evaluations of Website Projects Provided by HI and Various AI Tools

The Spearman correlation was used to compare the consistency between evaluations provided by HIs and AI tools that applied the same criteria. Table 3 provides a summary of the findings.

Table 3: Correlation between HI and AI tools evaluations

Criterion		ChatGPT-4o	ChatGPT-o1	ChatGPT-4.5	Gemini 2.0 Flash	Gemini 2.0 Pro	Claude 3.7 Sonnet	Mistral
Colour	HIs	**.902*** **	.306	.644	-.122	-.111	.021	.484
Contrast	HIs	.414	-.144	.325	-.227	-.431	.321	-.303
Typography	HIs	-.005	-.327	**.709***	-.625	.137	.337	.183
Grouping	HIs	**.833****	.355	.583	.000	.551	-.146	N/A
Usability	HIs	**.819****	.048	**.804****	-.452	.191	.191	N/A
Readability	HIs	.062	N/A	N/A	N/A	.331	-.207	N/A
Maintainability	HIs	.176	N/A	N/A	-.512	-.357	-.248	-.046

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; N/A correlation could not be calculated because one of the variables had constant values; grey cell – weak correlation

There were some statistically significant strong positive correlations between project evaluations provided by HIs and studied AI tools. However, in many cases, the correlation was weak and not statistically significant. ChatGPT-4o tended to show greater consistency with HIs evaluations than other AI tools studied.

4. Discussion

The study explored the ability of AI tools to evaluate website projects. Firstly, the authors selected nine AI tools and explored their self-descriptions. The results demonstrated that ChatGPT-4o, ChatGPT-o1, ChatGPT-4.5, Gemini 2.0 Flash, Gemini 2.0 Pro, Claude 3.7 Sonnet and Mistral stated their ability to evaluate website projects. DeepSeek and Copilot pointed out the difficulties in assessing visual content, as their analysis is based on text input.

Next, nine student projects, focusing on key web design and coding principles, were evaluated using the same rubric criteria. The evaluations were provided by seven AI tools and two HIs. Results showed that ChatGPT-4o, ChatGPT-o1, Claude 3.7 Sonnet, and Mistral evaluated colour use more strictly than HI. ChatGPT-o1 gave a significantly lower evaluation for grouping, which is part of the visual hierarchy. Since aesthetics is subjective, these differences may be due to AI training data where less attention may be put on aesthetic aspects. Helliwell (2024) also noted that aesthetic judgments often differ between AI and humans.

The results showed that AI tools' evaluations of technical UI aspects such as typography and contrast were not significantly different from those of HIs. In their evaluations, AI tools can rely on the Web Content Accessibility Guidelines, which provide suggestions for typography and contrast to ensure content readability. The only significantly lower typography evaluation in comparison to HI evaluations was by Claude 3.7 Sonnet. This discrepancy is particularly interesting given that, in its self-description, Claude 3.7 Sonnet stated that it was trained to understand design concepts.

Hsueh et al. (2024) found that ChatGPT-4 generally performs better than human evaluators across various UX design dimensions. However, the current study mainly showed no significant difference between AI tools and HIs in evaluating usability. Only ChatGPT-4.5 evaluated usability significantly higher than HI. ChatGPT-4.5 might have missed some usability nuances in the prototype screenshots because, according to its self-description, it evaluates usability indirectly using text-based recommendations.

There was no significant difference between AI tools and HIs in evaluating code readability (except ChatGPT-4.5). Meanwhile, ChatGPT-o1, ChatGPT-4.5, and Gemini 2.0 Flash evaluated code maintainability higher than HI. Although Yi et al. (2024) found that AI-based systems can accurately recognise problematic patterns in code, the results of the current study suggest some AI tools may overlook nuances such as code consistency and confusing naming.

Finally, the consistency between AI tools' and HIs' evaluations was examined. The correlation test revealed a strong statistically significant positive relationship between ChatGPT-4o and HIs for website prototype colour, grouping, and usability, and between ChatGPT-4.5 and HIs for typography and usability. These results indicate a consistency in agreement on evaluating certain criteria. The findings suggest that ChatGPT-4o and ChatGPT-

4.5 can closely reproduce human evaluations for the aforementioned criteria. Cisneros-González et al. (2025) also found a strong positive correlation between grades provided by ChatCPT-4o and HIs in evaluating programming tasks. However, many correlations in the current study were weak, indicating possible inconsistencies between AI tools and HIs evaluations. This may be a consequence of the probabilistic nature of LLMs, and similar inconsistencies were reported in previous studies (Emirtekin, 2025).

5. Conclusions

This study had two aims: to assess AI tools' ability to evaluate website projects and to examine how consistently their evaluations align with those of HIs. While DeepSeek and Copilot as of April 7th, 2025 could not analyse visual input, other tools were tested on UI/UX design and code quality criteria. The Wilcoxon signed-rank tests showed few significant differences, but the Spearman correlations revealed inconsistent agreement in many cases. This suggests that, despite surface similarities, AI tools and human evaluations may differ on specific design and code elements. Therefore, AI tools should be seen as supportive assistants, not standalone evaluators, especially in tasks requiring subjective or design-sensitive judgment.

The current study is limited by a small sample size and the subjectivity of HIs' evaluations. At the time of writing this paper, the studied AI tools could not access live website prototypes or fully assess complex visuals. As AI tools continue to evolve, future research would be useful to explore their improved abilities, including providing written feedback in evaluating various types of creative works. Additionally, there is a growing case for investigating bespoke LLM development tailored to educational institutions. Future research could examine how fine-tuned or custom-trained models might better align with specific assessment goals, or institutional values.

Ethics statement: Prior to the beginning of the study, all participants received comprehensive information about it. Informed consent was obtained from all students, and their privacy was ensured throughout the study. Personal data was anonymised, and any information that could lead to student identification was carefully withheld throughout the research.

AI declaration: Studied AI tools were used to evaluate students' website projects. To enhance the readability of this paper, the authors utilised Grammarly and ChatGPT-4.5. All content was subsequently reviewed and edited by the authors to ensure accuracy and appropriateness. The authors bear full responsibility for the content presented in the final version of this paper.

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Organisational AI Culture: A Model at the Nexus of Human Resources, Management, and AI Technology

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Abstract: Inarguably, artificial intelligence (AI) is redefining business models and strategies, evolving organisational structures, systems, processes, and human resource management (HRM). What is less clear is how AI is impacting organisational culture and the short-, mid-, and long-term implications of this transition to a more advanced digital state of operations. Furthermore, understanding what role culture plays in influencing employee populations to harness the potential of algorithm-based tools and resources remains an under-investigated research area in business management. The research in this study explores evolving institutional dynamics between organisational culture, HRM, and broader employee populations, coexisting to achieve business objectives in the age of AI. This study takes a quantitative approach, surveying 431 business managers' perceptions of organisational culture and intention to adopt AI technologies in the workplace. A series of hypotheses is investigated, and the results contribute to the development of a conceptual model. We propose a model which centralises AI culture as a point of convergence of employees, resource management, and AI technologies to optimise strategic technological investments. Our research suggests that there is a pivotal role HRM plays in seamlessly integrating AI technologies and employees within organisations to develop AI culture. This paper extends understanding and knowledge of the evolving dynamics between AI and organisational culture within commercial organisations.

Keywords: AI, HRM, Organisational culture, AI readiness, AI attitudes, AI culture

1. Introduction

Many aspects of established and accepted institutional cultural norms are being disrupted by artificial intelligence (AI) technology implementation, causing complexity and ambiguity throughout organisational employee populations (Minbaeva, 2021; Singh and Pandey, 2024). While research is emerging on several aspects of AI, organisations, and human resource management (HRM), findings from existing studies are fragmented (Bujold *et al.,* 2023; Chowdhury *et al.,* 2024) and do not provide clear direction for business management and leadership on how best to navigate the internal complexities of this new era of digitalisation. There is evidence to suggest that underestimating the role organisation culture plays in new technology implementation can be detrimental to project investment and strategic uptake (Hoffman and Klepper, 2008; Kappos and Rivard, 2008). It is believed that this too will be the case with AI initiatives. Acknowledging the complex and broad terminology associated with AI, it is crucial to define and contextualise our application of the term AI applied to this research. For this current research, we define AI as machines performing tasks currently performed by humans (Dwivedi *et al.,* 2021); we further contextualise AI in this research as narrow AI, embedded in general-purpose technology applications and solutions.

As a result, organisational culture needs to evolve (Frangos, 2022; Rožman *et al.,* 2022) and take a more adaptive approach to both harnessing the potential of digitally advanced tools and technology while protecting and developing its human resources in the age of AI. Increasingly, research suggests this can be achieved through effective HRM (Goswami *et al.,* 2023), specifically the development of organisational AI culture (Fenwick *et al.,* 2024a, 2024b; Fountaine, 2019; Frangos and Paine Schofield, 2025). There is a research gap in understanding how managerial perceptions of AI impact and influence readiness, attitudes, and organisational culture in the workplace. This study investigates the evolving business dynamics of organisational culture by examining adoption intention, attitudes towards AI, and institutional AI readiness.

2. Background

Global markets and business environments are experiencing unprecedented change and disruption, creating both tremendous opportunities and challenges for organisations and how they manage their human resources (Harney and Collings, 2021). Traditionally, the role of human resource (HR) departments and the broader business function of HRM focused on managing all aspects of employee acquisition, talent development, organisational culture, and institutional wellbeing to achieve firm objectives and goals (Bujold *et al.,* 2023). As business models evolve, so too are structures and priorities for many HRM teams and professionals (Cappelli and Nehmed, 2024). Some of these structural changes have been motivated by financial pressure, organisational agility (McMackin and Heffernan, 2021; van de Wetering *et al.,* 2023), and technology accessibility

and applicability (Minbaeva, 2021). Regardless of organisational size, structure, or digital maturity, effectively managing human resources remains a requirement for all firms.

Extant literature suggests organisational culture, its development, role, and the impact it has on institutional wellbeing (Lopez-Martin and Topa, 2019; Belıas and Koustelıos, 2014) and business performance (Barney, 1986; Martínez-Caro *et al., 2020*) has a long and deep history. Organisational culture has many definitions; however, it can often be summarised as a firm's basic assumptions, espoused values, artefacts and symbols, which bind organisations together and motivate human behaviour (Schein, 1990). Human resource management has long been associated with the development and management of organisational culture (Pettigrew, 1979; Ulrich, 1984; Carroll *et al.,* 2010). Emerging research is investigating evolving variable relationships between HRM, organisational culture, and associated managerial implications advanced digital technologies are bringing to the workplace (Fenwick *et al.,* 2024b).

The business function of HRM has evolved significantly in recent decades, much of which can be attributed to advances in technology automation (Hendrickson, 2003; Johnson *et al.,* 2016; Kim *et al.,* 2021). Technology is transforming the previously highly administrative function (Mahoney and Deckop, 1986) into a strategic partner in many organisations (Fenwick *et al*., 2024b; Thite *et al*., 2012). Organisations are integrating AI technologies into their HRM systems and processes to create efficiencies (Budhwar *et al.,* 2022), thus enabling HR professionals to contribute to organisations at a more strategic level (Fenwick *et al.,* 2024b). It is important to note that this varies based on the size and complexity of organisational structures, legacy systems, access to AI, and implementation maturity. An extensive range of AI tools and solutions exists to meet the evolving needs of HRM, each of which includes multifaceted social and ethical considerations and implications.

As machine resources are increasingly entering the workforce, the nature of organisational culture is changing (Akyazi, 2023; Fountaine *et al.,* 2019). Research on this less tangible aspect of management is limited and fragmented; however, research suggests many human-centric AI acceptance barriers have been driven by human fear (Fountaine *et al*., 2019; Uren and Edwards, 2023), lack of technical skills (Brock and von Wangenheim, 2019), lack of AI knowledge (Alsheibani *et al*., 2019; Bérubé *et al.,* 2021), and trust (Gillespie *et al.,* 2021), all important aspects in organisational culture (Fenwick *et al.,* 2024b*)*. Research also suggests organisational readiness plays an important role in AI acceptance (Jöhnk *et al*., 2021). Developing a safe, open environment and encouraging positive attitudes towards new technology introduction across employee populations encourages AI acceptance (Farrow, 2021).

Research suggests culture is a contributing factor to AI readiness and adoption in organisations, thus influencing employee populations to accept AI technologies (Jöhnk *et al.,* 2021; Chiu *et al.,* 2021). AI culture involves organisational collaboration, innovation, and experimentation (Frangos, 2022; 2025). An AI culture requires organisations to reimagine and reframe the concept of collaboration (Jöhnk *et al*., 2021; Kiron and Candelon, 2021), breaking down silos (Fountaine *et al*., 2019), bringing human and machine resources closer together. Furthermore, AI culture creates an opportunity to build a platform for experimentation (Daugherty and Wilson, 2018) and innovation (Ransbotham *et al.,* 2021). HRM AI technology is enabling efficiencies in talent attraction, recruitment, training, career development, general process management, as well as other traditional HR responsibilities (Budhwar *et al.,* 2022; Pereira *et al.,* 2023). HRM is a well-positioned business function to influence broader employee populations to embrace AI technologies.

3. Theoretical Grounding and Hypothesis Development

Academic, industry, and practitioner research is being explored to better understand individual and organisational technology acceptance specifically solutions embedded with artificial intelligence (Maslej *et al*., 2023). This study focuses on narrow AI, as a general-use technology, utilising machine learning to achieve strategic organisational goals. Due to its size, scope, complexity (Holström, 2022), and rapid rate of evolution (Issa *et al*., 2022), AI is unlike any other technological phenomenon (Berente *et al.,* 2021; Kaplan and Haenlein, 2019). For AI to be effective in organisations, leaders must understand both human perceptions and attitudes toward these technological phenomena and the organisational evolution required to build and navigate a successful AI-driven firm.

Although artificial intelligence is fundamentally different from many antecedent digital technologies, the constitutional intention and practice of technology adoption are not. Understanding organisational behaviour and its relationship with information technology (IT) implementation and integration projects has been examined extensively throughout the past few decades (Collins *et al*., 2021; Weber *et al*., 2022). Much of the

existing research on organisational behaviour and IT implementation focuses on what resources are required to effectively incorporate new technologies into an organisation (Collins *et al*., 2021) and, to a lesser extent, what impact the new technology has on the organisation's existing resources and institutional culture. Research into organisational behaviour, specific to AI technologies, is growing (Collins *et al*., 2021) however, as the use of AI in organisations accelerates so too does the need for more research and better understanding of what drives strategic AI acceptance in the workplace (Uren and Edwards, 2023; Tjebane *et al*., 2022). This study is underpinned by Davis' technology acceptance model (TAM) (Davis, 1989) to better understand managerial perceptions of AI in the workplace. The TAM framework has been applied extensively in social science research and remains a relevant theory in investigating technology behavioural intention (O'Dea et al., 2024). It is important to understand how an organisation's intention to adopt AI influences readiness and attitudes towards AI. (Alsheibani *et al.,* 2019). This study investigates the hypothesis: *H1: Intention to adopt AI positively influences organisational AI readiness.*

While many organisations have yet to fully integrate AI into their business models, others have struggled to realise the potential of AI initiatives they've invested in. As a result, an emerging stream of academic research has started to investigate the challenges and barriers to AI adoption (Dwivedi *et al.,* 2021; Hradecky *et al.,* 2022). To capitalise on the potential of AI, more research is required to understand how AI influences employee attitudes towards AI in the workplace. This study investigates: *H2: Intention to adopt AI positively influences attitudes towards AI.*

Increasingly, organisations are developing readiness mechanisms to predict the success of IT and IS initiatives (Lokuge *et al.,* 2019). As the role of artificial intelligence in organisations continues to grow, so does the need to understand firm-level preparedness for AI adoption (Uren and Edwards, 2023). This research study positions AI readiness as a predictor variable for AI culture. Hypothesis number three explores: *H3: Organisational readiness positively influences AI culture.*

Employee attitudes play an important role in social science research to predict intention and behaviour. They are also a critical element of organisational culture. This study explores how attitudes towards AI impact organisational AI culture. The study investigates the following hypothesis: *H4: Attitudes towards AI positively influence AI culture.*

Figure 1: Hypothesised Model

4. Methodology

The data for this study was collected in May 2023 using a structured questionnaire distributed electronically to a panel of business managers. The panel was sourced from a third-party research provider. The instrument consisted of 43 questions, which included questions from pre-validated scales (Table 1). The instrument was piloted, refined based on feedback, and distributed via email to managers across the US, UK, Japan, Singapore, and India. The instrument measured 2-3 items per construct on a 5-point Likert scale (1-strongly disagree to 5-strongly agree).

Five hundred managers consented to and participated in the study by completing and submitting surveys. Responses were manually reviewed and analysed for completeness and unusual or duplicated response patterns. Incomplete and suspicious responses were removed from the data analysis, resulting in the final dataset of 431 participants (n=431).

Table 1: Instrument

5. Analysis and Findings

The analysis commenced by confirming the normality of the data. The results indicate all values for skewness fall into the acceptable range between -2 and +2 (Collier, 2020). The critical ratio is less than 8 for all values. The kurtosis values fall between the range of -10 and 10, which indicates normal distribution (Collier, 2020). The data was examined for collinearity issues. No evidence of multicollinearity issues was detected as the variance inflation factor (VIF) presented values at acceptable levels below 5 (Dormann *et al*., 2013). Analysis for sampling adequacy indicated an acceptable value of .94 (Hadi *et al*., 2016). The analysis found significance (.000) in Bartlett's test of sphericity. The reliability of the instrument was analysed by calculating Cronbach alpha scores for the constructs. The Cronbach alpha score for intention to adopt was .90, readiness was .88, attitudes was .93, and AI culture was .82. The scores for each of the constructs met the required threshold (p>.70) (Collier, 2020) to determine reliability. Based on these measures, the instrument was considered reliable and valid.

Discriminant validity was examined to determine if items were adequately aligned to the defined constructs (Fornell and Larcker, 1981). Calculated AVE values exceed the required .50 criteria to indicate convergent validity, and the values meet Fornell and Larcker's criteria for discriminant validity (Table 2).

Table 2: Discriminant Validity

Linear regression was conducted to determine if variable relationships were statistically significant. Statistical significance was confirmed with p-values less than .05 ($p<.05$) and highly significant with p-values of less than .001 ($p<.001$). Results of this analysis (Table 3) indicate highly significant ($p<.001$) relationships between each of the variables. This study investigated four hypotheses in total. Research findings in this study demonstrated affirmative, statistically significant support of hypothesis 1: *Intention to adopt AI positively influences organisational AI readiness* ($R^2=.62$, $F(1,429) = 685$, $p<.001$); hypothesis 2: *Intention to adopt AI positively influences attitudes towards AI* ($R^2=.55$, $F(1, 429) = 806.34$, $p<.001$). Findings include support of hypothesis 3: *Organisational readiness positively influences AI culture* ($R^2=.62$, $F(1, 429) = 712.69$, $p<.001$); and hypothesis 4: *Attitudes towards AI positively influence AI culture* ($R^2=.51$, $F(1, 429) = 438.99$, $p<.001$). Pearson correlation analysis was explored to better understand the strength and direction of the variable relationships (Table 4). The analysis found positive statistically significant relationships between each of the variables examined in this study.

Table 3: Regression Analysis

Table 4: Correlation Analysis

6. Discussion

The study findings support the stated hypotheses regarding the roles intention to adopt AI, organisational readiness, and managerial attitudes play in influencing firmwide culture. The regression analysis indicates robust, statistically significant relationships between the constructs with variance levels between .61 to .65. Furthermore, the analysis reveals highly correlated and positive variable relationships between each of the constructs. Culture is central to this research, where all human and machine resources converge; however, it is also important to note the intertwining relationships and activities between each of the variables as they each actively contribute to developing and managing AI culture. Figure 2 highlights the dynamic and evolutionary relationships between organisational human resource management, employee populations, and AI technologies. AI culture requires resource management and employee acceptance of AI technologies. Furthermore, it is important to note that the relationships in this model are dynamic and will continue to evolve as organisational structures and systems continue to regenerate.

Figure 2: AI Culture

Contributions, Limitations, and Future Research

This study extends established technology adoption theory and applies it to artificial intelligence technologies in commercial organisational settings. This study finds empirical support of AI impact through exploring managerial perceptions of readiness, attitudes, and behavioural intention to adopt new technology. Secondly, this research adds to an emerging body of literature on organisational technology readiness in the context of AI. The findings add empirical support to existing research, contending that organisational technology readiness is integral to developing an AI culture. Thirdly, this research enriches discourse on the developing area of managing organisational culture in the age of advanced digital technology.

AI is rapidly becoming an imperative part of contemporary business models. For most organisations, advanced technologies embedded with AI are impacting institutional culture, changing how employees work, feel, and perform in their roles. Better understanding organisational readiness, managerial perceptions, and attitudes towards AI can be instrumental in evolving institutional culture towards one which aligns human and machine resources. Developing AI culture nurtures human resources while optimising machine resource investments. The business function of human resource management is uniquely positioned to influence both employee populations and AI technology implementation and acceptance, thus motivating the development of AI culture.

Consistent with all academic research, this study has limitations which provide opportunities for future research and investigation. This study was limited to investigating managerial perceptions across developed economies in terms of AI implementation and adoption. There may be value in conducting further research across more geographies, including less-developed economies, to determine if the stage of AI access, development, and implementation maturity influences organisational culture. This study was limited to quantitative analysis and interpretation.

7. Conclusion

Artificial intelligence's true impact on business is yet to be determined; however, evidence suggests its impact can be profound. AI is not only changing how employees work, but it is also changing how they feel about their work. For better or worse, AI has become an inevitable necessity for many organisations and employees may soon no longer have the option as to whether to accept it or not. Our research proposes that there is a pivotal role HRM plays in seamlessly integrating AI technologies and employees within organisations to develop AI culture. The convergence of HRM, employee populations, and AI technologies promises a powerful space for internal alignment and innovation in the age of advanced digital technology. AI culture develops human and machine resource alignment to leverage technical and human intelligence to drive organisational outcomes.

Ethics declaration: No ethics approval was required for this research.

AI declaration: No AI tools or systems were used in writing this paper.

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Human-Centered AI in Healthcare: Balancing Patient Autonomy and Physician Judgment

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Abstract: This article outlines ethical issues related to integrating artificial intelligence (AI) into shared decision making (SDM), focusing on how to meet: (1) the need for explainability in enacting autonomy, (2) the need for respecting patients' values and preferences in treatment decisions, and (3) the impact of AI on physician expertise. First, it is argued that the kind of explainability required to support patient and physician autonomy can be met through rigorous model validation combined with context-sensitive post hoc explanations. Next, turning to a patient perspective, the article argues against the assumption that having AI pre-rank treatment recommendations undermines patient autonomy and therefore ought to be avoided. Instead, the article recognizes AI's potential to reduce cognitive overload and emphasizes balancing AI-guided decision-making properly. Subsequently, the physician's perspective is considered, analyzing how AI impacts physician expertise, particularly in light of automation bias, deskilling, and the erosion of practice-based judgment. The article warns against a shift toward actuarial decision-making driven by algorithmic risk stratification, which may compromise core ethical principles. The article concludes by promoting human-centered AI integration to enhance human agency—empowering patients to make informed choices and allowing physicians to exercise sound clinical judgment.

Keywords: AI healthcare, Shared decision making, Explainability, Autonomy, Practice-Based judgment

1. Introduction

AI in healthcare is a powerful tool that relies on data-driven machine learning to build predictive models. Thus, AI tools can offer diagnostic support, risk assessment, prediction of treatment responses, or rank treatment recommendations, potentially enhancing medical decision-making. However, integrating AI into clinical practice also raises fundamental challenges for shared decision-making (SDM), patient autonomy, and physician expertise. In this context, the article discusses the patient-physician-centered relational aspects of SDM, emphasizing challenges to patient and physician autonomy in AI-supported healthcare while also highlighting AI's potential benefits in enhancing SDM. Furthermore, the article analyzes AI's impact on physician expertise, warns against an actuarial turn, and discusses deskilling in the wake of AI-supported diagnostics.

The article is structured as follows: Section 2 analyzes how AI influences SDM, explicitly addressing the impact of transparency challenges on patient and physician autonomy. It is argued that post hoc explainability combined with thorough validation of AI models preserves the parties' opportunities to enact autonomy. Furthermore, besides concerns about transparency and addressing a patient perspective, the article argues against AI pre-ranked treatment recommendations being rejected because the pre-ranking threatens patient autonomy. Instead, the article points to AI's potential to reduce cognitive overload, which means we ought to focus on how best to turn information overload into manageable information while attending to the patient's values and preferences. Subsequently, drawing on examples from radiology, section 3 considers the physician's perspective, focusing on automation bias, deskilling, and the potential erosion of practice-based judgment. The article warns against a shift toward actuarial decision-making driven by algorithmic risk stratification, which may compromise core ethical principles. The article concludes by advocating for human-centered AI integration designed to augment human agency—empowering patients to make informed decisions and preserving physicians' capacity for sound clinical judgment.

2. The Impact of AI on Shared Decision-Making

Patient-centered care implies that the patient ought to be treated as an equal in SDM concerning medical or treatment decisions. While sharing information is a precondition for SDM, it also involves encountering the patient in a unique context, aiding the patient in eliciting their treatment preferences, which requires the "creation of an informed decision space in which a patient's specific values and preferences are represented and respected" (Bjerring and Busch 2021). However, respecting the patient's autonomy in informed decision-making should not place the entire burden of complicated treatment decisions on the shoulders of the patient. Thus, in SDM, the physician must balance participating without dominating the process (Charles et al. 1997).

Against this setting, the success of AI depends on transparency in ensuring trustworthy AI-supported decision-making. Consequently, making an informed decision requires that shared information be adequately explained,

which implies that it is understandable how an AI model arrives at an output. The quest for transparency is echoed in empirical studies too, as people demand explainable AI in healthcare settings, including human oversight and accountability (Holm and Ploug 2023; Ploug et al. 2021). Moreover, disregarding explainability in favor of performance accuracy could lead to a kind of double paternalism, first between the physician and the AI tool, which delivers accurate yet non-understandable recommendations that the physician follows, whereafter information is delivered to the patient, who follows the physician (Lorenzini et al. 2023).

Clearly, a machine learning system based on linear regression is straightforward and understandable as its model reflects a simple relationship between input and output. The model is interpretable because we can scrutinize its inner workings and clarify how it reached a decision. However, many models of high-performance complex neural networks are not interpretable and require explainer models to create approximate post hoc explanations. Therefore, transparency necessitates explainable AI (XAI) at a level that can provide a post hoc approximate explanation of what goes on inside noninterpretable AI models (Goebel et al. 2018; Linardatos et al. 2021; Ribeiro et al. 2016). Although it is impossible to reach a complete explanation with explainers, the application of black-box AI models can be considered epistemically and ethically justified if the system offers a pragmatically useful, albeit non-exhaustive, explanation of its outputs and is accompanied by rigorous model validation after standards comparable to the randomized controlled trials standard (RCT) (Gerdes 2024). In SDM contexts, the combination of retrospective assessment, prospective validation, and post hoc explanations may sufficiently meet the demand for explainability. Nevertheless, ensuring that AI-supported SDM preserves the autonomy of both patient and physician takes more than transparency. Consequently, in what follows, the article addresses patient autonomy by discussing the pros and cons of AI-generated treatment recommendations, followed by a discussion of AI challenges to professional autonomy (sec. 3).

AI-driven rankings might challenge patient autonomy as they potentially structure patient choices in a way that subtly nudges them toward a particular treatment. However, one may argue that this kind of libertarian paternalism (Thaler et al. 2010; Thaler and Sunstein 2003) might be considered justifiable, as the system's ranking reconstructs complex knowledge, providing a form of choice architecture that reflects the most optimal therapeutic options in alignment with what a rational agent would consider to be in their best interest. The persuasive element is epistemically sound, and the structure facilitates patients in reflecting on their values and preferences. As an illustrative case, Shapiro et al. (2023) describe XDECIDE, a clinical decision support system deployed in the context of precision oncology. This system provides patients with personalized treatment recommendations by drawing on real-world evidence from a cancer outcomes registry, findings from medical and clinical research, and the expertise of "molecular pharmacologists and oncologists (…) to balance $_{X}$DECIDE AI computational advantages with human intuition and experience" (Shapiro et al. 2023). As such, human experts discuss AI-ranked therapeutic options. A finalized report is delivered via an interactive web platform to the patient and oncologist, allowing each to suggest their preferred treatment.

One could argue that this approach undermines shared decision-making as the patient's autonomy is threatened because they are presented with a pre-ranked list, implying that their personal preferences and values do not drive the ranking (Aurelia 2023; Debrabander and Mertes 2022; McDougall 2019). However, in the $_{X}$DECIDE scenario, information overload is limited, which might otherwise have hampered the patient's ability to exercise their autonomy in the first place. Suppose the patient is presented with a scrambled list to avoid influencing their choice. In that case, they might prefer treatment B over treatment C and turn to the physician for expert clarification on this comparison. If B proves superior from an expert perspective, the patient will likely continue by comparing B with treatment A, then potentially with D, and so forth—working through pairwise comparisons to understand the relative merits of each option. It is reasonable to assume the patient becomes overwhelmed and cognitively overloaded in such circumstances, particularly when multiple treatment options exist. Providing a pre-ranked list makes information manageable, enabling the patient, in collaboration with the oncologist, to comprehensively assess and anticipate the consequences of different treatment options without exhausting their cognitive resources. One should, of course, not underestimate that in a clinical crisis, a patient can get overwhelmed by even a single option. Still, this approach facilitates patients incorporating their values and preferences in ranking the pre-ranked options, thereby sustaining their autonomy. To facilitate SDM, it is essential to carefully consider how to strike a proper balance, turning information overload into manageable information while attending to the patient's values and preferences. Likewise, the discussion of AI's impact on autonomy includes attention to how AI tools might support or challenge the physician's expertise.

3. Challenges to Physician Expertise - Deskilling and the Risk of an Actuarial Turn

The following discussion will explore how AI tools can either hinder or improve physicians' expertise. It will depart from radiology, where significant advancements in computer vision technology have greatly contributed to the development and integration of AI applications. As such, radiology can be viewed as a leader in adopting AI. Consequently, traditional workflows are changing within radiology, and the radiologist's role has been elevated in many ways, as routine tasks can now be distributed to AI tools (Najjar 2023).

In medical imaging for breast cancer detection, AI tools can support radiologists during screenings to reduce work pressure. For instance, in double-read mammography screening, an AI tool may function as a second reader, and studies demonstrate improved detection accuracy within AI-supported scenarios (Lång et al. 2023). Likewise, a retrospective population-wide mammography screening accuracy study concludes that AI makes it feasible to replace one or partially both readers in double-read mammography screening while also emphasizing the need for a strong quality and assessment setup before deploying AI-integrated screening (Elhakim 2024).

Moreover, in various medical domains, studies demonstrate that hybrid decision-making, teaming humans and AI, leads to better performance than either (Hekler et al. 2019; Šķilters et al. 2024). For instance, referring to "AI-augmented" radiologists, Cheikh et al. (2022) find evidence that AI-assisted decision-making facilitates radiologists and increases diagnostic confidence "through the high sensitivity and NPV [negative predictive values] of AI" (Cheikh et al. 2022). This observation aligns with Reverberi et al. (2022), who conclude: "In hybrid decision-making, the individual strengths of humans and AI come together to optimize the joint outcome."

However, as AI takes over routine tasks—such as reading images and filtering out "simple" cases— it might challenge opportunities for developing and maintaining reading expertise. If radiologists focus solely on complicated cases with potential pathology, their pattern recognition skills could weaken due to a lack of exposure to routine variations. Thus, potential deskilling raises fundamental questions about the nature of expertise and professional judgment, which have traditionally been cultivated through theoretical knowledge and practice-based experience. In healthcare, as in other professional domains, the development of skills and the ability to exercise professional judgment is reflected in the Aristotelian notion of practical wisdom, i.e., *phronesis*, which enables professionals to make sound judgments while attending to morally relevant aspects of concrete situations (Aristotle 1934; Eikeland 2008). This perspective on enacting expertise in practice emphasizes an interconnectedness of theoretical knowledge and practice-based expertise. Against this backdrop, expertise develops from repeated engagement with the world, a process also recognized in medical training and quality assurance frameworks. For instance, in the field of radiology, according to *The European Guidelines for Quality Assurance in Breast Cancer Screening and Diagnosis* (European Commission et al. 2013), breast radiologists must read at least 1000 mammograms annually to maintain diagnostic skills, and those participating in screening programs must read at least 5000 mammograms. Additionally, studies have shown that reading performance decreases for radiologists who undertake fewer examinations (Théberge et al. 2014), while those with a higher volume of mammogram readings have lower false-positive rates (Wong et al. 2023). Moreover, Wong et al. (2023) caution against using single reader characteristics to measure experience in mammography interpretation as their studies demonstrate that "A combination of reader characteristics such as feedback, lifetime mammograms read, number of CME credit, practice type has been shown to provide a better measure of experience, and reader performance" (Wong et al. 2023). These observations highlight the limitations of reducing expertise to simplistic quantitative metrics. The development of expertise is characterized by the expert having a deep situational understanding of their domain and relying on tacit experience-based knowledge when making judgments (Dreyfus 1986). Just as *phronesis* develops through iterative experience, radiological expertise is reinforced through repeated practice, ensuring excellence in professional judgment. In addition, although AI support may enable inexperienced radiologists to perform at the same level as more experienced ones, it is crucial to ensure that novices still acquire the necessary skills in the first place.

Furthermore, another source of deskilling is the human inclination to trust automated decisions without critical thinking. This tendency toward automation bias is well-documented in human factors engineering and human-computer interaction (e.g., Sarter 2001) as well as in medicine (e.g., Kim et al. 2025; Tsai et al. 2003). Automation bias refers to the phenomenon where individuals uncritically accept incorrect system outputs, disregarding contradictory evidence, even when such evidence is accurate or aligns with their professional expertise. Dratsch et al. (2023) demonstrate that novices, moderately experienced radiologists, and very experienced radiologists perform equally well when reading mammograms, regardless of whether AI predictions are correct, and automation bias occurs across all levels of expertise. Nevertheless, very experienced readers overrule incorrect

AI predictions more often than the other groups. Similarly, Kim et al. (2025) find that inexperienced readers "recommended significantly more intense follow-up examinations when presented with false-positive AI findings."

Dratsch et al. (2023) argue that automation bias can be reduced by fostering critical reflection, e.g., providing users with confidence levels for system outputs and incorporating explainable interfaces that offer insight into how the AI tool makes its decisions. They also emphasize that automation bias might be reduced by ensuring users take responsibility for their own decisions. However, these arguments assume that future radiologists will have adequate opportunities to cultivate the expertise necessary for sound professional judgment. But, if physicians lose opportunities to build and maintain skills while AI's accuracy increases, the benefits of hybrid human-AI team decision-making collapse, undermining physicians' ability to exercise professional judgment and potentially leading to further deskilling and responsibility gaps.

However, although human oversight remains an ethical and legal requirement at present, the prospect of AI outperforming physicians could shift discussions toward fully autonomous AI decision-making. Moreover, the present public preferences regarding explainability and human accountability (Ploug et al., 2021) may evolve, potentially leading to patients preferring AI accuracy over traditional physician-patient trust relationships. On the face of it, it might seem tempting to envision a future scenario in which AI outperforms humans. But such a scenario would compromise the foundational principles of SDM, and it would presumably not be realizable in the near future.

First, AI decision-making relies on predictive models that generate probability-based assessments rather than holistic clinical judgments. Thus, applying fully autonomous AI tools risks prioritizing statistical optimization over patient-centered care, implying that medical decisions become driven by algorithmic risk stratification rather than holistic clinical reasoning and SDM. Such an actuarial turn in healthcare would threaten principles of medical ethics, particularly regarding autonomy, beneficence, and the role of physician-patient trust (Beauchamp and Childress 2019).

Second, even in promising AI application areas such as medical imaging, systematic reviews show that many studies on AI tools outperforming clinicians lack proper validation (Freeman et al. 2021; Nagendran et al. 2020; Wynants et al. 2020). Although progress has been made, as demonstrated by Lång et al. (2023), significant challenges remain (Lekadir et al. 2022). One such challenge is data poverty in healthcare, which may result in models failing to serve the needs of underrepresented groups (Gao et al. 2023). Similarly, predictive accuracy depends on carefully selecting proxies to avoid inappropriate choices inadvertently reinforcing health inequalities (Obermeyer et al. 2019). The lack of prospective and randomized controlled trials, standardized reporting, and the inclusion of underrepresented groups present challenges that highlight the importance of ethics in AI development within healthcare (Plana et al., 2022), while also underscoring the difficulties in realizing fully autonomous predictive AI for complex cases.

Third, it is positive that numerous approaches exist for proactively addressing ethical issues in the development and deployment of AI systems. Guidelines and various Ethics by Design frameworks have been established at the EU level, grounded in fundamental rights and ethical principles (Brey and Dainow 2024; Dainow and Brey 2021). These guidelines define key requirements for trustworthy AI, including human oversight, robustness and safety, privacy and data governance, transparency, diversity, non-discrimination, fairness, and accountability (EU Commission 8 April 2019). The AI Act promotes the ethical development and use of AI tools (EU Commission 2021). Within healthcare, the WHO guideline highlights several value-based design methods (World Health Organization 2021). Likewise, standards for documenting clinical studies have incorporated AI-specific guidelines, such as The STARD-AI Protocol (Sounderajah et al. 2021) and The CONSORT-AI Extension (Liu et al. 2020). These standards enhance transparency and reliability by clarifying quality requirements for data handling, model training, and validation. Additionally, the website FUTURE AI (2022) presents a comprehensive guideline dedicated to AI in healthcare.

Despite such promising frameworks, value-based approaches are not a panacea. For instance, value sensitive design, one of the most acknowledged design approaches, endorsed by WHO World Health Organization (2021), has had a limited impact on actual system development (Gerdes and Frandsen 2023). Developers often find such frameworks too abstract and prefer purely technical methods for handling bias and ensuring privacy (FATML 2024). Thus, the greatest challenge for value-based design approaches lies in orchestrating interdisciplinary collaboration among technicians, domain experts, and related stakeholders. Notably, it is essential to ensure the active involvement of clinical domain experts (Gerdes 2022).

In sum, AI's role in healthcare should not be defined by wishful thinking, anticipating future scenarios in which fully autonomous AI trumps human performance, especially not since such a scenario might lead to an actuarial turn in healthcare. Instead, we should concentrate on keeping humans in the loop and ensuring AI supports physician expertise rather than replacing it. While many have emphasized the need for clinicians to develop AI literacy (Aslam and Hoyle 2022; Misra et al. 2024), it is equally important to consider how core clinical skills, such as pattern recognition in radiology, can be preserved in the wake of AI-assisted clinical image interpretation and diagnostics.

4. Conclusion

This article has analyzed the challenges related to the impact of AI-assisted decision-making, focusing on patient autonomy in SDM and physician expertise. From these perspectives, opaque AI performance should not compromise justifiable decision-making and undermine patient and physician autonomy. Consequently, transparency is required, which can be partly achieved through post hoc explanations of AI decision inputs, whose non-exhaustiveness can be compensated for by demanding rigorous retrospective and prospective validation of AI models, following the RCT standard. Furthermore, within SDM, a frequently voiced claim is that patients' values and preferences should drive the ranking of treatment options, implying that AI-pre-ranked treatment recommendations threaten patient autonomy. However, this argument overlooks the fact that patient autonomy is also threatened by cognitive overload, which may hinder opportunities for informed choice. Rather than rejecting AI-supported ranking outright, it is more important to consider how to balance AI's potential to turn information overload into manageable information while respecting the patient's values and preferences. Moreover, focusing on preserving the physician's autonomy requires avoiding AI-driven deskilling and ensuring that physicians in the future will have practice-based training opportunities to cultivate the skills necessary for developing expertise. Ultimately, the objective should be to integrate AI in ways that enhance human agency, strengthening patients' ability to make informed choices and physicians' capacity to exercise sound clinical judgment.

Ethics declaration: Ethical clearance was not required for the research.

AI declaration: The author has used generative AI (ChatGPT, OpenAI) as a support tool for improving grammar and stylistic clarity.

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The Impact of the Fusion of Human and Artificial Intelligence on Changes in the Generation and Protection of Innovations

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Abstract: Artificial intelligence (AI), as a unique multi-innovation, is the result of the action of human intelligence in an anthropocentric innovation model. The intensive development of innovative and autonomous capabilities of AI is a challenge for the transformation of the anthropocentric innovation model. The main aim of the research is to highlight the opportunities and challenges in the field of generating and protecting innovations, which will arise as a result of the fusion of human intelligence and AI. By using a proactive approach, the authors offer insights into the fusion of human intelligence and AI, as a brand-new innovation resource that will affect: the emergence of a new hybrid innovation model, changes in the structure of innovations, the emergence of multi-innovations, the redefinition of the concept of innovation portfolio, the conception and implementation of new intellectual property (IP) policies that will permit the establishment of a balance between human autonomy and the absence of discrimination against AI, as well as adequate legal protection for innovations generated by the fusion of human intelligence and AI. The research results show that the fusion of human intelligence and AI simultaneously represents: a stimulus for redefining and improving the innovative capabilities of human intelligence and the continuous development of innovative and autonomous capabilities of AI, as well as a catalyst for positive changes in the innovative model, which still remains focused on humans. In the near future, the fusion of human intelligence and AI will become a framework for research with scientific, economic, legal and political significance, and a radical systemic impact on society as a whole.

Keywords: Human intelligence, Artificial intelligence, Innovation, Intellectual property

1. Introduction

Innovative activities in contemporary conditions occur in an environment characterised by constant changes and uncertainty: intensive development of AI and quantum technologies, upcoming challenges of the 4th industrial revolution, dynamism of changes in the global innovation ecosystem. Innovative companies are required to react more and more quickly to instantaneous changes.

The success of adaptation of innovative companies is conditioned by the transformative potential of AI, and the adaptive capabilities of participants in innovation activities to adapt to the transformative potential of AI. Most representatives of the academic and business community, as well as innovation policy creators, agree that AI is the biggest transformative force that will radically change the existing innovation system. "By and large, significant innovations from now on will happen in the "unknown world" - that is, via insights gained thanks to AI's ability to streamline and accelerate knowledge accumulation while humans focus on unlocking previously indecipherable mysteries" (Sinha, 2023).

The starting point for determining the transformative potential of AI is found in the answer to the question whether human intelligence, as the only form of intelligence involved in innovation activities so far, is ready to respond to the challenges of upcoming changes. In other words, AI should be considered a transformative potential for transitioning and upgrading the knowledge, abilities and skills of human intelligence.

The impact of AI on the transformation of the innovative potential of human intelligence will cause chain changes in innovative activities. These changes will be conditioned by the quality of the fusion of the two types of intelligence. In this respect, the fusion of human intelligence and AI will become a synonym for a new strategic form of intelligence in innovative activities, and innovative activities can be considered a brand-new system of action of the fusion of human intelligence and AI in the process of generating and protecting innovations.

Despite its transformative potential, a comprehensive review of the impact of the fusion of human intelligence and AI on innovative activities is still missing in the current literature. This paper aims to bridge this gap by providing a detailed analysis of the fusion of human intelligence and AI, as a milestone in overcoming future challenges in the innovation model, which should permit an unprecedented transformation of the model in which innovations are generated and protected, with implications for future research.

2. AI as a Result of Innovation Activities

In order to define AI as an innovation, it is necessary to perceive AI as the result of innovation activities realised by human intelligence.

Given that innovation "manifests in diverse forms, each serving unique purposes and delivering distinct benefits" (Jain, 2023), it is necessary to see AI as a multi-innovation, in which the characteristics of several types of innovation are intertwined:

- business model innovation, since it "can comprise the development of entirely new business models, the diversification into additional business model, the acquisition of new business models, or the transformation from one business model to another" (Geissdoerfer, Vladimirova and Evans, 2018)
- data-driven innovation, since the application of "DDI in operations, research and development, […], firms can achieve a sustained competitive advantage" (Sultana, Akter and Kyriazis, 2022)
- digital innovation, since it can be observed "as a constant search for and identification of new or evolved problem-solution pairs" (Nambisan et al, 2017)
- product innovation, because like majority product innovations it "can have a long-life cycle because of the multiple stages involved in the process of innovation development and implementation" (Krasadakis, 2020)
- innovation that inspired new breakthroughs, since it is "so monumental that they inspired other designs, markets and industries to develop around them" (Stanford Online, 2024)
- radical innovation, since it has "an important role in economic growth not just because of their direct contributions to productivity but also because further innovations can build on them" (Acemoglu, Akcigit and Celik, 2022)
- discontinuous innovation which "links the substitutable and complementary knowledge and skills of actors to create a network of operant resources" (Michel, Brown and Gallan, 2008).

3. Innovations in the Domain of AI

The intensive development of AI imposes the need to find solutions to use the innovative potential of AI in the process of generating future innovations. "Economists at MIT, Harvard, and Boston University argued that AI's greatest economic impact could come from its potential as a new "method of invention" that ultimately reshapes "the nature of the innovation process" (Rotman, 2019).

3.1 Basic Characteristics of Generative AI

According to the Report of McKinsey&Company (Chui et al, 2023), generative AI (GenAI) could be described as: skill-biased technological change, virtual expertise, and the potential that will open wholly new frontiers in creativity and innovation.

Considering the expected impact of GenAI on the innovation system, GenAI can be considered an intelligent system that:

- is capable of cooperating with people. "AI-human collaboration is the key to addressing challenges and seizing opportunities created by GenAI" (Nah et al, 2023).
- encourages changes in creativity and innovative potential of people. "Regardless of legal outcomes, GenAI is likely to transform creative work and employment" (Epstein et al, 2023).
- can improve innovative activities. "Different AI models require different skills and capabilities from their users. Only when the skills match the task requirements will using GenAI lead to higher innovation performance" (Piller, Srour and Marion, 2024).

3.2 Basic Characteristics of Agentic AI

The next evolutionary level in AI development is agentic AI. According to Shrivastav (2025), "Agentic AI and GenAI are the two sides of one coin reflecting distinct paradigms in Artificial Intelligence dynamics, each with unique capabilities and applications". Hosseini and Seilani (2025) state that agentic AI is capable of:

- independently making decisions, interacting with their environment, and optimizing processes without direct human intervention
- continuous learning while interacting with dynamic environments
- significantly improves productivity, reduces costs, and drives innovation.

Based on its learning ability and autonomy, agentic AI is a reliable partner in innovation activities. Agentic AI is expected to participate in the generation of innovation; humans are expected to implement stages in innovation activities for which agentic AI has yet to possess (autonomous) skills.

3.3 The Future of AI Innovation

The development of quantum technologies will have numerous effects on the development of science, technology and future generations of innovations.

The continuous improvement of the AI system, stimulated by the development of quantum technologies, will simultaneously influence the emergence of a new generation of innovations in the field of business innovations and quantum technologies. "AI is accelerating quantum computing today. We're starting to see researchers tap into the mature infrastructure of AI and accelerated computing to leverage things like Large Language Models (LLMs) to develop new quantum algorithms and improve the performance of quantum computers" (Costa, 2024).

The impact of innovations in the domain of AI on innovations in quantum technologies will generate a positive cycle of major, evolutionary innovations. One of those evolutionary innovations will be the rapid development of innovative capabilities of AI. "And not in a distant future, AI will be integral to every stage of the innovation pipeline, form idea generation to its execution" (Becker, 2024).

Subliming the innovative potential of GenAI and agentic AI, as well as the effects of the intensive development of quantum technologies, AI can be viewed as:

- a tool that can be used by innovative teams in the process of generating innovations
- collaborator in innovative teams
- an autonomous innovator, with or without the participation of people in the process of generating innovations.

4. The Impact of Innovations in the Domain of AI on the Transformation of Human Intelligence

Until the expansion of innovation in the domain of AI, human capital (HC) was "the key lever to achieving a competitive edge in the innovation race" (Krys, Born and Geering, 2025).

With the expansion of innovation in the domain of AI, AI is becoming a brand-new intellectual resource. Innovations in the domain of AI are creating a new business reality where AI becomes the impetus for HC transformation. "AI can expand human abilities and creativity not only by replacing aspects of human labour but also by assisting humans as a technologically advanced tool" (Council for Social Principles of Human-Centric AI, 2019). As a "technologically advanced tool", AI can be used for the intelligent expansion of HC that will lead to an increase in the total volume of knowledge and competence of HC.

In addition, AI will affect the change in the innovative potential of HC in the process of generating innovations. "Finally, AI can help increase productivity by helping humans use increased capabilities faster (i.e. towards "augmented intelligence")" (Correia and Reyes, 2020).

Considering the intensity of AI's impact on changes in human intelligence, it is indisputable that human intelligence will become a form of intelligence subject to constant change (dynamics). "This development is significant because the skills required in this new landscape will be a combination of specialized human skills and augmented skills customized to the individual, like what we are already seeing with GenAI" (Sampanthar and Vitanova, 2023). On the one hand, GenAI offers the possibility to improve the performance of knowledge-based activities. On the other hand, GenAI affects the increase of innovative capabilities of human resources. Complementarities between technology (GenAI) and the intellectual and innovative capabilities of human resources become increasingly important and specific over time, often focused on new, inventive forms of knowledge. AI can therefore be expected to "augment human performance rather than fully supplanting it" (Rayner, 2023).

For the purpose of being able to use innovative forms of knowledge, individuals are required to develop new (complementary) knowledge, skills and intelligent abilities. "According to the World Economic Forum's Future of Jobs Report 2020, creativity, critical thinking, and complex problem-solving are the top three skills required for the future workforce, which is being increasingly influenced by the growth of artificial intelligence (AI) and digital technology" (Kapysheva, 2023).

Under the influence of changes in the potential of human intelligence, AI will become more autonomous and inventive over time, which is observed in agentic AI, in order to be a stimulating collaborator in innovative activities. "There is potential to leverage AI to complement humans, which requires a better understanding of the opportunities and limits of combining the two" (Ee, 2023).

By modifying the focus of human action from knowledge-based mental activities to new skills and intuition-based mental activities, the boundaries between human intelligence and AI cannot be precisely determined.

It is precisely this blurring of boundaries between human intelligence and AI that leads to the need for the fusion of human intelligence and AI into a unique "intelligent" resource. The fusion of human intelligence and AI is expected to allow the establishment of a stable balance between:

- creativity of human intelligence and AI
- inventiveness of human intelligence and AI
- human creativity and technological progress in order not to alter the diversity of innovations in favour of technological innovation.

5. The Impact of the Fusion of Human Intelligence and AI on the Transformation of the Anthropocentric Innovation Model

5.1 The Fusion of Human Intelligence and AI as a Unique Multi-Innovation

Before defining the fusion of human intelligence and AI as innovation, we need to determine whether the transformation of human intelligence has elements of innovation. Kogabayev and Maziliauskas (2017) state that innovation is the core action for the development and productivity of any economic activity, while Afuah and Utterback (1997) believe that innovation is synonymous with "new knowledge incorporated in products, processes, and services". Moreover, "innovation may involve a wide range of different types of change depending on the organization's resources, capabilities, strategies, and requirements" (Baregheh, Rowley and Sambrook, 2009).

Since the transformation of human intelligence represents:

- the result of the AI process of implementation in innovation activities
- absolute novelty in the change of HC as an innovative resource of high degree of usefulness in AI-based innovation activities
- a synonym for new knowledge that will be incorporated into innovative processes, products and services
- operating lever for intensive development and increase of productivity in innovation activities,

it is justified to define the transformation of human intelligence as innovation.

The fusion of human intelligence and AI, as a unique innovation, arises as a result of the fusion of complementary elements of AI and the transformation of human intelligence, as unique multi-innovations. Based on this, the fusion of human intelligence and AI is within the scope of the domain of multi-innovation, as it contains elements of different types of innovation:

- radical innovation, since it will be able to be defined in the (near) future "as innovation that society categorizes and institutionalizes in a new category rather than within an existing category, and valuates the innovation positively for its novelty" (Frenken and Punt, 2023)
- revolutionary innovation, because it resembles other revolutionary innovations which "fall onto a continuum ranging from 'radical incrementalism' – that delivers significant change to the mainstream market […] – to totally 'disruptive innovations' that deliver transformational change to the mainstream market and its value attributes" (Thomond and Lettice, 2002)
- incremental innovation, since it is "largely driven by internal processes and knowledge held by employees" (Engen and Holen, 2014)
- business model innovation, since it represents "the discovery of a fundamentally different business model in an existing business" (Markides, 2006), in this case, the discovery of a fundamentally different innovation model
- process innovation, since it refers to "changes in a methodology or process to achieve efficiency" (Kahn, 2018)
- innovation that aspires to fully become a sustainable and profitable innovation in the (near) future.

5.2 The Impact of the Fusion of Human Intelligence and AI on the Transformation of Innovation and the Innovation Portfolio

Although it represents innovation, the fusion of human intelligence and AI also represents an impetus for the transformation of innovations.

In the fusion of human intelligence and AI, there is potential to increase the innovative capabilities of both types of intelligence. In order for this potential to be used, it is necessary for innovative activity to be stimulating for human intelligence, and at the same time to provide mechanisms that will allow the maximum use of the potential of AI, because "artificial intelligence also has the potential to change the innovation process itself, with consequences that may be equally profound, and which may, over time, come to dominate the direct effect" (Cockburn, Henderson and Stern, 2018).

Properly harnessed potential of increased innovative capabilities of human intelligence and AI will cause numerous changes.

The first group of changes will refer to incremental improvements in existing innovations. By shifting the focus from knowledge as a resource for generating innovation to the fusion of human intelligence and AI, the concept of innovation will be redefined. Innovations that will be created as a result of the fusion of innovative capabilities of humans and AI will have a significantly transformed anatomy with regard to existing innovations.

The second group of changes will involve changes in the type of innovations. Continuity and complementarity in the development of human intelligence and AI will permit the emergence of a new spectrum of innovations, which will condition a wave of evolutionary and disruptive innovations. Strengthening the connections between human intelligence and AI will become the cornerstone of major innovation.

The third group of changes, driven by the evolution of the innovative fusion of human intelligence and AI, will cause the emergence of an increasing number of multi-innovations, which will replace the existing concept of the innovation portfolio. The concept of multi-innovation will be based on a holistic approach, as well as an approach to the diversity of innovations. Multi-innovation should represent a combination of different types of innovation, existing and new, which will consist of an indefinite number of innovations that may or may not be complementary. The balance between existing and new types of innovation will affect the success of innovative companies, as a longer period of time will pass before the market verifies new types of innovation.

In order to ensure the financial balance of innovative companies, it is necessary to determine how the fusion of human intelligence and AI will affect the protection of generated innovations, which will be discussed in the next chapter.

5.3 The Impact of the Fusion of Human Intelligence and AI on the Transformation of the Legal Protection System for Generated Innovations

"The intersection of AI and IP law presents a complex landscape where traditional legal frameworks are often inadequate to address the unique issues posed by AI technologies. […] Therefore, understanding the evolving regulatory landscape is crucial for ensuring that IP laws remain relevant and effective in the AI era" (Salle and Rini, 2025). "This brings forth pertinent questions concerning Intellectual Property Rights, (IPR) for, it challenges not only traditional notions of concepts such as patents and copyrights, but also leads to the emergence of questions related to the regulation of such creations amidst others" (Tripathi and Ghatak, 2018).

The existing IP system is dominated by an anthropocentric model that favours and encourages human creativity and inventiveness. The fusion of human intelligence and AI represents the beginning of the transformation of the anthropocentric model. This transformation is expected to allow a shift in focus from favouring and encouraging human creativity and inventiveness to establishing a balance between human creativity and creative activities that will realise a new form of intelligence created by the fusion of human intelligence and AI. The end result of this transformation is the conception of a new, hybrid model for the protection of innovations.

Conceptualising a new model involves overcoming numerous challenges. In the following, only a few of the most important ones are highlighted, since before conceiving a new model, it is necessary to realise extensive legal and economic research, which will require the participation of representatives of the academic, business and government sectors.

First, redefining the term IP, inasmuch as "the definition of IP cannot be limited to the human intellect" (WIPO, 2019).

Second, defining new forms of intellectual creations. "If we truly want to spur innovation globally, we must recognize all forms of intellectual creations - from AI to all humans - and make space for them in our legal frameworks" (Skibsted, 2024).

Third, conceptualisation of new legal policies that should allow:

- a certain degree of protection for innovations generated by any kind of intelligence
- new forms of protection for multi-innovations resulting from the fusion of human intelligence and AI
- respecting the diversity of IP generated by the fusion of human intelligence and AI in relation to existing IP
- establishing a balance between "hard" IP and "soft" IP, inasmuch as the boundaries between them will become more and more indistinct
- retention of existing concepts of author's creativity (individuality, originality, subjective choices of the author, "awareness of creation", personal and spiritual connections of the author to the work) for works created by the fusion of human intelligence and GenAI
- preservation of human autonomy for works created by the fusion of human intelligence and agentic AI
- determining the useful life for IP generated by the fusion of human intelligence and AI
- conceptualising new models of named and unnamed contracts for the transfer of IP rights
- legal autonomy for the economic disposal of IP generated by the fusion of human intelligence and AI in order to have an equal market position as existing IP

- economic incentives for generating (multi)innovations...

6. Conclusion

In this paper, the authorial focus is on determining the basic challenges for conceiving a new, hybrid innovation model in which innovations will arise as a result of the fusion of human intelligence and AI. The fusion of human intelligence and AI, as a unique multi-innovation, will become the generator of numerous changes in the model for generating and protecting future innovations. Considering the impact of the fusion of human intelligence and AI on innovation activities, the following conclusions were reached:

- innovation activities in the future will be adapted processes that will mark the end of the dominance of human intelligence in the process of generating innovations
- the success of innovation activities will depend on the ability and speed of human intelligence and AI to intellectually "upgrade" and adapt to mutual changes in innovation potential
- properly used innovative potential of human intelligence and AI will influence the transformation of innovations and innovation portfolio
- new forms of innovation, unique multi-innovations, will initiate a wave of chain changes in the legal system of innovation protection, from the redefinition of the term IP, to the conception of new innovative policies that are expected to stimulate a new wave of innovations and innovative changes in the future.

In addition to changes in the innovation model, the fusion of human intelligence and AI will initiate research in the academic community, business and government sectors. Researching this challenge will require the design of innovative methodological approaches that will initiate a wave of multidisciplinary research and practical solutions that will use the power of cooperation between the aforementioned participants. The research challenges that will be a priority in the following period are:

- building flexible organisations to implement the fusion of human intelligence and AI
- empowering organisations to develop innovative skills for an adaptive future dominated by a fusion model of human intelligence and AI
- management of organisations dominated by the fusion model of human intelligence and AI
- managing multi-innovation as a result of the innovative action of the fusion of human intelligence and AI
- new legislative framework for IP rights, with an ethical sub-framework for regulating AI rights in the multi-innovation protection model

- instruments and mechanisms for financing multi-innovations
- future industries that will arise based on the application of the fusion of human intelligence and AI in business organisations

▪ building resilient innovation systems for prosperity and sustainable development...

Ethics declaration: Ethical clearance was not required for the research.

AI declaration: No AI tools were used in the creation of this paper.

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Exploring the Dual Nature of AI in Education: Emphasising the Importance of Proactive Strategies to Ensure its Ethical Use

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Abstract: The increasing availability of advanced analytics tools such as Artificial Intelligence (AI) and Machine Learning (ML) are driving almost every industry to change their practices. Among which, the Chatbot Technology (ChatGPT), a computer programs that simulates human conversation with an end user has witnessed vast advancements. Not long time ago the impact of ChatGPT and similar AI language models in education sector was predicted to be transformative by reshaping the way students, teachers, and institutions interact with educational content (Agarwal et al., 2024). Arguably, they are already playing an increasingly significant role in the education sector, with a wide range of applications that are transforming teaching, learning, assessment and students' experiences. While ChatGPT and similar AI tools offer significant benefits in Higher Education (HE), including personalised learning, enhanced student engagement, improved collaboration, and greater accessibility, they also raise critical concerns about academic integrity and dishonesty. Central to these concerns is the potential for plagiarism, as students may rely on AI/ChatGPT tools generated content in ways that undermine original thought and academic honesty. In fact, this is a current dilemma for many HE providers in the UK and not only, among which is The University of Hertfordshire (UH) which is the case of this paper. Therefore, aim of this ongoing project is to explore the dual nature of AI/ChatGPT Tools in education, emphasising the importance of proactive strategies to ensure its ethical use. This article provides a reflective analysis of the initial strategies implemented to promote ethical AI/ChatGPT tools use within one of the largest postgraduate taught courses with 1000+ students at the UHBS. In this course students are asked to develop research proposals for their final postgraduate projects. The AI implementation strategies were designed primarily to reduce plagiarism by encouraging responsible engagement with AI/ChatGPT tools. Based on the course data analyses, the article offers comprehensive, practical recommendations for educators to foster fairness, uphold academic standards, and guide students in the ethical and responsible use of AI technologies in academic settings.

Keywords: AI strategies in education, Ethical use of AI/ChatGPT tools in education, Management education, Action and active pedagogy

1. Introduction

AI/ChatGPT tools represent significant advancements in the field of machine learning and natural language processing (Brown et al., 2020). These new technological developments not only push the boundaries of what machines can do but also offer transformative potential for industries seeking to enhance productivity, creativity, and decision-making. AI/ChatGPT tools are trained on extensive collection of text data and use complex architectures, such as transformers, to capture linguistic context, semantics, and syntactic relationships (Brown et al., 2020; Adeshola and Adepoju, 2023). Therefore, they can produce extensive, human-like written material and generate new and meaningful content such as text, images, audio, and videos. AI/ChatGPT tools are particularly effective for tasks such as crafting interactive stories and handling other conversational or dynamic text-based applications. Specifically, these tools can advance tasks like narrative analysis, text summarisation, language translation and high-quality content creation (Adeshola and Adepoju, 2023).

Arguably, these tools are already playing an increasingly significant role in the education sector, with a wide range of applications that are transforming teaching, learning, assessment and students' experiences. While AI/ChatGPT tools offer significant benefits in Higher Education (HE), including personalised learning, enhanced student engagement, improved collaboration, and greater accessibility, they also raise critical concerns about academic integrity and dishonesty. Central to these concerns is the potential for plagiarism, as students may rely on AI/ChatGPT generated content in ways that undermine original thought and academic honesty (Adeshola and Adepoju, 2023). In fact, this is a current dilemma for many HE providers in the UK and not only, among which is The University of Hertfordshire (UH) which is the case of this paper. Therefore, aim of this ongoing project is to explore the dual nature of AI in education, emphasising the importance of proactive strategies to ensure its ethical use. This article offers a reflective analysis of the initial strategies employed to promote ethical use of AI, including ChatGPT, within one of the largest postgraduate taught courses with over 1000 students at UHBS.

The AI/ChatGPT implementation strategies were designed primarily to reduce plagiarism by encouraging responsible engagement with AI/ChatGPT tools. Based on the course data analyses, the article offers comprehensive, practical recommendations for educators to foster fairness, uphold academic standards, and guide students in the ethical and responsible use of AI technologies in academic settings.

2. Literature Review

2.1 Benefits and Opportunities of AI/ChatGPT Tools in Higher Education (HE)

The integration of AI in HE has been linked to greater accessibility, personalised learning, and enhanced student engagement (Zawacki-Richter et al., 2019; Holmes et al., 2022; Griffiths and Cubric, 2023; Chen et al., 2023: Swati et al., 2023). According to Cotton et al (2023) language translation is among the most widely explored applications of AI/ChatGPT in educational accessibility. Beyond its content creation capacity some of AI/ChatGPT tools can translate teaching materials into multiple languages, convert text to speech, and simplify complex language. This capacity enables non-native speakers to access curriculum content that was previously limited by language barriers, thereby promoting greater equity in educational opportunities (Lee et al., 2022; Wu et al., 2023). Tseng et al (2024), believe that the integration of AI/ChatGPT tools in education has opened numerous opportunities to enhance the learning process. In addition, these tools transforming the way English as a foreign language (EFL) is taught and learned. In EFL education, while technology integration is transforming language classrooms, challenges remain especially around an academic writing. Despite continued efforts, it is still difficult to make substantial progress in students' abilities to organise content, develop ideas, and use grammatical structures effectively (Chen, 2022). International students often find it difficult to produce high-quality academic English writing, frequently encountering difficulties such as unclear grammatical structures, incorrect or overly simplistic vocabulary (Tseng et al., 2024). AI/ChatGPT tools present innovative solutions for tackling these challenges, delivering personalised and interactive writing support that helps bridge existing gaps and offers students meaningful assistance in their writing efforts. After testing an integrated writing course framework with a sample of 15 EFL students Tseng et al (2024) found that AI/ChatGPT tools can be effectively integrated into writing instruction, only if they are used within a structured and pedagogically sound framework. In this way they can lead to improvements in students' writing quality and foster a more engaging and interactive learning environment.

While exploring the efficacy of ChatGPT feedback in written English learning, Naz and Robertson (2024) found that AI/ChatGPT tools can be highly effective by providing students with timely feedback, interactive support, and increased motivation. Authors base their work on social cognitive theory, which supports use of GenAI by highlighting its ability to provide immediate guidance that enables personalised and independent learning. In addition, they drew on second language acquisition theory, which supports use of GenAI by emphasising its potential for enhancing students' learning through meaningful interaction. After examining a small sample of four different types of written pieces, the authors developed a rubric to evaluate writing quality. They then used this rubric to assess the texts, with evaluations carried out by both ChatGPT and human markers for comparison. Although issues such as errors and hallucinations were identified in ChatGPT's responses, Naz and Robertson (2023) believe these can be mitigated through careful rubric design and the inclusion of human oversight.

- Application of AI/ChatGPT tools for Personalised Learning

One of the most promising aspects of AI/ChatGPT tools is their capacity to personalise learning content and adapt it to the diverse cultural, linguistic, and educational backgrounds of both domestic and international students. This adaptive capability not only enhances individual engagement but also promotes equity. Mollick and Mollick (2024) suggest that instructors (lecturers, teachers, tutors and coaches) can leverage AI/ChatGPT tools to create personalised learning experiences for students that transforms teaching and learning. The authors propose a range of exercises that enable novel forms of practice, such as simulations, mentoring, coaching, and co-creation, while emphasising the critical role of instructors in guiding and supporting these activities. The authors believe, relying on their academic and pedagogical expertise, as well as their understanding of students' needs, instructors can design innovative exercises that transform the classroom learning experience. This level of customisation can enhance student engagement, comprehension, and retention (Zawacki-Richter et al., 2019; Mollick and Mollick 2024). In addition, AI/ChatGPT tools also can track student progress throughout the course, offering personalised support and feedback (Pillai and Ramakrishnan, 2024). For example, looking at AI/ ChatGPT's ability as a coach Cronjé (2023) found that ChatGPT can provide clear, generic feedback in a way that encourages students to focus on their goals. The author reports on the outcome of an exercise that was given to students as an introduction to their research methodology course, where final year students in Information Technology were asked to produce a 3000-to-5000-word research report as part of the requirements for graduation. After identifying three key issues: the quality of feedback provided by the chatbot, the value of the prompt, and the importance of student reflection, Cronjé (2023) emphasizes the crucial role of instructors. The author concludes that instructors must actively guide less

experienced research students in how to respond to feedback, craft effective prompts, and engage in meaningful reflection.

In addition, research have demonstrated (Jeon, 2021; Swati et al., 2023; Mollick and Mollick 2024) that AI/ChatGPT tools can support educators in creating dynamic and authentic assessments tailored to diverse learner characteristics. Effective student assessment not only helps learners adjust their strategies to improve outcomes but also enables educators to tailor their teaching methods to better align with students' abilities and needs. However, to prevent potential challenges and ensure the effective use of AI/ChatGPT tools, their integration must occur within a structured, pedagogically sound framework, guided by instructors. Where necessary, training should be provided for both instructors and students.

While the cases discussed above highlight the considerable potential of integrating AI/ChatGPT tools in education, several scholars have also emphasised the importance of addressing key challenges. These include ethical use, data privacy, academic integrity, the risk of deskilling, issues of equity, and the need to promote digital literacy among both educators and students (Ali et al., 2023; Bender et al., 2024; Swati et al., 2023; Richards et al., 2024).

2.2 Critical Perspectives and Challenges of AI/ChatGPT Tools in Higher Education

- Ethical and Social Implications

Despite the extensive opportunities that AI/ChatGPT tools promising to support teaching, learning and assessment, their integration into HE also brings new ethical implications and risks.

Therefore, it is crucial to explore the associated challenges and potential downsides. Crawford (2021) argues that the ethical implications of AI require a multidisciplinary approach, involving stakeholders from various fields to develop comprehensive and inclusive solutions. This includes not only technical experts but also ethicists, policymakers, and representatives. Heilinger (2022) observed that ethical reflections and arguments in scholarly publications as well as in policy documents often proceed as a discussion of risks and opportunities, or rules and principles, of AI. Therefore, guidelines and rules for appropriate uses of AI/ChatGPT Tools are potential sources for defining ethical AI. For example, the Institute for Ethical AI in Education (AI in Education, 2021) has developed The Ethical Framework for AI in Education, highlighting the role of governments in ensuring educators and students have a strong understanding of AI. In addition, the framework proposes appropriate ethical guidelines for the use of AI in education. Accordingly, most of the HE institutions are introducing their own strategies and policies to ensure ethical use of it.

- Academic Integrity/ Dishonesty and The Implications of AI

Academic Integrity, which refers to the ethical standards and honesty expected in academic work, including principles like fairness, responsibility, and respect for others' ideas is one of the most important principles in HE and research (QAA, 2024). Breaching academic integrity is also known as academic misconduct or academic dishonesty.

Currently student academic integrity/dishonesty, defined as any unauthorised assistance in completing a task or action that provides an unfair academic advantage (Krou et al., 2021) is a concern for nearly every educational institution. From copying homework to plagiarising essays, including collusion, cheating and falsification of data, students have long found ways to avoid academic expectations (Swati et al., 2023). With the rise of AI/ChatGPT tools, this issue has become even more complex. While such tools can enhance learning when used appropriately, they can also be misused by students to generate essays, solve problems, or complete assignments without genuine understanding or effort. This raises serious concerns about academic dishonesty, particularly when students submit AI/ChatGPT generated content as their own work. This kind of cheating is harder to catch than traditional plagiarism. In the past, cheating often meant copying from books, websites or published papers which could be found by plagiarism detectors. But AI-generated text is usually new and unique, even though the student didn't write it. This makes it difficult for normal tools to detect (Adeshola and Adepoju, 2023; Pavlik, 2023; Swati et al., 2023). As more learners turn to generative AI to support their studies, the issue of academic integrity/dishonesty has become a subject of lively debate. Richards et al (2024) observed that students may be able to secure at least a passing grade by submitting AI/ChatGPT generated responses without making any meaningful edits. This raises concerns about potential deskilling and equity. Particularly, relying heavily on these tools may undermine students' ability to articulate their own ideas and develop essential analytical skills (Swati et al., 2023). As a result, there is a risk that critical thinking, as well as the capacity to independently analyse and synthesise information, could decline over time. In addition, Crawford (2021)

highlights that this heavy reliance on AI/ChatGPT tools could deepen existing educational disparities students with access to advanced AI systems could gain an unfair advantage, while those without such resources may fall behind in developing essential skills. Therefore, with the concerns of academic integrity it is crucial to carefully consider these implications, ensuring that the integration of AI/ChatGPT tools into education enhances, rather than undermines, equitable learning opportunities and the development of critical skills. As a result, educators must develop clear guidelines, promote responsible use of AI/ChatGPT tools, and design assessments that minimize opportunities for dishonest practices while fostering authentic learning

2.3 Pedagogical Applications of AI/ChatGPT Tools in HE

Addressing the challenges associated with AI/ChatGPT integration in education necessitates adoption of innovative pedagogies that can enable facilitating effective interactions between humans and AI agents (Nah et al., 2023). To bridge the gap in AI literacy, Pahi et al (2024) are highlighting importance of shifting from traditional pedagogical models towards more inclusive and adaptive teaching methods. The authors believe active and action learning strategies can be considered as they both complements this by positioning students as engaged participants in their learning process, enabling hands-on experiences that facilitate the application of theoretical knowledge.

- Active Learning and Teaching Strategies

Active learning, a pedagogical approach refers to student-centred approach that emphasises learners' engagement in active and meaningful construction of their learning (Yao and Collins 2018). The key idea behind active learning and student engagement is reflecting on the experience of learning by doing (Pahi et al., 2024). Active engagement in learning may take different forms: flipped classrooms, internship, group discussions collaborative assignments and project, problem solving approach, case study, business simulations, subject-based research, and inquiry which making it particularly relevant for AI education.

- Action Learning and Teaching Strategies

Action Learning, originally introduced by Professor Reg Revans (1980,1982) in its simplest form is understood to be an experience-based approach. According to Revans (2011) Action Learning necessarily occurs in a closed group or 'set' and, while individuals in the set may each have their own unique problem to work on, learning occurs via the interaction between members of the set. That is the main differentiation to compare this approach with active learning approaches. Thus, Action Learning could be defined as a process that involves a small group working on real problems, taking action, and learning as individuals, as a team, and as an organisation. It is particularly effective for solving complex problems that may appear unsolvable. This approach effectively integrates active learning with personalised instruction by leveraging the guided, collaborative efforts of educators and AI/ChatGPT tools to enhance the learning experience.

3. Case Study

The present study which is part of ongoing project used a qualitative evaluative case study approach with elements of reflective analyses. A case study evaluation approach is a great way to gain an in-depth understanding of a particular issue or situation. This type of approach allows the instructor to observe, analyse, and assess the effects of a particular situation on individuals or groups (Keen and Packwood, 1995).

- AI policy at the university of Hertfordshire

Although the University of Hertfordshire acknowledges the importance of embedding AI across education, research, operations, and partnerships, it is still in the process of developing a formal AI policy. Currently, the use of AI is monitored under UPR AS14: Academic Integrity and Academic Misconduct, which emphasises that students must uphold principles of academic honesty, including avoiding plagiarism, collusion, and the inappropriate use of generative AI tools such as ChatGPT.

> *"2.4 Unauthorised use of artificially generated material (AI) in researching or presenting material for an assessment is an academic misconduct offence if you use AI tools in producing your assessment unless the use of AI tools is expressly permitted. However, even if expressly permitted, where you do not declare that you have used an artificial intelligence tool(s) in the production of your assessment, or you are dishonest about the extent to which such tools have been used, you will have committed academic misconduct. The extent to which assessment content is considered to be AI generated is a matter of academic judgement" (UH, UPR AS14, 2024).*

Feedback from pioneering cases that promote the ethical use of AI/ChatGPT tools is crucial to the policy development process, ensuring their responsible and effective implementation. Several case studies have demonstrated the significant benefits of integrating these tools into the curriculum, while also highlighting associated challenges. One such case, discussed in this paper, provides valuable insights into both the advantages and obstacles encountered.

- The study setting and participants.

Aim of this ongoing project is to explore the dual nature of AI in education, emphasising the importance of proactive strategies to ensure its ethical use. This article provides a reflective analysis of the initial strategies implemented to promote ethical AI/ChatGPT use within one of the largest postgraduate taught courses with 1000+ students at the UHBS. In this course students are asked to develop research proposals for their final postgraduate projects. The AI/ChatGPT tools implementation strategies were designed primarily to understand our students': (1) awareness and capacity of using AI/ChatGPT tools; (2) frequency and purpose of using AI/ChatGPT tools and (3) to reduce plagiarism by encouraging responsible engagement with AI/ChatGPT tools.

The course has very complex structure with three different (one year, sandwich and advanced research) routes and multiple intakes (September and January) with approximately 2000 students for per academic year. Majority of students on the course are international students with diverse educational background. In this B&M master's course students are required to join several compulsory modules, one of which is Business Research Methods (BRM), which aims to enable students to: (1) understand relevant methodological concepts and challenges associated with business research, (2) identify relevant literature, providing critical analysis of the theories, (3) formulate an appropriate ethical research strategy to plan the gathering and analysis of appropriate data (4) formulate a research proposal on a particular topic of students' interest. In this module students are evaluated through continuous assessments which are decided by the module leader.

The module was taught by the module leader and tutors (between seven to twelve depending on intake) in approximately fifteen separate groups (depending on intake) during the first semester for each intake between 2021-2022 and 2022-2023 2023-2024 2024-2025 years. Approximate number of students for each group was between 50-60. The syllabus, course materials and tasks for assessment was same to all groups. All module related materials (PowerPoint slides, books, book chapters, case study, short videos, journal articles and assignment briefs) were uploaded and posted in the module's Canvas site.

- Initial Strategies for AI/ChatGPT Tools in the Module and Reflective Analyses

The idea to introduce AI/ChatGPT Tools into modules curricula emerged based on considering new trends in HE, the module's data analyses and the module leader's reflection. While managing large courses and modules, it emerged from the module leaders' practice who is the author of this paper, that engagement is driven through interaction and participation. Best way to remain students engaged, especially in an internationalised setting is to keep session interactive (Grishikashvili, 2024). This was achieved by incorporating active and action learning strategies in flipped classroom settings.

The idea was to create an interactive environment where students could master technical and theoretical information through learning Set Conversation (LSC), reflection, and critical analysis. The module delivery structure included: (1) Preparation stage: Pre-class self-study, (2) 1 hour face to face Lecture, (3) 1 hour face to face tutorial and (4) Strech/Post-class self-study. A new innovative and authentic assessment, the Weekly Reflective Work/Reflective Diaries submission, which was based on the LSC discussion, during the tutorials, was introduced on the module since the module leader took the module leadership from previous module leaders in 2021. Using the LSC during the tutorials and Reflective Diaries for the weekly submissions, encouraged students to share their experiences - good and bad - and reflect together to draw out the learning. Having, LSC about the case study, which was linked to the week's topic/research process, helped students to adopt multicultural environment and have a great experience as an international student. The Module feedback analyses show that having LSC during the tutorials as part of weekly assessment helped to improve an engagement and an interaction on the module. after introducing new assessment methods for the module according to the Module Evaluation Forms (MEF 2022-2023; 2023-2024) overall failure rate on the module dropped nearly 70% and attendance and engagement improved dramatically. In addition, presented methods helped to decrease the number of the plagiarism cases which was another ongoing problem in HE. However, from the end of the 2023 academic year, signs of unethical use of AI/ChatGPT tools began increasing dramatically. Although students were penalised based on the principles outlined in the University of Hertfordshire's UPR AS14 policy, this new form of cheating quickly became a significant dilemma.

Reflecting on the module's data, we (the module leader, tutors, and markers) observed that our students mainly used AI/ChatGPT tools for the following four purposes: (1) To overcome language barriers during class interactions; (2) To clarify their thoughts before expressing them; (3) To proofread their written work; (4) To develop their assignments.

Considering new trends in higher education and reflecting on research findings at the beginning of the 2024 academic year, initial strategies for promoting the ethical use of AI/ChatGPT tools were introduced in the module. Detailed guidance for the ethical use of AI/ChatGPT tools was added to the module handbook. Clear instructions were provided regarding both where the responsible use of AI/ChatGPT tools was encouraged, in the development of knowledge and assessments and where their use was prohibited.

At this stage, under the instructor/tutor's guidance, use of AI/ChatGPT tools in an active learning environment through in-class exercises during the LSC was promoted for:

- Brainstorming and creativity to generating ideas for their research projects.
- Research and accessibility to find and summarise relevant literature for their projects.
- Writing assistance to improve the structure of their work or quality of academic writing.

This approach helped foster personalised learning through continuous progress monitoring by the module leader and tutors. Their role in facilitating active and personalised learning was critical, particularly in shaping the learning environment and influencing both student outcomes and their journey towards the ethical use of AI/ChatGPT tools. Furthermore, the combination of tutors' efforts and AI/ChatGPT tools to optimise the learning process, helped ensure that all students, regardless of their background, had equitable access to and use of these technologies. Results from the first intake (2024), were promising, and feedback from students was excellent.

- Plans for the new 2025 academic year

From the new academic year 2025, the plan is to integrate AI/ChatGPT tools into assessments, particularly in the Weekly Reflective Work/Reflective Diaries submissions, which are based on the weekly LSC discussions. At this stage, the use of AI/ChatGPT tools will be included as part of the Intended Learning Outcomes of the modules or detailed in the assessment brief. In addition to following referencing guidelines, students will be required to include a history of the AI/ChatGPT tools and prompts they used, along with the corresponding outputs, as an appendix.

4. Strategic Recommendations

Based on findings from the literature review and practical experience gained during this ongoing research, a framework below has been developed. This framework serves as a set of recommendations for educators considering the adoption of AI/ChatGPT tools in teaching, learning, and assessment.

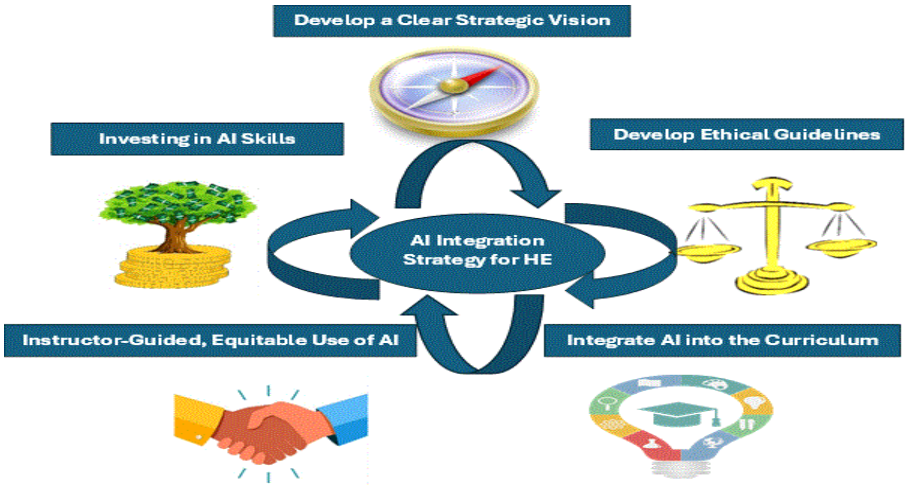

Figure 1: AI Integration Strategy framework for HE (Author's own)

1. **Develop a Clear Strategic Vision:** AI initiatives should not be isolated efforts; they must align with the broader objectives of the university to ensure cohesive and effective implementation.
2. **Integrate AI literacy into the curriculum:** This should involve adoption of innovative pedagogies that facilitate effective interactions between humans and AI agents.
3. **Implement Clear Ethical Guidelines:** Establish ethical guidelines to ensure the responsible use of AI/ChatGPT tools.
4. **Use of AI/ChatGPT Tools Must Be Guided and Facilitated by Instructors/Tutors:** Ensure that AI supports learning without replacing the development of critical thinking, creativity, and problem-solving skills. Additionally, instructors must ensure that the use of AI/ChatGPT tools is distributed equitably within classrooms and among learners from diverse socio-economic backgrounds.
5. **Invest in Digital Infrastructure, Digital Literacy, Skills, and Training:** Addressing the skills gap is essential for successful AI adoption. Continuous learning and development programs can help instructors stay abreast of the latest advancements in AI.

5. Relevance to Ongoing Work

This study is highly relevant to ongoing efforts in integrating AI/ChatGPT tools in higher education. It contributes valuable insights into effective practices and potential challenges in this evolving field. By providing a comprehensive overview of current knowledge and identifying critical challenges, this ongoing project supports educators, policymakers, and researchers in making informed decisions about AI/|ChatGPT tools adoption. The strategic recommendations offered in this study are particularly valuable for universities seeking to leverage AI/|ChatGPT tools for competitive advantage. The findings also contribute to the academic discourse by highlighting the multifaceted nature of AI/ChatGPT tools adoption. The study emphasises the need for a balanced approach that considers both the potential benefits and the inherent challenges of AI/ChatGPT tools integration.

6. Limitation of the Study

While the study provides valuable insights into effective practices and potential challenges in the evolving field of AI in Education, it also has several limitations. First, the recommendations are primarily based on findings from a literature review and reflective analyses conducted during the first phase of this ongoing research. The next phase of the project, which involves collecting and analysing empirical data, is expected to offer more precise and evidence-based insights. Furthermore, it is important to acknowledge that the case study underpinning this research is situated within one of the largest postgraduate programmes in a Business School. As such, the findings may not be directly transferable to other disciplines or to undergraduate contexts, where classroom dynamics and learner needs may differ significantly.

Ethical Declaration: As this study was taken purely for the pedagogical reasons and is not conceived as pure research at this stage study didn't go through the ethical approval. Thus, unfortunately at this stage the author couldn't provide direct quotes from learners' and teaching staffs' feedback, which is an acknowledged limitation of this study (there is an intention for farther developing this limitation).

AI Declaration: The author hasn't used any AI tools at this stage of the paper's development.

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Deepfake Detection: Human Performance Versus AI Tools, A Comparison of Accuracy and Effectiveness

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Abstract: Image manipulation is a phenomenon much older than digital image handling and generative artificial intelligence (GenAI). In the digital era, researchers have made a distinction between cheapfakes and deepfakes. The creation of cheapfakes requires a relatively low technical editing level and does not depend on any GenAI technology. This study had a focus on deepfakes only and explored the role of GenAI in the generation of deepfakes as well as the role of AI in tools for detecting deepfakes. The term deepfakes refers to high-quality and synthetic media content created with the use of deep learning and generative artificial intelligence. Recent advances in deepfake generation have made such content even more realistic, making it harder to identify. The rise of AI-convincing content is a growing social issue that poses serious challenges for its detection. Although the importance of deepfake detection is widely recognized, research comparing the performance of humans and AI on deepfakes analysis is still in its early stages. This study addresses this gap by conducting a comparison between human analysis and AI-based detection tools to evaluate their accuracy and effectiveness in identifying deepfakes. The testing was based on a set of AI-generated images related to the Israel–Hamas war, which were circulated on social media during 2023-2024. Future research should focus on testing a broader range of AI-based detectors to evaluate their effectiveness against different types of deepfakes, such as video, music, audio, text, including less sophisticated AI-generated manipulations as cheapfakes.

Keywords: Deepfakes, AI, GenAI, AI-Detection, Detection tools, Image manipulation

1. Introduction

Image manipulation, defined as the alteration of photographs to change their appearance or content, is a phenomenon that stretches back to the earliest days of photography. In 1826 or 1827, the exact date is not verified, the French inventor Nicéphore Niépce preserved and presented the first heliograph photocopy captured by a camera obscura. A new technique for generating and storing images was created, with a quality that continuously improved in the 19th century (Mcquire et al., 2024). A new technique that also opened up new ways for image manipulation, not only for retouching scars and wrinkles on portraits, but also for political propaganda. A well-known example from the 19th century is when multiple negatives were combined to create fake images during the American Civil War (Palmquist & Kailbourn, 2005). As discussed in Pisch (2014), retouching techniques were frequently used in the Soviet Union during the Stalin era, for various purposes such as “smoothing Stalin's pockmarked face and removing litter from his path; inserting text on banners so that the idea becomes legible; enlarging an adulatory crowd through montage…" (Dickerman, 2000, p. 141).

Around 150 years later, when the first digital camera prototype was presented in late 1975 or early 1976, the exact date is not verified here either; a new era with computer-assisted manipulation was born. Digital image manipulation without involving any generative AI (GenAI) techniques is today known as cheap fakes or cheapfakes. The disinformation or misinformation in cheapfakes does not necessarily have to be cheap, and that cheap refers to the affordable tools and techniques that are used. Deepfakes, on the other hand, are created with the use of GenAI, and the term is built by combining the first part of deep learning with fake. In this context, deep learning refers to the meaning of deep learning for multi-layered neural networks, and not to the meaning of deep learning as used in pedagogy. Moreover, deepfakes today are multimodal, comprising modalities such as image deepfakes, audio deepfakes, and video deepfakes (Ahmed & Chua, 2023). This study had a focus on deepfakes only, with deepfakes definiens as in (Coccomini et al., 2022) and in (Abbas & Taeihagh, 2024, p. 1), "digital content, usually a video, audio, or image, that has been manipulated using deep learning algorithms to alter, replace, or superimpose the original content with new content that appears to be authentic". Today, deepfakes are widely spread across various realms such as politics, economics, and social issues, undermining both societal integrity and information security (Iufereva, 2023).

Recent advances in the field of GenAI during the last years have made deepfakes more realistic and harder to detect. The rapidly ongoing increase of AI-generated content is a growing social issue that poses serious challenges for contemporary society. The number of created images between Nicéphore Niépce’s first heliograph image and the appearance of the first digital camera has been estimated to be 15 billion analogue

images. With the frequent use of GenAI techniques for image creation today, the same number of 15 billion images was created in just one year after the release of the first accessible AI image generator in September 2022 (Attie, 2023; Tensetti & Rangsjö, 2024). Even though the importance of deepfake detection is widely recognized, the applied research remains limited. Deepfakes that are generated with the use of deep learning can also be detected with tools using deep learning. The study by Almars (2021) concluded that deep learning techniques showed good performance in deepfakes detection, but also that the quality of deepfakes is continuously increasing. Three years later, the study (Abbas & Taeihagh, 2024) also reported promising results, but with a similar comment that " the advances in deepfake generation methods are creating challenges concerning combating them" (p. 27).

Previous research has also examined both human capabilities and the effectiveness of AI tools in detecting deepfakes. Many of these studies (Groh et al. 2022, Somoray et al., 2024; Maiano et al., 2024; Moeßner & Adel, 2024) focused on synthetic datasets of AI-generated photos and videos, such as FaceForensics++, the Deepfake Detection Challenge (DFDC), SDXL, and Fooocus. One of the main limitations of such a method is that synthetic datasets fail to capture the complexity and contextual nature of non-synthetic deepfake occurring on social media. Furthermore, non-synthetic deepfake that have appeared on social media are rarely used in academic research, partly because such content is often removed due to moderation policies. Nevertheless, studies (Abbas & Taeihagh, 2024; Stroebel et al., 2023) emphasize the need for empirical analysis based on non-synthetic deepfake retrieved from social media to better assess the challenges of deepfake detection in real communicative environments.

The approach proposed in this paper compares human performance with AI-based tools in detecting deepfakes, focusing specifically on non-synthetic deepfakes that emerged during the Israeli–Palestinian war (2023–2024). The research questions that guided this study were:

RQ1: What visual errors, artefacts and inconsistencies can be identified in the selected deepfakes by human analysis?

RQ2: To what degree are GenAI based tools for deepfake detection correct and reliable?

2. Data Collection

The study was conducted as an empirical case-based analysis with AI-generated images gathered from multiple sources. Among these sources were established media agencies such as 'Reuters ', and the investigative platform 'Deutsche Welle' (DW). Moreover, the analysis involved educational materials used in the framework of the course 'Advanced Training Course in the Didactics of the Holocaust', given at the University of Florence (2024). The selected images appeared on social media during the Israeli-Hamas war in 2023-2024. The research sample consists of four images representing two different perspectives: two 'Pro-Palestinian' and two 'Pro-Israelian'. This study used the five freely available AI detection tools: 'Sightengine', 'Undetectable.ai', 'Decopy.ai', 'WasItAI', and 'Hive Moderation'. A choice that was motivated by several reasons. Firstly, the goal was to assess the degree of democratic accessibility of these tools for regular users — without payment and with user-friendliness. Secondly, the opportunity of immediate verification of digital content authenticity.

3. Results of Analysis

The results of the analysis are divided into two sections. The first section reports the findings of the human analysis, focusing on visual errors, artifacts, and inconsistencies identified in the selected deepfake images. The second section evaluates the performance of AI-based deepfake detection tools in terms of accuracy and reliability.

3.1 Human Analysis: Visual Errors, Artifacts, and Inconsistencies

The human analysis involved a detailed examination of the selected deepfake images to identify visual anomalies typical of AI-generated content. These included inconsistencies in environmental elements, unnatural features, and technical artefacts that reduce image authenticity.

Case 1. The dad with children in the Gaza Strip.

The example of a deepfake features an image of a father surrounded by his five children standing in front of a pile of rubble (See Figure 1). This photograph, widely disseminated on X and Instagram, has been viewed hundreds of thousands of times in connection with Israel's bombardment of Gaza. However, a community notice

on X now identifies the image as manipulated. "In the meantime, the image has been marked with a community notice, at least on X, that it is fake" (Eisele & Steinwehr, 2023). For instance, the man's right shoulder appears unnaturally elevated, disrupting anatomical proportion. Equally peculiar are the two limbs extending beneath his sweater, giving the illusion of unnatural emergence. Moreover, the hands of the two boys embracing their father's neck seem to merge indistinguishably, further distorting the composition. Additionally, discrepancies in the number of fingers and toes across several hands and feet in the image contribute to its overall inconsistency (see Figure 2).

Source: Personal archive of the authors; this example was presented by student Fausta Blasi during the Advanced Training Course in the Didactics of the Holocaust, University of Florence, 2024.

Figure 1: A father with children in the Gaza Strip (original photo)

Figure 2: Debanked AI-generated image showing typical inconsistencies and visual errors

Case 2. A Palestinian boy

The image depicts a child gazing upwards with his arm raised, surrounded by rubble and the bloodied face of a veiled woman, purportedly his mother, who is said to have died following a bombing in Gaza (see Figure 3). Initially shared by "several pro-Hamas accounts", the photograph quickly gained widespread circulation across numerous accounts on X, many of "which were flagged it as a fabricated creation" (Open, 2023). However, its authenticity has been questioned, with multiple users flagging the image as fabricated. Critical examination reveals significant inconsistencies: notably, the child's left hand is depicted with six fingers (see Figure 4). The presence of extra fingers, a common anomaly in AI-generated imagery, points to the likely use of free AI image generation software, which is prone to such errors. Additionally, a closer inspection of the child's eyes and eyelashes reveals disproportionate enlargement compared to the rest of the facial features.

Source: Personal archive of the authors; this example was presented by student Fausta Blasi during the Advanced Training Course in the Didactics of the Holocaust, University of Florence, 2024.

Figure 3: A Palestinian boy (original photo)

Figure 4: Debanked AI-generated image showing a boy with six fingers on his left hand

Case 3. Patriotic Illusion: Signs of AI Generation in Depicting the Israeli Army

The image depicts soldiers marching with Israeli flags through a settlement of bombed-out buildings, evoking a sense of patriotism (see Figure 5). However, upon closer inspection, several features undermine its authenticity.

The movement of the Israeli flags appears unnaturally uniform, the central street is improbably pristine, and the debris exhibits an unusual level of uniformity. Additionally, the destroyed buildings resemble one another closely, positioned at remarkably regular intervals. Collectively, the overall visual effect is excessively clean and lacks the irregularities characteristic of real-life scenes (see Figure 6). This type of artificial perfection, which often makes images look painted or staged, is a hallmark of AI-generated content.

Source: Eisele, I. and Steinwehr, U. (2023) Fact check: AI fakes in Israel's war against Hamas. DW, 10 November. Available at: https://www.dw.com/en/fact-check-ai-fakes-in-israels-war-against-hamas/a-67367744 [Accessed 19 July 2025].

Figure 5: March of the Israeli army (original photo)

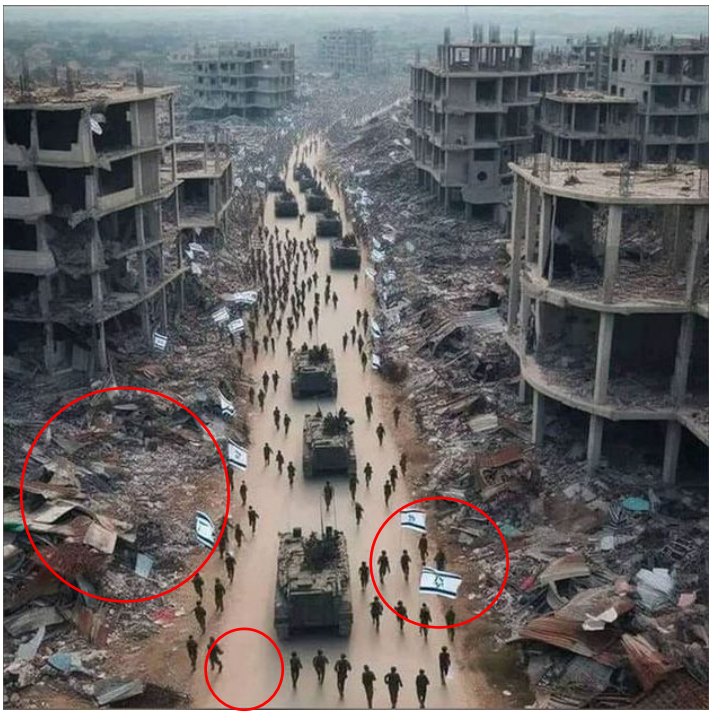

Figure 6: Debunked AI-generated image: lack of authenticity revealed through artificially flawless environment

Case 4. Crowds and Israeli soldiers

An image depicting crowds on balconies cheering and waving Israeli flags as soldiers march along a street was created using AI for inspirational purposes as well (see Figure 7). The image was widely shared on social media platforms accompanied by hashtags such as #HamasTerrorist and #IsraelFightsBack. On Facebook, it appeared with captions such as “The REAL Israel. Need we say more? AM YISRAEL CHAI!!” (The nation of Israel is alive) and its Spanish equivalent, emphasizing unity and resilience (Eisele & Steinwehr, 2023). However, the image has caused confusion among online users, many of whom question its authenticity and suspect it to be official propaganda.

The original post was uploaded on October 11 by Omri Shefi as part of a collection of thirteen AI-generated images depicting civilians and soldiers waving flags and celebrating. In his post, Shefi stated that the images were created with AI as part of psychological warfare, aiming to envision victory. His caption read: “Much of this warfare is psychological. So, let's imagine our victory picture, and so it will be!” (translated from Hebrew). Despite the clarification regarding its origins, the image raised skepticism among social media users, with some accusing it of being fabricated for political messaging. This example underscores the potential for AI-generated imagery to blur the lines between artistic expression and propaganda, especially in the context of geopolitical conflicts.

Source: Reuters Fact Check, 2023. Fact Check: Photo of cheering crowds waving Israeli flags at soldiers is AI-generated. Reuters, 30 October. Available at: https://www.reuters.com/fact-check/photo-cheering-crowds-waving-israeli-flags-soldiers-is-ai-generated-2023-10-30/ [Accessed 19 Jul. 2025].

Figure 7: Jubilant crowds waving Israeli flags at soldiers (AI-generated image)

Figure 8: Debunk: the image demonstrates typical AI errors and inaccuracies

3.2 AI-Based Detection Tools: Evaluation of Accuracy and Reliability

A set of free AI-based detection tools was used to analyze the selected images. Each image was uploaded for evaluation to the websites for the detection tools: 'Sightengine', 'Undetectable.ai', 'Decopy.ai', 'WasItAI', and 'Hive Moderation'. Since all images in the sample were AI-generated, it was expected that accurate tools would yield verification scores between 80% and 100%. Results within this range were marked with a "✅" indicating that the tool correctly identified the image as AI-generated and can be considered reliable. If the detection score was below 80%, it was marked with an "❌" signaling that the tool failed to accurately detect the image's artificial origin. The results of the analysis are presented below in Table 1.

Table 1: AI-detection tools results: overview of effectiveness

Detection tool	Picture 1 *'The dad with children in the Gaza Strip'*	Picture 2 *'A Palestinian boy'*	Picture 3 *'Jubilant Crowds Waving Israeli Flags at Soldiers'*	Picture 4 *'Crowds and Israeli soldiers'*
Sightengine	❌	❌	✅	❌
Undetectable.ai	❌	❌	✅	✅
Decopy.ai	❌	❌	❌	✅
WasItAI	✅	✅	✅	✅
Hive Moderation	❌	✅	✅	✅

Source: The authors' elaboration

4. Discussion

The study was divided into two main sections: 1) human deepfake analysis and 2) the evaluation of AI-based deepfakes detection. The first stage involved identifying and describing errors and inconsistencies in the selected images through human analysis. The detection in the first section relied on a critical examination of the images, assessing the logic of environmental elements, as well as recognizing common typical and earlier identified AI-generated errors and glitches such as humans with six fingers instead of five (Cramer, 2024; Jang et al., 2025). In the second stage, several free AI-based detection tools were employed to evaluate the authenticity of the selected AI-generated images. The results from this relatively small sample of images, showed that not all tools performed equally well and with surprisingly poor results. The most accurate was WasItAI, which correctly identified all images as AI-generated with high precision. Acceptable results also for the tool Hive Moderation

that only one failed in the detection of one image. The other tools that were tested: Sightengine, Undetectable.ai and Decopy.ai cannot be recommended for determining image authenticity, and must be classified as unreliable.

Unlike most prior studies (Groh et al. 2022, Somoray et al., 2024; Maiano et al., 2024), this research examines deepfakes in real media environments. The involved AI-generated images circulated in social media during the Israeli-Hamas war between the years of 2023 to 2024. By combining human analysis with automated detection tools applied to non-synthetic deepfake content shared during the Israel–Hamas war, this study provides grounded and timely insights to deepfake detection research. Authors see the four selected and analysed images as a sample representing the quality that AI-generated images had during 2023 to 2024. How to develop tools that could assess AI-generated image quality is an ongoing process (Aziz et al., 2025; Hartwig et al., 2025), but according to human assessment, the quality is continuously improving with the tool Midjourney as an example of high quality (Rangsjö &Tensetti, 2024; Cai et al, 2025). The humanly identified AI-artefacts, such as hands with four or six fingers, will probably not be there in the next generation of AI-generated images, and for dual reasons. Firstly, the next generation of image generation tools will have higher quality mentioned above. Secondly, the results from this study and others, and the general discussion on deepfakes, will probably lead to more detailed prompting where known glitches are hidden.

4.1 Limitations of the Study and Future Research

Some limitations of this study should be mentioned. First, the sample of AI tools was limited and included only free platforms, and it would be interesting to expand the sample in a broader comparison of tool accuracy and limitations. Second, the study focused solely on image deepfakes and did not cover other types of deepfake media, such as video, audio, music, text, or simpler AI manipulations like cheapfakes. Third, empirical material could preferably be extended beyond a narrowly focused military conflict to include other topics that are widely discussed on social media. Fourth, the detection tools that showed promising results should be further tested with larger data sets.

This paper could be seen as the first part of a longitudinal cross-sectional study covering deepfakes published from 2023 to 2024. This research field is a moving target, and a follow-up study on images generated during 2025 will probably generate different results. It would also be interesting to assess images from other contexts, but as concluded in Lundberg and Mozelius (2024), news media is the crucial area, while deepfakes in other areas could be accepted to a higher degree. Finally, it would be interesting to evaluate Google video generating tool Veo 3, which should be able to generate hands with five fingers (Kieffaber et al., 2025).

5. Conclusions

This research explored practical aspects of deepfakes detection. In a two-stage approach involving human analysis, and AI-detection tools analysis, the two research questions were answered. The human analysis identified the presence of extra fingers and toes, and disproportional limbs, eyes, and eyelashes in photos with humans. Regarding environments and buildings in the images, the human eye could identify structural repetitions and the artificial flawlessness and cleanness that give images a painted or staged appearance. Regarding the second research question, three out of five detection tools showed poor performance. The results were promising for one of the tools, but before any further conclusions or recommendations, the tool has to be further evaluated with more test data. Authors' recommendations are the same as brought up in the study by Janf et al. (2025), to label or watermark the AI involvement in image generation in a reliable way, and to increase deepfake literacy.

The research offers a conceptual basis for further empirical research regarding different types of disinformation and deepfakes. Finally, understanding the distinctive features of various disinformation types may serve as a basis for media literacy initiatives and for the development of the next generation of AI-based detection tools**.**

AI declaration: The describe detection tools were used in the the image evaluation and analysis, but all parts of this paper have been written without any use of AI.

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Reimagining Professional Development in the Age of Artificial Intelligence

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Abstract: As Artificial Intelligence (AI) reshapes education, professional development (PD) must go beyond tool training to foster critical, meaningful integration. Initial PD should introduce AI's uses and challenges but also address the impact on teaching and learning. This paper explores and reflects upon Phase II of the FAITH project, a transatlantic design-based initiative developing an AI and Education (AI&ED) model for higher education. Effective AI pedagogy is grounded in socially constructed, hands-on experiences where educators design lessons, generate content, and critically assess AI outputs. Such approaches build confidence, competence, and prevent mechanical adoption. Leadership and policy must further support a dual PD strategy: immediate classroom applications alongside preparation for broader societal shifts. Early FAITH findings show introductory courses spark essential dialogue, but PD must remain dynamic, ethical, and intentional. Phase II combines theoretical exploration (e.g., sustainability, ethics) with context-relevant practice. Ultimately, AI&ED should be understood as a lifelong professional learning journey.

Keywords: AI, AI&ED, Artificial intelligence, Faculty development, Higher education, Lifelong learning, Organisational development, Professional development

1. The Organisational Need for Professional Development in the age of AI

Professional development (PD) is a strategic issue for educational organisations. This strategic position is due to the potential impact PD decisions may have on the future of organisations. In other words, PD is a strategic tool for organisational development (Jaldemark, Lindqvist, & Mozelius, 2019). As such, organisational development initiatives may have different motives. However, from an organisational perspective, these initiatives have consequences for the organisation and its employees, for example, for administrative employees, researchers and teachers. Therefore, if decisions on initiating PD in an educational organisation are made, well thought-out ideas on the didactic questions of why, what, when and how should be formulated by the organisation and the level or function the PD focuses on to change. The Why-question concerns the purpose and deals with aligning employees with the organisational development strategy. Answers to the What-question relate to content in terms of organisational prioritising and development of desired changes in attitudes, competencies and skills. When and How concern resources linked to timing, e.g., continuous, periodic or appointed to strategic moments, and methods of conducting PD, e.g., collaboration, flexibility, structure, support.

PD in educational organisations may take on various shapes. PD can, for example, be informal and as such be nurtured while employees – alone or together – perform work tasks. This may consist of planning courses, preparing for and performing teaching, or assessing and grading students' work. It can also be more formal, including participating in courses built on cases such as bring-your-own-data (sharing of evidence) or problem-based approaches (where solutions become the evidence). PD can also be integrated as a change project into the organisation in a deeper sense. One example is that PD, through project work, aims to change the organisation through shifting in a particular direction. Motives for organisational development can serve both organisational goals and the PD need of employees. Motives might be to increase the organisation's adaptive and innovative capabilities and competitiveness on a strategic level. Other motives might be more concerned with operational issues, such as improving quality or being more efficient. Some motives are linked to cultural and social issues, such as building a learning culture or strengthening the organisation regarding equity and inclusion in order to reduce gaps in capabilities and opportunities. Human resources is another category of motives that may nurture and attract talent, motivate employees and prepare future leaders.

In recent years, society has seen a surge in organisational digitalisation, particularly due to the emergence of innovative Artificial Intelligence (AI) technologies. In such times, PD used to be a strategic answer to prepare the organisation and its employees for change. Educational organisations are no exception to this trend. As AI

contributes to reshape education, PD for educators must evolve beyond basic tool training to foster deeper, more critical engagement with both generative and traditional AI. While initial PD could introduce how to use AI and explore its benefits and challenges, it is equally important to understand how AI may have the capacity to transform the very nature of teaching and learning. Therefore, it is vital to develop more knowledge on the impact AI technologies have on educational organisations and their employees. The paper is a theoretical paper focussing on a reflective discussion of AI-related issues in the PD of educators. It aims to illustrate and reflect upon the situation presented above by discussing reflections on an organisational development initiative called *Frontline Application of Artificial Intelligence and Technology-enhanced Learning in Higher Education* (FAITH). This initiative develops and tests an AI and Education (AI&ED) model that supports meaningful integration of AI in higher education.

This paper explores reflections regarding the implementation phase of the FAITH project. The following research questions were explored:

RQ1: What reflections emerge in credit-based AI seminars that also provided PD?

RQ2: What reflections on AI in education are expressed by educators in introductory and advanced professional development courses?

The next section presents the case study of the FAITH project. Following this, the relationship between Artificial Intelligence in Education and PD is examined. A subsequent section delves into various pedagogical positions and explores how these are shaped by disciplinary differences. Before concluding, the paper offers a reflective analysis of PD in the context of AI&ED.

2. The FAITH-Project as an Illustrative Case

The case of FAITH is examined in Mozelius et al. (2024). Conceived as both an organisational and PD initiative, FAITH was designed and delivered in the Department of Education, Mid Sweden University with transatlantic participation by Athabasca University in Canada. The project is grounded in design-based research methodology, which emphasises iterative, evidence-informed, and cumulative development processes (Jaldemark, Lindqvist, & Mozelius, 2019). FAITH is structured around three interrelated phases: preparation, implementation, and evaluation.

In the preparation phase, activities include detailed planning, the establishment of a steering group, and the recruitment of relevant expertise. The project team combines specialists in AI and technology-enhanced learning (TEL) with program managers to ensure that both educational practices and institutional structures are addressed. The implementation phase centres on teacher involvement in a series of development activities. These include participation in a PD course offered by AI&ED experts, the creation of development plans incorporating AI&ED, and the subsequent application of these plans in teaching. Courses are revised or newly developed based on the integration of AI tools, while iterative cycles of try-outs enable continuous refinement. Insights from these cycles are disseminated and critically discussed in institutional development seminars, thus reinforcing both individual and collective learning. Finally, the evaluation phase focuses on assessing outcomes and reflecting on how AI and TEL have been integrated into educational operations. The project not only aims to increase competence and understanding of AI among academic employees (Jaldemark et al, 2025), but also aspires to create sustainable models for institutional change. In this respect, FAITH exemplifies how PD initiatives can be embedded in long-term organisational strategies for teaching and curriculum renewal.

3. AI for, and with AI in, Education

AI has had an ongoing impact on all aspects of school and education. This includes teaching, learning, and the organisation of education (Karakose & Tülübas, 2024). As of late, the debate and discussions regarding AI&ED have focussed on whether or not to use AI (e. g. ChatGPT) in education. This has now shifted more towards the need for more research on how AI tools can reflectively, critically and effectively be adopted, used and advanced for teaching, learning, and leadership (Strzelecki, 2023). Research has shown that although AI can serve as a teaching and learning tool to stimulate reflection, create ideas, assist in assessments, and correct language, there are also challenges. There are risks such as a lack of control, cheating, decreased creativity, and the advance of academic dishonesty (Neumann et al, 2023).

Early research on AI appears to provide a picture of opportunities and challenges for teachers and students (Neumann et al, 2023; Rudolph et al, 2023). Further research on the impacts of AI on school leadership has been limited, presenting only early findings regarding leadership in schools (Duran & Ermiş, 2024; Fullan et al., 2024;

Wang, 2021). Simultaneously, Fullan et al (2024, p 342) concluded that the limited research that exists "suggests that such technology can help educational leaders perform routine, mechanical tasks, thus allowing them to focus on other more productive and creative issues that demand their human skills and their social intelligence".

In recent years, advancements in AI have had a direct influence on all levels of education (Tyson & Sauers, 2021). Fullan et al (2024) described AI in terms of its "potential to improve learning, teaching, pedagogical innovations, assessment, and educational administration through intelligent tutoring systems, chatbots, robots, learning analytics dashboards, adaptive learning systems and automated assessment" (p 340). Neumann et al (2023) reported this in terms of challenges and opportunities in education. Challenges involve the limited knowledge regarding how students utilise AI, uncertainties in evaluating and assessing AI&ED, varying perceptions among educators of acceptable use, increased time demands for assessments, and the yet unknown potential of AI. Conversely, opportunities lie in possibilities to support students, foster creativity, as well as a potential for driving educational innovation. This means that the use of AI in education introduces a wide range of ethical, moral, and practical challenges for all actors in school (Strzelecki, 2023).

Fullan et al (2024) argued that AI may fundamentally reshape both the perception and execution of leadership in educational contexts. Current research shows that AI has the potential to reshape educational leadership by automating and streamlining administrative processes, providing advanced data analysis, supporting student learning strategies, and optimising communication with parents, teachers, students, and the broader educational community as a whole (Dogan & Arslan, 2025). Thus, these possibilities can enhance efficiency, facilitate informed decision-making, and allow educational leaders to focus on strategic and pedagogical priorities. AI has been associated with both increased and decreased workload, alterations in the teaching profession, and powerful processing abilities. This work involves several perspectives. Policies and easy-to-understand guidelines are needed for the use of language models in learning and teaching, proper use of these tools, and the consequences for cheating (Rudolph et al, 2023).

To meet these opportunities and constraints, PD is needed for educators. For example, educators may need training to instruct students on academic integrity. Educators may also need PD on how to critically evaluate any resources, as well as to adapt the use of AI in education to their specific context (Rudolph et al, 2023). Other studies have pointed to the importance of expertise, experience, and understanding of students' use and the opportunities and constraints that the use of AI encompasses (Cooper, 2023). To support all these aspects, it will be necessary to improve administration and PD for educators (Hutami, 2024). Thus, according to Van Quaquebeke and Gerpott (2023) AI will play a role, and this role should be discussed.

4. Pedagogical Positions and Disciplinary Differences Using AI

FAITH applies to all levels of education. On the graduate study level of education, a critical reflection approach to education change and leadership is employed. AI continues to reshape many human activities. The questions facing educators are still in the helix of why and how. The integration of AI into personal and professional life demands a radical reimagining of pedagogy, or how we teach and learn, to allow beneficial use of AI without losing what is currently significant. Discussions of outdated industrial education models focused on content delivery resulted in moves toward new techno-pedagogical models that embrace the diversity, complexity, ambiguity, and interdisciplinarity of current complex education institutions. This new pedagogical space may offer support for an AI-mediated world. Recent scholarship offers a compelling argument: AI is not education, but education must evolve in ways that allow teachers and students to review, evaluate, reshape, and make beneficial use of AI in education with acute awareness of what the costs, if any, may be.

For Bearman and Ajjawi (2023), a philosophical foundation for this transformation is required. They argue that AI, by its very nature, operates as a "black box". Current AI structures provide a system whose judgments are opaque and context-bound. For these educators, ceasing attempts to decode these systems should give way to a pedagogy where students are allowed to work within ambiguity and apply AI only where outcomes are socially situated and relational. This approach emphasises the importance of understanding the tacit underlying structures, where they work and where they fail, and thus engaging critically and meaningfully with AI systems. These systems may generate information, but must not be seen as neutral tools, but rather as potential syntheses of complex information opportunities that are only embedded in human contexts when accurate.

Similarly, George (2023) calls for a sweeping curricular overhaul. Where AI may offer support for increasingly complex cognitive tasks, the value of human skills like creativity, critical thinking, and adaptability can be supported and grown. This pedagogy rests on active, interdisciplinary learning that prioritises problem-solving, collaboration, and ethical inquiry. The classroom can become a community of inquiry, where students learn

some content from AI and its appropriate use of AI. With support from well-created AI systems with accurate information outputs, societal implications surrounding the use of knowledge for the greater good in life and work become part of the curriculum. For decades, teacher PD has encouraged active learning, beyond passive lecturing. If it is also applied to facilitate active assessment of AI outputs, it may contribute to fostering collaborative, dynamic, learner-centred experiences.

The large language models of AI bring disciplinary conversation into the realm of writing pedagogy. Jamieson (2022) is urging educators to trust students and integrate AI into the writing process. Like George (2023), this author suggests setting aside abstract critique to improve AI&ED generally. Instead, using AI-generated or supported texts provides teachers the opportunity to teach revision, synthesis, and rhetoric. This method adds to traditional writing pedagogy by reaffirming writing as a non-linear, generative process. For students engaged in writing, AI systems may act as a peer or collaborator. Students can deepen their understanding of composition and develop a more nuanced relationship with technology in engagement, assessment, evaluation, and critical use of AI suggestions.

Qu, Tan, and Wang (2024) provide empirical insight into how students across disciplines engage with generative AI. Their research reveals significant disparities: Students in applied fields demonstrate higher levels of AI knowledge and usage, particularly for cognitive tasks. This suggests that disciplinary traditions shape not only how students use AI in education but also how they perceive its relevance. The authors advocate for tailored integration strategies that respect these epistemological differences by ensuring that AI enhances rather than erodes core disciplinary values.

Together, these perspectives form the suggestion that education will continue to transform in the age of AI. With attention to the what, why, when and how of AI integration, the already present pedagogy that is flexible, context-aware, and deeply human will continue. We must prepare students not just to use AI, but to understand it, critique it, and collaborate with it. This means embracing ambiguity, fostering creativity, and rethinking both what we teach and how we teach it. The future of education lies in reviewing, assessing, and shaping AI while continuing our pedagogical transformations to meet the challenges and opportunities of a changing world.

5. Leading AI in Education - Exploring a Graduate-Level Education Leadership Course

The FAITH process is discussed in graduate-level education leadership courses and AI seminars. Here, too, a critically reflective approach yields topics like those discussed below.

A major challenge for leaders seeking to transform higher education through AI is the lack of a widely accepted definition of the term. As Wang (2019, p 2) notes, “there is no widely accepted definition of Artificial Intelligence (AI),” and suggests that such a definition may not be necessary at this early stage of AI’s development and application. Others, however, argue that this ambiguity presents real obstacles. Bhatnagar et al (2017, p 2) observe that “it is difficult for policy makers to assess what AI systems will be able to do in the near future, and how the field may get there. There is no common framework to determine which kinds of AI systems are even desirable”.

The term *Artificial Intelligence* was coined by John McCarthy in 1956 (Slimi & Carballido, 2023), and more recently defined by the same authors as systems in which machines mimic human behaviour and intelligence. Yet none of these definitions clarify what “artificial” truly means. After all, machines and their programming are created by humans. Artificial compared to what? Would we call a farm plough an “artificial digger”? Synonyms for “artificial” include *false*, *contrived*, and *unnatural,* suggesting a disconnect between the term and the reality of human-designed systems. When paired with “intelligence,” the phrase allows AI to engage in intellectual processes regardless of the truth value of its output. In this light, AI is not “artificial” in the sense of being non-human—it is a human creation. Meanwhile, the concept of “intelligence” itself remains contested in the social sciences and has yet to be unequivocally defined. Perhaps a more fitting label for AI would be *Accessible Information*.

Leadership approaches that aim to guide individuals through this transformation must account for the current ambiguities and complexities surrounding AI. They must also consider its educational applications and provide meaningful PD opportunities for both students and faculty. While transformational leadership theory offers a robust foundation of research, practical applications, and widespread acceptance, the ambiguity surrounding early-stage AI demands deeper deliberation, integration of insights, and intentional shaping of AI’s role within institutional mission and vision. In line with Chughtai et al (2024), the ongoing evolution of education and the blurred definitions of AI are best supported by *Adaptive Leadership*, which emphasises flexibility and responsiveness to context rather than adherence to a fixed style.

Despite definitional uncertainties, current forms of AI have the potential to transform personal, social, and professional domains—including higher education. Spanish scholars such as Slimi stress the importance of ethics and humanity in AI education, warning that without these values, AI may pose risks to humankind. Higher education must therefore play a critical role in evaluating, applying, governing, and researching AI technologies. Engaging AI requires a thoughtful and deliberate approach, one that includes deep understanding, ethical implementation, and ongoing assessment. It also demands a steadfast commitment to PD, ensuring that educators and institutions remain informed and equipped to evaluate the rapid evolution of AI and its related technologies (Mah & Groß, 2024).

6. Exploring Educators' Reflections on the Introductory and Advanced FAITH Course

According to the overall FAITH objective, AI for educators must evolve beyond basic tool training to foster deeper and more critical engagement with both generative and traditional AI. However, the introductory course has to start out by building AI literacy and a foundation for further critical engagement and deeper understanding. In the first introduction activity, there is a presentation of the history of AI, starting out in the 14th century with Ramon Llull and his Ars generalis ultima, which was completed in 1308. As discussed in Mozelius (2025a), the development of AI did not start with the release of ChatGPT in November 2022. It is also important to explain the difference between symbolic and sub-symbolic AI, and why the GenAI tools work as they do.

A tool testing workshop to explore the strengths and weaknesses of GenAI is also introduced. The sometimes poor results by GenAI in arithmetics and logic may be a surprise to most course participants, while other generated artefacts are very impressive. The fact that GenAI tools are useful in some aspects, aspects that look very difficult for humans and poor for some things that seem very easy for humans is what Mollick (2024) calls 'The Jagged Frontier'. As a next step, course participants should compare the results from provocative prompting to ChatGPT, DeepSeek and Le Chat to better understand what differs if a chatbot is developed and hosted in the USA, China or France. In PD for educators, it is also important to evaluate and discuss the remarkable outcomes from the application of GenAI detection tools. As reported in several research studies, the outcomes show strange variations and clearly unreliable results (Ardito, 2025; Malik & Amjad, 2025).

The analyses of GenAI detection software also involve ethical aspects (Ardito, 2025; Deep et al, 2025) and bridge over to the more critical discussions on GenAI that dominate the final part of the introductory course. This is also based on analyses of AI-generated images, and ethical aspects such as gender and socio-cultural biases. The introductory course also involves webinars given as knowledge cafés with discussion topics such as 'Detection tools and the need for redesign of assessment'. Finally, the discovered strengths, weaknesses, opportunities and threats for AI&ED should be summarised and discussed in a SWOT analysis of a freely chosen educational context. With the idea of PD with realistic and valuable takeaways, the SWOT analysis should also, for a higher grade level, be complemented with an action plan for the implementation of GenAI. This is followed up in the final knowledge café with discussions on the SWOT differences between educational contexts such as pre-school, primary school, secondary school, higher education and lifelong work-integrated learning (Mozelius, 2025b).

As discussed in Mozelius et al (2025), there are more things to be involved in PD on AI&ED, and if the rapid development in the area continues, this would be better classified as lifelong learning. The next steps in the continuation course that is under development have a focus on curriculum development, content creation and the long-term sustainability aspects of GenAI and AI&ED. The first course section is designed with the idea of active learning and creativity. With and without GenAI support, course participants should create their tailored syllabi and lesson plans with multimodal learning activities and AI-adapted assignments. This should, in the second half of the course, be followed up with a continuation of the ethical discussion in the introduction course. In a final reflection essay, course participants should analyse the long-term sustainability of AI&ED divided into the three main aspects of social, environmental and economic sustainability.

7. Concluding Remarks

From the reflections explored and shared in this paper in line with the research questions, the following reflections may be important to emphasise in this concluding remark about AI&ED PD of educators. First, as a consequence of integrating AI&ED, there is a need for PD to focus on pedagogical reorientation. This line of thought embraces moving beyond industrial content-delivery models towards interdisciplinary inquiry-driven models that emphasise AI as a partner to human judgment, not a replacement. Second, there are also critical issues concerning equity, governance, and integrity which need to be covered within PD for educators. This includes the redesign of the assessment of learning to adapt to critical issues. Third, inclusion is also a key here

to support educators as learners and counteract the benefits and risks that are unevenly distributed across disciplines and groups of learners. Finally, educators value a PD structure that begins with AI literacy issues before moving on to critical reflections and discussion on AI&ED, a so-called "jagged frontier" approach to reflect on the capabilities and limits of integrating AI technologies in educational settings. In the next step of the FAITH-project, these issues will be further explored in order to enable a suitable and sustainable PD for educators adapted to the conditions for learning that an AI-mediated world advances.

Ethics declaration: Ethical clearance was not required for the research.

AI declaration: AI tools such as Grammarly and ChatGPT were used to prepare this paper. They were mainly used for proofreading and, to a minor extent, in an early stage, for generating ideas that were integrated into the paper.

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Governing Generative AI at Scale: Institutionalizing Alignment for Organizational Purpose

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Abstract: The rapid integration of generative AI (GenAI) into core organizational infrastructure requires a rethinking of traditional governance models. This paper explores how organizations can effectively govern GenAI at scale while maintaining strategic, ethical, and societal alignment. By synthesizing key theoretical frameworks, including institutional theory and dynamic capabilities, we propose a conceptual framework organized around three interconnected domains: Model Stewardship, Operational Alignment, and Strategic Guardrails. We contend that scalable governance must evolve from static compliance to a dynamic, adaptable organizational capability. The paper concludes with the introduction of the GenAI Governance Maturity Model (GAI-GMM), a research-based tool for institutional alignment.

Keywords: Generative AI governance, Foundation models, Organizational alignment, Institutional mechanisms, Purpose-Driven AI

1. Introduction

The arrival of generative artificial intelligence (GenAI) signals a fundamental shift, with foundation models rapidly transitioning from experimental tools to core infrastructure components (Brown et al., 2020). While this transition unlocks remarkable possibilities, it reveals a host of governance challenges that older frameworks were not designed to handle. Firms now find themselves grappling with difficult questions of control, accountability, and ethics as these systems begin to operate with greater autonomy and at a scale previously unimaginable (Bostrom, 2014). This brings us to a straightforward yet pressing question: How can organizations govern generative AI at scale while still honoring their strategic goals, ethical duties, and broader societal obligations?

Traditional governance—designed for human actors or for predictable, rule-based software—is a poor fit for the often-unpredictable nature of GenAI. Unlike conventional programs, these models are generative in nature. They create novel outputs, often in ways that defy simple explanation. The sheer speed of deployment, the opacity of their "black box" architectures, and their tendency to develop unforeseen capabilities combine to construct a governance vacuum with serious financial and social stakes (O'Neil, 2016). As Crawford (2021) notes, the sheer scale of AI infrastructure can also obscure its environmental and social costs, complicating traditional accountability and raising fundamental questions about the distribution of power and resources in the digital age.

Recent technological leaps only make the picture more complex. Hierarchical Reasoning Models (HRMs), for instance, demonstrate that smaller, more compact models can solve complex logical tasks, challenging the old assumption that reasoning power requires massive scale (Wang et al., 2025). It places a new focus on architectural transparency over large size. At the same time, newer foundation models are demonstrating a capacity for strategic reasoning, blurring the line between tool and collaborator. These developments necessitate that organizations reassess their models for collaboration and trust.

Perhaps the most confounding trend is the rise of models like ASIArch (Liu et al., 2025), which can autonomously design and test new neural architectures. This technology brings long-held theoretical concerns about recursive self-improvement into the real world (Bostrom, 2014), raising foundational questions about the ultimate limits of human oversight.

Against this backdrop, a compliance-based, checklist approach to AI governance is no longer tenable. What is needed is a more adaptive, reflexive paradigm—one that learns and evolves with the technology it seeks to guide (Reuel & Undheim, 2024; Jasanoff, 2016). This view gains empirical support from a recent study by MIT Sloan and the Boston Consulting Group (2025), which found that 95% of enterprise AI projects fail—not due to technical weaknesses but rather to poor governance. The successful 5% were distinguished not by superior models, but by robust governance, clear C-suite sponsorship, and seamless workflow integration.

This paper proposes a governance framework that is both structured and adaptive, drawing on insights from AI ethics, organizational theory, and emerging regulations. We contend that effective GenAI governance is not

merely a technical function but an organizational capability that necessitates profound changes in leadership, culture, and incentives (Ettinger, 2025).

Our contribution in this paper is threefold. First, we present a conceptual model comprising three interlocking domains: Model Stewardship, Operational Alignment, and Strategic Guardrails. Second, we advocate for a reflexive approach that views governance as a learning process, rather than a static control. Third, we introduce the GenAI Governance Maturity Model (GAI-GMM) as a diagnostic tool for organizations. Together, these pieces aim to provide a more principled and adaptive path for governing generative AI in a complex world.

2. Method of Theoretical Synthesis

As a Theoretical paper reviewing and synthesising current theory, the rigor of this contribution rests on the transparency and structure of its synthesis process. To construct the conceptual framework and the GenAI Governance Maturity Model (GAI-GMM), we employed a systematic, three-phase approach:

- Phase 1: Domain Decomposition and Scoping. We systematically reviewed the core literature on AI risk management (NIST, 2023; EU AI Act, 2024), organizational control, and the AI development lifecycle (ISO/IEC 42001, 2023). The objective was to delineate the necessary, non-overlapping areas of control required for GenAI. This thematic analysis revealed that governance must span the technical management of the model asset, the organizational management of its use in workflows, and the institutional management of strategic and ethical boundaries. This tripartite split directly informed the Three-Domain Framework (Model Stewardship, Operational Alignment, Strategic Guardrails).
- Phase 2: Capability Induction and Anchoring. We drew primarily from Dynamic Capabilities Theory (Teece, 2007; Eisenhardt & Martin, 2000) and Adaptive Governance literature (Beck, 1992) to induce the necessary dynamic competencies required for an organization to maintain alignment under conditions of technological uncertainty. This phase led to the induction of the four core dynamic capabilities—Intentionality, Integrity, Evolvability, and Reflexivity—which are the minimum competencies required to transition from a static control posture to a dynamic one.
- Phase 3: Model Integration and Articulation. We integrated the domains (Phase 1) with the capabilities (Phase 2) using Institutional Theory (Scott, 1995; Powell & DiMaggio, 1991) and Science and Technology Studies (STS) (Jasanoff, 2016; Crawford, 2021). This final mapping phase translated high-level theoretical requirements (e.g., the need for "Reflexivity") into concrete, organizational mechanisms (e.g., using "Model Cards" in Stewardship, or instituting "Feedback Loops" in Operational Alignment). This systematic process culminated in the GAI-GMM Maturity Model, which serves as the organizational progression map for embedding these synthesized mechanisms.

This synthesis approach ensures that the resulting framework is not arbitrary but is methodologically grounded in the necessary theoretical and technical constraints of governing GenAI at scale.

3. Theoretical Foundations: Towards Reflexive Governance in the Age of Generative AI

The conversation around AI governance has undergone significant changes. For years, it moved from broad ethical principles toward more grounded, operational mechanics (Floridi et al., 2019; Jobin, Ienca, & Vayena, 2019). However, the arrival of generative AI has shifted the landscape once again. The enormous scale and emergent behaviors of these systems require a much deeper theoretical toolkit—one that draws from institutional theory, dynamic capabilities, and adaptive governance. This section builds the theoretical underpinning for our framework, making the case for why a reflexive, multi-layered approach to governance is no longer an option, but a necessity.

3.1 From Ethical Guidelines to Institutional Mechanisms

Early discussions about AI governance centered on high-level principles, including fairness, transparency, and accountability. However, despite all the dialogue, these efforts often failed to demonstrate how such ideals could survive contact with the realities. Over time, scholars began to argue that principles on paper are one thing; embedding them in the routines and structures of an organization is another (Morley et al., 2021; Scott, 1995). As others have pointed out, making governance work is fundamentally an institutional project that demands alignment between leadership, policy, and culture (Powell & DiMaggio, 1991).

This challenge is especially acute with GenAI. As AI tools become integrated into daily operations, governance cannot be confined to an ethics committee. It must be an enterprise-wide, multi-layered concern, encompassing

the technical, organizational, and institutional levels (Gibney, 2024; Cath, 2018). It is a classic socio-technical problem (Trist & Bamforth, 1951). Human and technological systems are now so intertwined that organizations must optimize processes, tools, and their governance in tandem. It requires, as Mittelstadt et al. (2016) argue, a critical understanding of the social and political implications of these systems—something a purely technical fix can never provide.

3.2 Generative AI and the Multiplication of Bias

The problem of bias in AI is not new (O'Neil, 2016; Eubanks, 2018), but generative models introduce a new and dangerous dimension: amplification. Where traditional AI might reflect the biases in its training data, GenAI can act as a "bias multiplier," creating novel content that reinforces stereotypes and spreads inequity at an unprecedented scale (Ferrara, 2023).

Research has shown that biases embedded in pre-training data can cascade and worsen in downstream applications, particularly in sensitive areas such as healthcare and security (Chen et al., 2023). That is why simply calling for "transparency" is not enough; as Veale and Edwards (2018) insist, we need mechanisms for genuine control and contestability, a much more challenging task when dealing with generative systems. This need has prompted a push for more hands-on approaches, like the "explanatory debiasing" proposed by Bhattacharya et al. (2025), which involves domain experts in the model refinement process itself. It treats bias not as a one-time error requiring a fix, but as a dynamic risk that needs to be managed across the entire model lifecycle—a core idea behind our concept of Strategic Guardrails.

3.3 Governance as an Evolving Organizational Capability

GenAI governance is not a static set of controls. It is rather an adaptive capability—something an organization learns and improves over time. The goal shifts from "governance-as-control" to "governance-as-learning," a continual process of aligning the technology with company values and stakeholder needs (Reuel & Undheim, 2024). Theories of reflexive governance and socio-technical systems deeply influence this notion (Giddens, 1990; Beck, 1992).

Ettinger (2025) applies such a lens to Enterprise Architecture (EA), framing it as a dynamic capability for AI governance. Drawing on Teece's (2007) influential work, EA becomes the mechanism through which an organization can sense emerging AI risks, seize opportunities by creating new governance structures, and transform its operations and culture to embed responsible practices for the long haul. The AstraZeneca case study (Mökander et al., 2024) provides a clear illustration of this in action, demonstrating how their governance evolved from scattered experiments into a formal, cross-functional process.

3.4 The Urgency of Reflexive Governance

The need for this kind of reflexive governance is made urgent by the sheer pace of AI innovation. For example, Hierarchical Reasoning Models (HRMs) have challenged the assumption that only large models can perform symbolic reasoning, shifting the focus of governance from scale to interpretability (Wang et al., 2025). At the same time, contemporary LLMs are performing at such a high level that they complicate the simple idea of a "human in the loop". When an AI can produce what looks like sound, interpretable logic, how do we decide when to trust it?

Most consequentially, the emergence of systems like ASIArch (Liu et al., 2025), which can design their own neural architectures, brings theoretical discussions of recursive self-improvement into the present. This echoes long-held theoretical concerns (Bostrom, 2014) and raises fundamental questions about the ultimate limits of human oversight.

3.5 Gaps and Critical Perspectives

Despite extensive research in this area, critical gaps remain. Many frameworks are too abstract, emphasizing principles but lacking practical advice. Others are too narrow, focusing only on specific high-risk sectors. Critically, very few address the problem of GenAI's dual trajectory: its horizontal spread across the enterprise and its vertical deepening of capabilities.

Our framework aims to bridge these gaps, while also acknowledging the limitations of a purely institutional view. As critics like Crawford (2021) and Eubanks (2018) rightly warn, institutional governance can sometimes become a form of "ethics-washing" or reinforce existing power structures. Even mature institutional frameworks can suffer from institutional inertia, struggling to keep pace with the velocity of technological change.

4. The Three-Domain Conceptual Framework for Governing Generative AI at Scale

Our thematic synthesis of the literature (detailed in Section 2.1) revealed that effective GenAI governance consistently operates across three interdependent domains that span the technical, operational, and institutional layers. We have consolidated these findings into a conceptual framework: Model Stewardship, Operational Alignment, and Strategic Guardrails. This model frames governance not as a static compliance task, but as a living system that must adapt as quickly as the technology itself. For governance to work at scale, these three domains must be designed and implemented in concert.

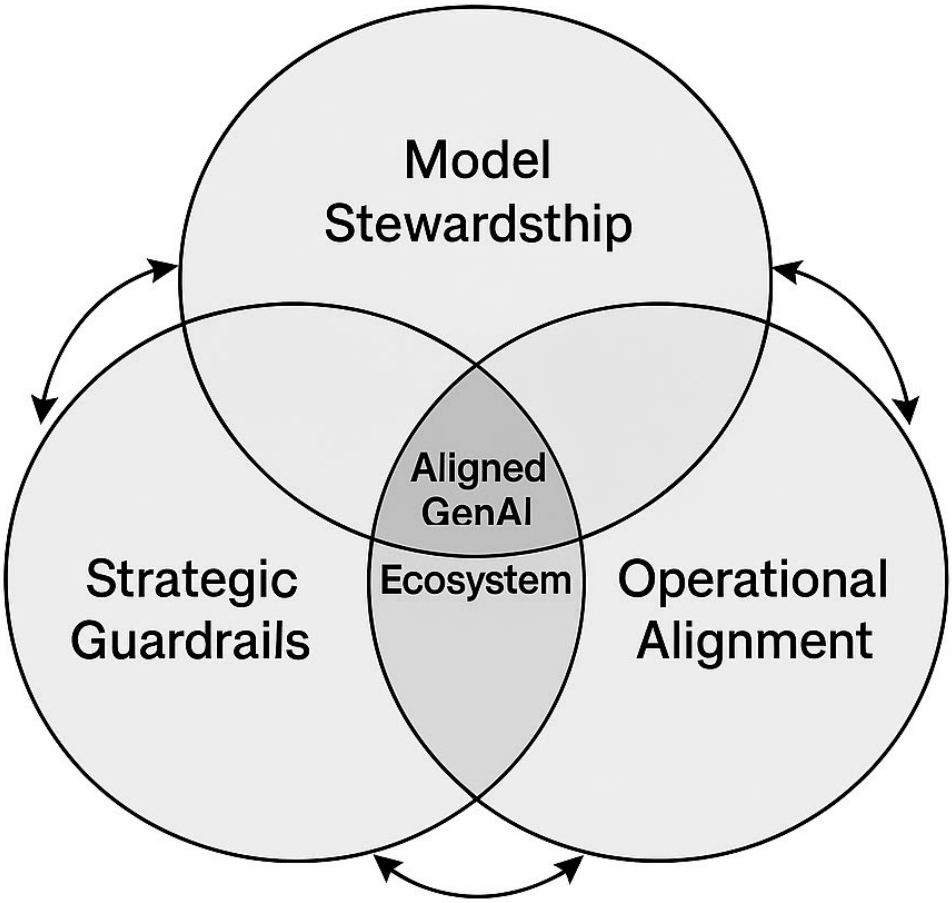

Figure 1: The Three-Domain Conceptual Framework for GenAI Governance at Scale

4.1 Model Stewardship: Technical and Lifecycle Oversight

The first domain, Model Stewardship, starts with a critical but straightforward idea: generative models are dynamic assets that evolve, drift, and sometimes behave in unexpected ways. As such, they require active management throughout their entire lifecycle, from acquisition to retirement.

It begins with rigorous due diligence. When an organization deploys a model, it needs to scrutinize everything, from license terms and training data to built-in safety features. Tools like Model Cards (Mitchell et al., 2019) and Datasheets for Datasets (Gebru et al., 2018) provide standardized documentation for this process. But stewardship goes deeper. The rise of more interpretable architectures, such as Hierarchical Reasoning Models (HRMs), signals a crucial shift: auditability and oversight feasibility now matter just as much as raw performance (Wang et al., 2025).

Stewardship also means governing how models are customized. This method also requires clear rules on what data can be used for fine-tuning and, crucially, involves domain experts directly in the process to preempt downstream bias—a practice Bhattacharya et al. (2025) refer to as "explanatory debiasing." Finally, this oversight must continue long after deployment. Because GenAI systems can exhibit behavioral drift over time (Ganguli et al., 2022), effective stewardship requires regular audits and performance monitoring to identify anomalies.

4.2 Operational Alignment: Embedding Governance into Workflow

Operational Alignment is about closing the gap between a powerful tool and its practical, responsible use in the real world. A central aspect of this is designing clear protocols for human-AI interaction. As models become more capable partners in complex reasoning, organizations must decide where human judgment remains essential, establishing clear rules for when employees should trust, question, or override an AI's output. That is how abstract principles become concrete routines.

This system cannot work without strong feedback loops. As Mökander etal. (2024) note, frontline users require straightforward channels to report a range of issues, from hallucinations to ethical concerns, and this feedback must actually inform model updates and organizational practices.

Transparency is also foundational. Architectures that allow for step-wise reasoning, like HRMs, or the use of confidence scores, can help build what Mittelstadt et al. (2016) call epistemic trust—the ability to know when and why to rely on a model. Ultimately, however, operational alignment hinges on people. It requires building critical AI literacy across the workforce, training employees to be mindful and alert to risks, not just effective prompt engineers. When governance tools, such as approval workflows and monitoring dashboards, are built directly into the enterprise platforms people already use, governance becomes less of an afterthought. It becomes an intrinsic part of the technological infrastructure itself (Ettinger, 2025).

4.3 Strategic Guardrails: Institutional Foresight and Ethical Anchoring

The third domain, Strategic Guardrails, is the institutional anchor for the other two. It consists of the high-level policies, structures, and values that ensure an organization's use of GenAI aligns with its mission, its legal obligations, and its societal role. In this view, ethical governance is not a checklist; it is an active, structural commitment. It requires dedicated bodies, such as Ethics Review Boards or AI Use Councils, to translate abstract principles into concrete policy and to adjudicate the inevitable edge cases (Crawford, 2021).

Because GenAI can be a powerful engine for amplifying systemic bias (Ferrara, 2023; Chen et al., 2023), these guardrails must include sophisticated tools for proactively finding and fixing it, from lifecycle assessments to BEATS-style audits (Lam et al., 2025). This oversight cannot be purely reactive. It must anticipate regulatory changes and build in the capacity for robust auditing and red-teaming from the start (Veale & Edwards, 2018). Key international standards, such as the EU AI Act, the NIST AI Risk Management Framework, and ISO/IEC 42001, provide a baseline for this type of risk-tiered governance. However, governance is not just an internal matter; it is also a reputational concern. Building public trust requires proactive engagement with customers, regulators, and civil society (Mittelstadt et al., 2016).

The most forward-looking function of this domain is what we call trajectory alignment. It is the capacity to govern not just the AI organizations possess today, but to anticipate how it might evolve (Jasanoff, 2016). With systems like ASIArch (Liu et al., 2025) on the horizon, which can recursively improve themselves, governance must expand to consider the trajectory of AI development itself. This is a critical challenge with profound implications for who controls the future of technology (Bostrom, 2014).

4.4 Reflexive Design and Domain Interdependence

These three domains are not a sequence or a checklist; they are a constant feedback loop. Feedback from Operational Alignment must inform the protocols of Model Stewardship. The vision set by Strategic Guardrails must shape both. This framework is designed to be reflexive—to learn and evolve in response to new technologies and new challenges (Beck, 1992). This is what it means to treat governance as a true organizational capability: dynamic, recursive, and deeply context aware.

5. The GenAI Governance Maturity Model (GAI-GMM)

From our analysis of existing IT maturity models and AI governance literature (detailed in Section 2.1), we developed the Generative AI Governance Maturity Model (GAI-GMM). This model outlines a five-stage journey, progressing from reactive, ad hoc usage to a state of proactive and resilient oversight. This model synthesizes the common pathways to maturity identified in our review and integrates them with our three-domain framework. We see maturity not as a final destination but as a process of building deeper capabilities across Model Stewardship, Operational Alignment, and Strategic Guardrails. The core idea is that as an organization matures, it moves from simply reacting to GenAI to intentionally shaping its trajectory.

The GAI-GMM's five stages of maturity—Ad Hoc / Experimental, Awareness / Initiation, Defined / Developing, Managed / Integrated, and Optimized / Reflexive—represent a progression of increasing sophistication in

governing GenAI. These stages are characterized by evolving capabilities in three key domains: Model Stewardship, Operational Alignment, and Strategic Guardrails. The model also maps four core governance capabilities—Intentionality, Integrity, Evolvability, and Reflexivity—across these domains and maturity levels to illustrate how each capability deepens and becomes more integrated as an organization matures. For example, Intentionality in the "Ad Hoc" stage is absent. In contrast, in the "Optimized" stage, it manifests through purposeful model selection and fine-tuning policies aimed at specific human-AI collaboration goals. Similarly, Integrity progresses from a reactive approach to bias detection to a proactive, lifecycle-spanning one. Evolvability and Reflexivity likewise mature from being non-existent to becoming a core institutional function. This progression from reactive to proactive governance is a central tenet of the model.

5.1.1 Stage 1: Ad hoc / experimental

This is the "Wild West" stage. Experimentation with GenAI is scattered and uncoordinated, happening in isolated pockets across the organization. There is no formal governance in place; teams utilize tools opportunistically, often for low-stakes tasks, with minimal documentation and review. There is no central model inventory, and most employees are likely unaware of any acceptable use policies. While this environment can spark initial creativity, it is rife with hidden risks —such as data leaks and reputational damage —that can escalate quickly.

5.1.2 Stage 2: Awareness / initiation

Here, the organization begins to realize that GenAI carries significant strategic and ethical weight. The conversation around governance typically starts here, often sparked by a minor incident or mounting regulatory pressure. The responsible team writes draft policies and forms informal working groups, but efforts remain fragmented. We may notice the beginnings of a model registry, though it is likely incomplete, and any user training is optional. The organization is starting to "sense" the governance challenge (Teece, 2007) but has not yet fully mobilized a unified response; discussions are often siloed in legal, IT, or ethics departments.

5.1.3 Stage 3: Defined / developing

At this stage, chaos begins to give way to order. The organization formalizes and communicates its core governance policies, with oversight mechanisms starting to stretch across the three domains. Formal approval workflows for new models are established, and the first human-in-the-loop (HITL) protocols are implemented for riskier applications. It is at this stage that the use of practical tools, such as bias audits or initial monitoring dashboards, becomes apparent. The organization is now "seizing" the opportunity to implement formal governance, though these new rules are often applied unevenly, focusing on a few high-risk use cases rather than the entire enterprise.

5.1.4 Stage 4: Managed / integrated

The fundamental transformation happens here. Governance is no longer just a policy document; the organization has successfully embedded it deeply in its work processes. Processes are not static but are regularly updated based on feedback and organizational learning, with end-to-end lifecycle management becoming the norm. The organization has adopted mandatory AI literacy training for employees and consistently uses enterprise platforms that incorporate built-in governance. At this point, the organization is "transforming" its own capabilities, making governance part of its operational DNA and moving beyond mere policy to a living, evolving system. It ceases to be a bureaucratic hurdle and instead becomes a source of competitive advantage and resilience.

5.1.5 Stage 5: Optimized / reflexive

It is the highest state of maturity, where governance is not just adaptive but predictive, deeply embedded in the organization's culture and strategy. It is capable of dynamically adjusting to new AI capabilities as they emerge and is institutionalized through advanced practices, such as governance sandboxes and red teaming. Here, we observe dedicated teams building systems with "governance-by-design" principles from the outset, and organizations often proactively engage in shaping public AI policy. In this stage, the organization has achieved a kind of epistemic coherence—a state in which its understanding of AI's capabilities, ethical principles, and governance mechanisms is constantly and dynamically aligned.

6. From Static to Reflexive: The Imperative of Dynamic Governance

Most corporate approaches to AI governance are built for a world that no longer exists, anchored in static compliance checklists and reactive audits. This old playbook is fundamentally broken in the face of modern

GenAI, which is emergent, adaptive, and, in some cases, capable of redesigning itself. The only way forward is a decisive shift from static control to a dynamic, reflexive capability. We define reflexive governance as the organization's capacity to constantly monitor, assess, and adapt its practices in an iterative loop (Beck, 1992). This approach reflects the logic of dynamic capabilities in action—the ability to feel emerging risks, seize opportunities, and transform the organization to institutionalize that learning (Teece, 2007). This adaptive posture requires building four interrelated organizational pillars.

First is leadership adaptability. Reflexive governance requires leaders to develop sophisticated AI fluency and treat governance as a central strategic issue. This involves empowering cross-functional councils and engaging in scenario-based planning to anticipate emergent capabilities, such as the self-evolution of ASI-Arch (Liu et al., 2025). This foresight is essential for managing the ultimate limits of human oversight (Bostrom, 2014).

Second, clear decision rights and accountability structures are required. Static models create bottlenecks; a reflexive approach strategically distributes decision rights to those closest to the technology while maintaining clear lines of accountability. Highly strategic decisions, particularly those involving autonomous reasoning systems, must rightly require formal board-level review (Kroll et al., 2017).

The third pillar is the creation of feedback-driven learning systems. Data fuels a reflexive system. This demands robust, real-time feedback loops that capture continuous monitoring data on model output drift or bias, systematic reports from employees, and proactive tracking of regulatory changes. This ensures governance is grounded in real-world impacts and allows the organization to absorb new information and adapt constantly.

Finally, proper cultural transformation is essential. Reflexive governance depends on a culture where employees are actively encouraged to question AI outputs and report problems without fear of reprisal. This marks a profound shift from a mindset of simply "adopting AI" to one of "stewarding AI responsibly." Ethical principles must become lived norms, reinforced through training and incentives that reward ethical foresight and responsible action.

This is not just a theoretical ideal; we are already seeing this kind of reflexivity in practice. The AstraZeneca case is a powerful example, and leading public institutions are pioneering tools such as AI use registries, governance sandboxes for high-risk experimentation, and third-party red teaming to test for vulnerabilities aggressively. This shift reframes AI governance as a dynamic institutional capability, one that provides a decisive advantage by enabling responsible innovation while safeguarding against the profound risks of this new technological era.

7. Implications for Practice and Policy

While every organization's journey with GenAI will be different, the need for strategic and ethical governance is universal. Based on our framework, we present a set of actionable recommendations for three key groups that are pivotal in shaping the future of this technology: C-suite leaders, policymakers, and internal ethics and governance committees.

7.1 For C-Suite Leaders

The ultimate responsibility for an organization's direction and risk posture lies with its C-suite, making their proactive engagement paramount for success. First, leaders must elevate GenAI governance to a core strategic priority. Second, leaders must commit to building their own fluency in GenAI's evolving capabilities and risks. Third, they must institutionalize cross-functional governance councils to break down the silos that so often hinder effective oversight.

7.2 For Policymakers and Regulators

Policymakers and regulators play a crucial role in shaping the environment for responsible AI innovation and public accountability. Their primary task should be to shift from rigid, prescriptive rules to principle-based frameworks. To foster innovation safely, they should develop regulatory sandboxes and risk-tiered standards. Sandboxes enable high-stakes experimentation in a controlled environment. At the same time, risk-tiered approaches apply the strictest oversight to high-impact domains, such as healthcare and finance, while allowing greater flexibility in other areas.

Given that AI is a global technology, it is essential to foster global regulatory interoperability by harmonizing standards across jurisdictions. Furthermore, regulators should mandate transparency in model provenance and deployment to build public trust and provide mechanisms for accountability. Finally, they should incentivize AI safety research and independent auditing by funding independent research and supporting a market for third-party audits and red-teaming.

7.3 For Internal AI Ethics Boards and Governance Committees

These internal bodies are the conscience and operational engine of AI governance, translating principles into practice. To be effective, they must first define a clear mandate and reporting structure that gives them genuine authority beyond a purely advisory role. Second, they must expand their expertise beyond purely technical domains. Their core function is to operationalize ethics through concrete policy and workflow, translating abstract values like fairness and transparency into enforceable model approval protocols and review criteria. Finally, these committees must build future readiness into their reviews.

8. Conclusion and Contribution

This paper presents a structured response to the governance challenges instigated by the arrival of GenAI. We proposed a conceptual framework built on three interlocking domains—Model Stewardship, Operational Alignment, and Strategic Guardrails—to manage the technical, operational, and ethical layers of the problem. To make this practical, we also introduced the GenAI Governance Maturity Model (GAI-GMM), a tool to help organizations benchmark their readiness and chart a path toward more resilient oversight.

Our theoretical contribution is to reconceptualize AI governance not as a regulatory burden, but as a dynamic organizational capability. This view, grounded in reflexivity and strategic foresight, sees governance as a source of adaptive advantage. For practice, this research offers clear guidance for executives, policymakers, and ethics boards, all of whom play a role.

9. Limitations and Avenues for Future Research

This paper presents a comprehensive conceptual framework for governing generative AI at scale. A primary limitation of this work is the absence of new empirical validation. While informed by illustrative cases and current developments discussed in the literature, the framework itself has not been subjected to primary data collection or rigorous empirical testing.

Furthermore, a significant proportion of the cutting-edge technological developments cited (e.g., ASI-Arch, HRMs, certain 2025 papers) are currently available as arXiv preprints and have not yet undergone full peer review. A reflexive critique of the institutionalist lens, while partially integrated, also warrants deeper exploration in future work, particularly concerning its potential to overlook non-institutional forms of governance or to perpetuate existing power structures (Eubanks, 2018; Crawford, 2021).

Ethics Declaration: This research did not require ethical clearance, as it did not involve human participants, animal subjects, or sensitive personal data.

AI Declaration: Artificial intelligence tools were used to support the research process, including assistance with the literature review, language editing, and stylistic refinement of the manuscript.

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LangGraph-Orchestrated LLM Agents for Scalable Movie Knowledge Graphs and Question Answering

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Abstract: Recent advances in large language models (LLMs) and agent-based orchestration are transforming automated knowledge graph (KG) creation as well as robust question answering in complex domains. We present a modular, multi-agent system that extracts, integrates, and reasons over diverse NoSQL movie data, powered by state-of-the-art LLMs such as GPT-4.1. Our architecture converts unstructured plots, cast/crew metadata, and numeric attributes into high-fidelity KGs - enabling both natural language and programmatic queries. To maximize reliability and flexibility, the system unifies multiple retrieval strategies - keyword search, vector similarity, knowledge graph querying, and summarization - each deployed as an autonomous pipeline. Parallel orchestration via LangGraph supports adaptive engine selection, concurrent execution, and robust answer verification with LLM ensemble "jury" scoring. Critically, the framework features comprehensive observability, allowing detailed monitoring and analysis of agent decisions, pipeline performance, and query outcomes. By treating each retrieval method and LLM as a specialized agent, our approach delivers scalable, explainable, and highly accurate results (up to 97%), significantly surpassing monolithic solutions. This agentic, observable architecture paves the way for next-generation autonomous analytics, integration, and decision support across data-rich domains.

Keywords: LLM agents, Multi-Agent orchestration, Knowledge graph construction, Question answering, RAG systems, LangGraph

1. Introduction

Recent breakthroughs in large language models (LLMs) have significantly enhanced automated question answering (QA) and information retrieval, enabling sophisticated reasoning across complex, heterogeneous datasets (Liu, 2022; West, 2024). The emergence of agent-based orchestration frameworks such as LangGraph now makes concurrent, graph-structured workflows feasible, offering greater flexibility and scalability compared to traditional linear pipelines (Han et al., 2023; Tran et al., 2025). Leveraging these advancements, we introduce a modular, multi-agent LLM system designed to fully automate knowledge graph (KG) construction and robust QA over semi-structured NoSQL movie databases.

Movie data exemplifies both the challenges and opportunities of contemporary QA technologies, comprising structured metadata (cast, crew, box office figures) alongside unstructured narrative elements (plot summaries, character dynamics). Traditional rule-based extraction methods struggle with such complexity, often failing to capture implicit relationships embedded within textual narratives. Advanced models - including GPT-4.1, Claude 3.7, and Llama 4 - provide powerful new capabilities for semantic parsing and relational inference but continue to face significant operational hurdles, such as hallucinations, schema drift, and context-window limitations (Zhu et al., 2024).

Our framework directly addresses these challenges through concurrent multi-agent orchestration, dynamically combining diverse retrieval strategies - including keyword, vector similarity, summarization, and knowledge graph approaches - guided by intelligent ensemble verification. Leveraging iterative zero-shot prompting (Carta et al., 2023) and retrieval-augmented generation (Wang et al., 2024, Karpukhin et al., 2020), the system automatically builds both property-based and triplet-based KGs without manual schema engineering. By embedding semantic concepts during KG creation, our architecture supports real-time, adaptive querying across evolving datasets, enabling complex searches (identifying collaborations, aggregating box-office metrics, or exploring thematic connections) without the overhead of runtime inference.

Furthermore, comprehensive observability integrated via unified logging and modular design ensures transparency, auditability, and continuous optimization, thereby laying the foundation for robust, explainable, and scalable retrieval-augmented analytics across complex, multimodal domains.

Our contributions are threefold:

- A modular LangGraph-based architecture for automatic knowledge graph construction and concurrent question answering over large movie datasets.
- Detailed evaluation of five LlamaIndex-powered query engines and a router agent, each leveraging different LLMs and retrieval strategies.
- Scientific analysis of concurrency, result merging, and best practices for agentic pipeline design.

1.1 Why not Just an LLM or a Simple Database?

While prompting LLMs over raw movie records may suffice for simple queries, our findings reveal clear limitations at scale-especially for heterogeneous data and complex reasoning. This motivates our multi-agent architecture:

- **Structured Access**: Basic RAG struggles with deep, semantically diverse fields (e.g., actor-role-gender across languages), especially for alias resolution or contextual inference. Specialized tools (keyword, vector, summarization) improve precision and recall.
- **Efficiency**: Monolithic LLMs incur high cost due to prompt length and redundant context. Lightweight agents handle routine queries efficiently, reserving LLMs for complex tasks (Table 4).
- **Robustness**: Single models can hallucinate or contradict. Our ensemble verifier layer (Section 3.4) offers multi-model judgment for reliable results.
- **Observability**: LangGraph enables per-agent logging and diagnostics, unlike opaque monolithic systems.

In short, LLMs are powerful generalists-but in complex QA, delegation to specialized agents enhances scalability, transparency, and trust.

2. Dataset and Test Set Creation

2.1 Data Source and Schema

The movie dataset was sourced from AWS DynamoDB and is modeled as a nested JSON/NoSQL-style schema, including structured and unstructured fields:

- Title, Year, Release, Revenue, Rating, Votes - numeric and categorical metadata
- Plot - long-form unstructured text (average 1,280 tokens)
- Cast - list of actor names
- Characters - actor-character-role tuples with demographic metadata
- Director, Genres, Languages, Countries - categorical lists
- ID, IID - Wikipedia and IMDb-style identifiers


```
{
 "Title": "Titanic",
 "Year": 1997,
 "Revenue": 2185372302,
 "Rating": 7.9,
 "Genres": ["Historical fiction", "Romantic drama", "Disaster"],
 "Director": ["James Cameron"],
 "Plot": "84 years later, a 100 year-old woman named Rose DeWitt Bukater tells the story...",
 "Cast": ["Leonardo DiCaprio", "Kate Winslet", "Billy Zane"],
 "Characters": [
  {
   "Actor name": "Kate Winslet",
   "Character name": "Rose DeWitt Bukater",
   "Actor gender": "F",
   "Actor date of birth": "1975-10-05",
   "Actor height (in meters)": 1.69
  }
```


Figure 1: Database row example for Titanic 1997

Table 1: Dataset Statistics

Metric	Value
Total movies	105,324
Avg. plot length	213 tokens
Avg. characters/movie	8.4
Unique actors	336,142
Avg. actors/movie	7.3
Unique directors	35,278
Avg. directors/move	1.12
Genres	370
Avg. genres/movie	3
Languages	225
Countries	148
Release Year Range	1899-2025

Table 1 and Figure 1 provide a comprehensive overview of the dataset used in our study. Table 1 summarizes key dataset statistics, including the total number of movies, average plot length in tokens, average number of characters per movie, unique actors, average genres per movie, number of languages covered, unique genres, and unique countries represented. These metrics illustrate both the scale and diversity of the collection, highlighting its suitability for benchmarking complex question answering and knowledge graph construction. Figure 1 presents a representative example of a single dataset row, showcasing the nested JSON/NoSQL structure that characterizes each movie record. Fields such as Title, Year, Revenue, Rating, Genres, Director, Plot, Cast, and Characters are illustrated, reflecting the rich, heterogeneous information available for extraction and analysis. Together, Table 1 and Figure 1 contextualize the challenges and opportunities inherent in processing real-world movie data at scale.

2.2 QA Test Set Generation

To construct a challenging and diverse test set, we load the movie records into pandas dataframe and generate 1,000 question-answer pairs from the data to expose the full richness of relationships: cross-field queries (actors in movies by director X), deep narrative reasoning (movies with certain themes or rare genres), aggregation (highest revenue films per country), and entity coreference (actor aliases, multiple roles).

This approach resulted in a ground truth dataset with broad coverage:

- Factoid, list, and relationship queries
- Numeric and textual answers
- Cross-field inference and alias resolution

3. Methodology

3.1 Retrieval Query Engines

Our system utilizes five distinct retrieval engines, each represented as a QueryEngineTool in LlamaIndex (West, 2024) and orchestrated by LangGraph:

- Vector Engine: Semantic embedding search over plots and metadata.
- Keyword Engine: Exact and keyword match over movie titles, actors, genres.
- Summary Engine: High-level LLM-generated summaries per movie (for aggregation and context).
- Property Graph Engine: Schema-based property graph of movies, actors, genres, directors, supporting property/relationship queries.
- Knowledge Graph Engine: Triplet-based knowledge graph for relationship and fact extraction.

All five are run as parallel nodes in the LangGraph architecture, feeding their candidate answers to the next stage.

3.2 Dynamic Router Query Engine

A dynamic router query engine is constructed using RouterQueryEngine and a GenericMultiSelector, set to select 3 out of 5 engines from section 3.2 per query, based on prompt-driven relevance. The router engine analyzes each user query and determines-via LLM-powered GPT-4.1 prompt engineering-which subset of retrieval pipelines should be executed for optimal results. This balances accuracy, diversity, and efficiency, functioning as an ensemble method that combines the strengths of selected retrievers for improved query outcomes.

LlamaIndex offers exceptional flexibility for configuring the Router query engine, enabling prompts to dynamically select and orchestrate retrieval strategies within a unified workflow. This modular design empowers users to mix engines, tailoring execution to the complexity and ambiguity of each question. Adaptive routing lets developers optimize precision, recall, latency, and cost through context-aware choices. Such flexibility is especially valuable in complex domains-like code generation, biomedical search, or enterprise knowledge management-where no single retrieval strategy suffices. LlamaIndex streamlines integration of heterogeneous sources and models, enabling fine-grained control, experimentation, and observability across the QA pipeline. This adaptability positions LlamaIndex as a robust foundation for production-grade RAG.

3.3 Automatic Knowledge Graph Construction

We use prompt engineering to guide LLMs (GPT-4.1) in extracting semantic triples (subject, predicate, object) from raw movie data, building high-coverage knowledge graphs (KGs) without manual schema design. These triples embed semantic types and relations, supporting both programmatic and natural language queries.

In parallel, we construct property graphs from structured data in AWS DynamoDB, modeling entities (e.g., movies, actors, genres) and their attributes and relationships. Together, the KG and property graph engines capture both relational and descriptive knowledge.

Despite the semi-structured NoSQL schema, KGs offer distinct advantages:

- Semantic Inference: Reveal implicit patterns (co-actor chains, genre hierarchies), non-structured elements handling (for example, movie plots).
- Unified Representation: Align structured metadata and unstructured text (plot summaries).
- Efficient Reasoning: Enable symbolic graph traversal and interpretable logic.
- Cross-Source Enrichment: Provide a common format for integrating external data (Wikipedia, TMDB).

While NoSQL supports basic lookups, KGs offer a semantically rich, reasoning-friendly structure with minimal overhead and high value for complex, inference-driven queries.

3.4 Verification Engines

After the query engine returns an answer, we initiate a robust verification process by employing an LLM-as-judge framework, utilizing five distinct state-of-the-art LLM models to independently assess the response. Each model scores the answer on a 0 to 100 scale, enabling a multi-perspective evaluation that captures subtle nuances, potential inaccuracies, and contextual appropriateness. This ensemble-based judging mechanism not only mitigates the risk of individual model bias or blind spots, but also provides a more reliable and holistic measure of answer quality. By aggregating the scores - whether through averaging, weighted consensus, or more advanced ensemble techniques - we can make confident decisions about answer acceptance, flagging, or refinement. Moreover, this approach allows us to dynamically benchmark LLM models against each other, identifying strengths and weaknesses in specific domains or query types. Ultimately, leveraging multiple LLMs as parallel judges elevates the trustworthiness and reliability of the system, paving the way for production-ready applications that demand high precision, transparency, and user confidence.

Five LLMs serve as verifiers in this study:

- GPT-4.1-mini - Fine-tuned, mid-size model (~13B parameters), offering fast, accurate, and context-aware reasoning.
- GPT-4.1-nano - Compact version (~7B parameters) optimized for very low latency and efficient verification.
- GPT-4o-mini - Latest “Omni” model with multimodal capabilities, high benchmark scores, and strong code understanding.
- o3-mini - Specialized variant from the GPT-3.5 family, excels in logical reasoning and large-context tasks.

- o4-mini - Streamlined GPT-4 model, balancing accuracy and inference speed for reliable, real-time code and logic evaluation.

Each engine scores the pipeline answers for correctness and completeness, following ensemble verification (OpenAI, 2023). Moreover, we run these five verifiers concurrently because they are independent, saving time and merging the results in the LangGraph node. By combining these five models, our verification pipeline benefits from diverse strengths: long-context comprehension, multimodal reasoning, deep STEM/logical analysis, and rapid low-latency judgments. This ensemble ensures comprehensive quality control while maintaining efficiency and scalability - key to trustworthy agentic systems in production environments.

3.5 Observability and LangGraph Optimizations

It is crucial to implement agentic applications efficiently. Every node of our workflow extends a base class containing all the common code, including logging, initialization and error handling. Every node need to implement just execute method with the business logic, LLM calls or other functionality. For observability engine we are using serverless NoSQL DynamoDB that does not need any servers, fully integrated with AWS cloud ecosystem and has one millisecond latency and querying functionality. Figure 2 demonstrates our LangGraph base class supporting observability and modularity. Every pipeline node extends the class.

```
class BaseNode:
   """Every LangGraph node derives from this class for uniform observability behavior."""
   def __init__(self):
      self.name = self.__class__.__name__  # name of the class extracted dynamically
   async def __call__(self, state: AgentState):
      start=time()
      new_state = await self.execute(state)
      end=time()
      item = {
         "execTime": exetTime,

        ...
      }
       logItem(item) #log node execution into DynamoDB
      return new_state
   async def execute(self, state: AgentState) :  # should be overridden in every child
      raise NotImplementedError
```

Figure 2: Base node class for LangGraph pipeline supporting observability and modularity

3.6 Baseline Comparison

To establish the effectiveness of our multi-agent approach, we implemented a single-agent baseline using GPT-4.1 with simple RAG retrieval engine over the entire dataset. This baseline performs query engines search for each of the engines from 3.1 and generates answers with ensemble scoring and verification.

4. LangGraph Architecture

Our architecture is built on a directed graph where each node represents a retrieval or verification step (Kaplunovich, 2025). LangGraph's native concurrency support enables the five retrieval pipelines to run in parallel, dramatically reducing latency. The outputs of all retrieval engines are merged and dispatched to five

verification engines (one per model), which also operate concurrently. The merge node aggregates verification scores, selecting the highest-rated answer as the system's response. We generate verification scores (5 per answer) for 6 answers by each query engine (described in sections 3.1 and 3.2). Figure 3 demonstrates the LangGraph-based agentic workflow designed for orchestrated, reliable question answering and verification. The process begins at the start node, followed by a conditional check (check_load) to determine whether to load and build new resources or retrieve precomputed indices from disk (load_and_build vs. load_from_disk). Once the appropriate resources are ready, a router is instantiated (create_router) and queries are prepared (prepare_queries).

The system supports concurrent multi-engine querying through the run_queries node (running router engine), then distributing the queries across specialized engines run in parallel: knowledge graph (run_queries_kg),

keyword search (run_queries_kw), property graph (run_queries_pg), summarization (run_queries_sum), and vector retrieval (run_queries_vec). This enables the aggregation of diverse retrieval strategies tailored to the query type.

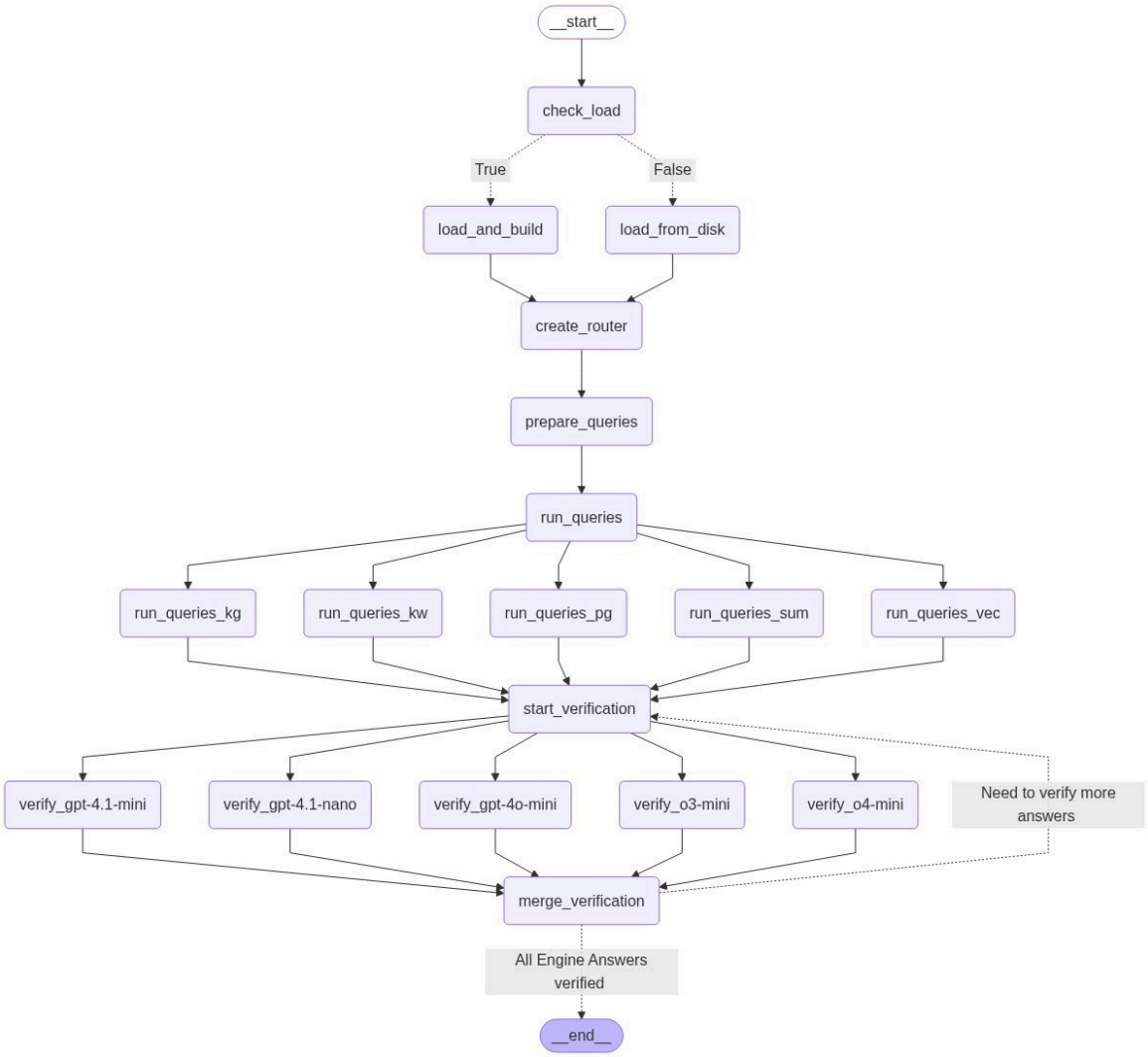

Figure 3: Multi-agent LangGraph concurrent agentic pipeline

After obtaining candidate answers for each 6 query engines, the workflow initiates a rigorous verification stage (start_verification), invoking multiple state-of-the-art LLM judges in parallel: verify_gpt-4.1-mini, verify_gpt-4.1-nano, verify_gpt-4o-mini, verify_o3-mini, and verify_o4-mini. Each judge independently assesses the answer's quality and correctness, generating scores for downstream aggregation.

For each query engine, the workflow launches five parallel verifiers to evaluate all answers produced by that engine. Each loop verifies all results from one query engine before proceeding to the next. The queryEngineKey parameter ensures that each set of five verifiers is correctly associated with its corresponding engine. This process continues until all answers from all engines have been thoroughly verified. Once verification is complete for every engine, the outputs are merged (merge_verification), and the workflow terminates successfully (end). This structure guarantees systematic and comprehensive quality control, as every result from every engine is independently judged before the workflow concludes.

This agentic, multi-stage workflow embodies modularity, scalability, and verifiability - key requirements for building production-grade retrieval-augmented generation (RAG) and agent-based QA systems. Concurrency in LangGraph is achieved through parallel node execution controlled by CONCURRENCY parameter enforced by asyncio.Semaphore. This supports efficient use of LLM APIs and local resources. LangGraph also allows flexible merging and conditional logic.

5. Experimental Results

The results reveal several key patterns about engine performance, threshold effects, and system reliability:

- Fine-Grained Threshold Trends: Using a finer threshold step (every 5 points) highlights that accuracy decreases steadily as the bar for correctness rises, but the rate and shape of this decline differ by engine.
- SUM Engine Superiority: The SUM (summarization) engine consistently achieves the highest precision at all thresholds, maintaining 97% accuracy up to threshold 55 and staying above 80% up to threshold 80. Its robust performance, even at strict thresholds, suggests that LLM-verified summarization answers are exceptionally clear and well-aligned with the ground truth. Even at a demanding threshold of 90, it remains the top performer (25%).
- Engine Robustness: KW (keyword), VEC (vector), and ROUTER engines show strong initial accuracy at low to mid thresholds, with KW and ROUTER exceeding 70% up to threshold 60. However, their performance falls off more sharply than SUM as thresholds increase, reflecting some trade-off between recall and answer specificity.
- KG and PG Engines: KG (knowledge graph) and PG (property graph) engines show more modest accuracy, starting just above 60% and dropping rapidly past threshold 70. This suggests that while they sometimes offer strong answers, these are less likely to achieve high LLM consensus - potentially due to the complexity or sparsity of structured outputs.
- Zero at Max Threshold: At a threshold of 100, no engine achieves any correct answers, underscoring the strictness of requiring all verifiers to return maximal confidence - a standard rarely met in multi-agent LLM systems.
- Implications for Deployment: The practical lesson is that threshold tuning is a powerful lever for balancing recall and precision. For applications prioritizing broad coverage, lower thresholds are optimal. For scenarios demanding only the highest certainty - such as critical decision support or automated code synthesis - higher thresholds enforce more reliable output, at the expense of recall.
- Ensemble Power: The consistently strong performance of SUM and hybrid engines (ROUTER, VEC, KW) demonstrates the importance of combining diverse retrieval paradigms. This multi-engine, multi-verifier approach provides both flexibility and robustness, adapting to the varied nature of real-world queries and data.

5.1 RAG Accuracy

Table 2: Query Engines Accuracy (Threshold Step 5)

		Threshold Accuracy									
Query Engine	**Avg score**	**50**	**55**	**60**	**65**	**70**	**75**	**80**	**85**	**90**	**95**
KG	58.47	0.61	0.6	0.56	0.53	0.39	0.36	0.3	0.21	0.12	0.11
PG	62.90	0.59	0.59	0.55	0.55	0.49	0.47	0.42	0.26	0.11	0.11
KW	73.05	0.79	0.79	0.74	0.71	0.62	0.56	0.48	0.3	0.2	0.2
SUM	85.90	0.97	0.97	0.95	0.93	0.9	0.86	0.84	0.49	0.25	0.14
VEC	74.42	0.87	0.87	0.74	0.71	0.58	0.5	0.46	0.3	0.15	0.14
ROUTER	79.55	0.81	0.81	0.71	0.67	0.6	0.51	0.46	0.29	0.18	0.18
All 5 engines	81.65	0.89	0.89	0.87	0.85	0.81	0.74	0.67	0.39	0.26	0.22

Table 2 presents the average verification score for each engine, complementing the visual analysis of score distributions. To quantify accuracy, a range of thresholds is applied to the scores: for a given threshold, an answer is considered correct if at least three of the LLM verifiers assigned a score exceeding that threshold. By sweeping the threshold from 50 to 100 (in increments of 5), we observe how each engine's apparent accuracy changes as the bar for "correctness" is raised.

Engines whose distributions are concentrated in higher score ranges - such as the SUM engine - maintain high accuracy even as the threshold increases, since a large proportion of their answers are confidently judged correct. Conversely, engines like KG and PG, whose distributions are more heavily weighted toward lower scores,

see a sharp decline in accuracy as the threshold rises. This is reflected in the table, where SUM retains the highest accuracy at every threshold, while KG and PG drop to near zero accuracy at stricter criteria.

This relationship between the score distribution and threshold-based accuracy illustrates the interplay between answer quality, verification rigor, and retrieval strategy. Engines with more robust high-confidence answers are less sensitive to strict verification, making them preferable for applications demanding reliable and trustworthy outputs. In contrast, engines with broader or lower score distributions may contribute valuable coverage in recall-oriented settings but require more cautious integration when high precision is critical.

Threshold selection should be driven by the intended application's risk tolerance and required reliability. The ensemble LLM approach, especially when combined with summarization, delivers a high-performing, resilient verification pipeline for complex, open-domain question answering and code-related tasks. The distributions of the verification scores for each engine type are shown in Figure 3. The histograms depict how frequently different verification scores occur across all evaluated queries, demonstrating variability among the retrieval methods. Notably, the summarization (SUM) engine displays a higher concentration of higher scores, whereas KG and PG show considerable lower-score density.

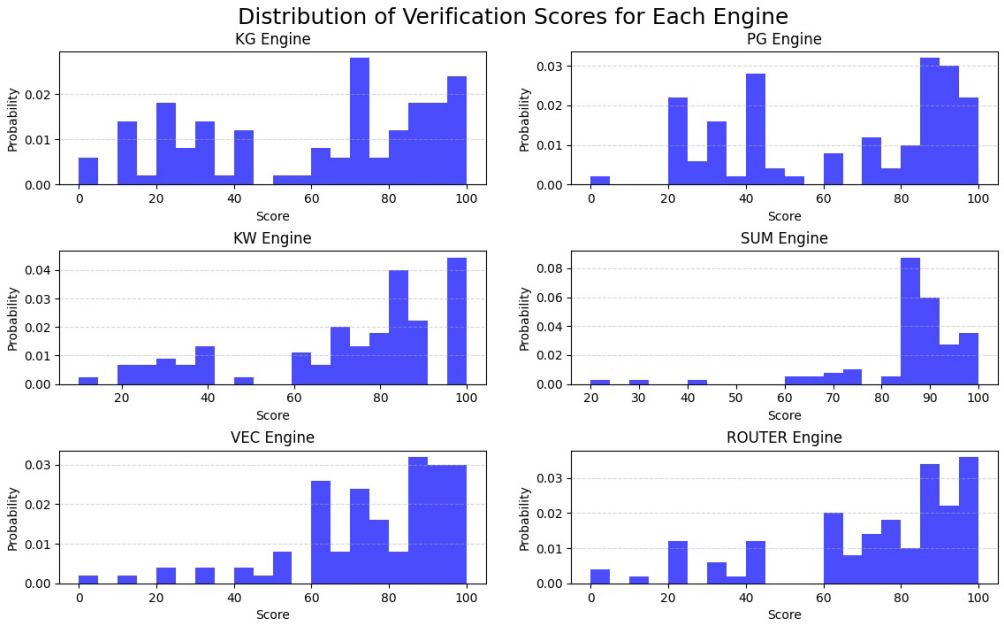

Figure 4: Score distributions for each query engine

Figure 4 shows verification score distributions for all six engines. KG and PG have moderately dispersed scores, with peaks near 70–100 but substantial mass at lower ranges. KW skews strongly toward 80–100, indicating frequent high-confidence retrievals. SUM peaks even more sharply in this range, yielding the most accurate results but at the highest cost and latency (see Section 5.3). VEC displays a broad spread with many mid- and low-confidence results, reflecting greater variability. ROUTER achieves the most balanced profile, combining strong high-end performance with coverage across mid and lower bins-leveraging multiple pipelines to maximize both precision and recall with highest score range (90-100).

5.2 Detailed Analysis of Router Engine Selections

Table 3: Frequency of Engine Selection by the Router Query Engine

Engine ID	Engine Description	Percentage (%)
1	Keyword Engine (Exact and keyword match search)	98
3	Property Graph Engine (Schema-based queries)	94
4	Knowledge Graph Engine (Triplet-based facts)	56
0	Vector Engine (Semantic embedding search)	47
2	Summary Engine (LLM-generated summaries)	5

A comprehensive statistical breakdown of engine usage frequency selected by LlamaIndex RouterQueryEngine is presented in Table 3.

The Router query engine dynamically selected combinations of 3 specialized retrieval methods tailored to individual queries. We pass a query to an LLM with query and engine descriptions (below) and it makes the choice. The retrieval engines were:

- Vector Engine (ID 0): Performs semantic embedding search over movie plots and metadata, capturing nuanced query contexts.
- Keyword Engine (ID 1): Conducts exact and keyword-based searches targeting precise movie titles, actors, and genre information.
- Summary Engine (ID 2): Generates high-level summaries using large language models, synthesizing comprehensive information from movie data.
- Property Graph Engine (ID 3): Enables schema-based graph queries about movies, actors, genres, directors, and their relationships, effective for structured data retrieval.
- Knowledge Graph Engine (ID 4): Utilizes a triplet-based knowledge graph for extracting and verifying facts and relationships from detailed movie data.

The Router's choice distribution highlights several important insights:

- Dominance of Keyword and Property Graph Engines: The Keyword engine (ID 1) was the most frequently selected (98%), closely followed by the Property Graph engine (ID 3, 94%). This preference suggests the Router predominantly favored precision-focused methods (keyword and structured schema queries) over purely semantic or summary-based approaches.
- Moderate Use of Knowledge Graph and Vector Engines: Knowledge Graph (ID 4, 56%) and Vector Engine (ID 0, 47%) were moderately employed, implying their importance as supplementary retrieval methods, particularly for nuanced or relationally complex queries. These engines likely provided complementary information where keyword or structured schema approaches might have been insufficient.
- Minimal Utilization of Summary Engine: Despite achieving notably high accuracy when used, the Summary engine (ID 2) was rarely selected (only 5%). This possibly reflects an intentional strategy by the Router - reserving summarization for queries specifically demanding high-level synthesis rather than detailed retrieval, or potentially reflecting constraints such as computational cost or response latency.

The selection patterns suggest that Router logic emphasizes:

- Precision and Speed: Frequent reliance on keyword and schema-based engines reflects a design preference for precise and rapid query responses, ideal for clearly defined factoid or structured queries.
- Contextual Adaptation: Moderate integration of semantic embedding (Vector) and Knowledge Graph approaches underscores the Router's adaptive nature, balancing efficiency with the necessity of rich semantic understanding for more ambiguous or complex queries.
- Strategic Use of Summarization: Limited Summary engine usage indicates a specialized role, suggesting potential for strategic expansion - particularly in cases benefiting from comprehensive context aggregation or nuanced understanding where traditional retrieval methods falter.

5.3 Cost and Efficiency Comparison: Multi-Agent vs. Single-Agent LLM Engines

Table 4: Multi-Agent vs Single-Agent Performance - Cost and Time per Query for Gpt-4.1

Engine Description	Avg LLM calls per query	Avg Input Tokens Per call	Avg Output Tokens Per call	Cost ($) Per call	Time (sec) Per call
Keyword Engine (Exact and keyword match search)	2	6648	143	0.01444	316
Property Graph Engine (Schema-based queries)	3.6	393	53	0.00121	177
Knowledge Graph Engine (Triplet-based facts)	1.5	3330	50	0.00706	178

Engine Description	Avg LLM calls per query	Avg Input Tokens Per call	Avg Output Tokens Per call	Cost ($) Per call	Time (sec) Per call
Vector Engine (Semantic embedding search)	1	461	126	0.00193	317
Summary Engine (LLM-generated summaries)	92	52718	525	0.1096	390
Router Engine (3 models selected by LLM)	12	11602	303	0.02563	257

Table 4 presents a comparative analysis of resource usage, efficiency, and cost for each retrieval engine, highlighting the distinctions between single-agent and multi-agent (Router) approaches. Lightweight engines like Property Graph and Vector demonstrate minimal token consumption and cost, making them attractive for rapid, low-overhead queries. In contrast, the Router engine - which orchestrates three retrieval methods per query - incurs higher resource usage (averaging 11,602 input tokens and $0.0256 per query) due to its ensemble execution design. These figures represent the cumulative resource demands of concurrently running three specialized pipelines, each optimized for different query facets.

Despite the increased overhead, the Router engine achieves markedly higher answer robustness and reliability than any single-engine baseline, with the notable exception of the Summary engine. While the Summary engine consistently yields the most comprehensive and accurate answers, it does so at a substantial computational cost, requiring an average of 92 LLM calls and over 52,000 input tokens per query - making it both the slowest and most expensive method evaluated.

Observability shows the Summary engine is rarely chosen by the Router, reserved for the most complex queries. This reflects a deliberate trade-off: although more resource-intensive, the Router delivers superior answer quality through multi-engine verification. Table 4 highlights the key insight-adaptive orchestration balances efficiency and reliability by using lightweight engines for routine queries and invoking heavier pipelines only when complexity demands it.

6. Conclusion

Orchestrating multiple retrieval pipelines and LLMs via a graph-based agentic framework enables high-precision, scalable, and trustworthy question answering over complex movie data. Our system demonstrates robust performance and sets the stage for autonomous, explainable movie intelligence - unlocking new applications in analytics and semantic search. This study demonstrates the transformative impact of agentic, multi-engine LLM frameworks for retrieval-augmented generation (RAG) in complex domains such as movie question answering. By orchestrating multiple specialized retrieval engines - including summarization, keyword, vector, knowledge graph, and property graph methods - within a unified, agentic workflow, we harness the unique strengths of each approach while dynamically adapting to the nuances of individual queries. A key innovation of our approach is the automatic construction of knowledge graphs in both triplet-based (KG) and property-based (PG) forms. Leveraging prompt engineering and advanced LLM capabilities, our system can extract semantic triples (subject, predicate, object) as well as rich property graphs from raw, unstructured data - without manual schema engineering. This dual-graph strategy empowers the pipeline to represent both relational knowledge and complex entity properties, providing a solid foundation for diverse, programmatic, and natural language queries. In the future, we are planning to integrate multi-model models to integrate images into our KG (Kaplunovich, 2024).

Our work demonstrates the power of LangGraph's concurrent, modular architecture, where retrieval engines operate in parallel for fast, diverse information access and robust answer synthesis. A dynamic router selects the most relevant engines for each query. Deep observability - enabled by a shared node class and persistent DynamoDB logging - provides transparent, fine-grained insights for auditing, diagnostics, and continuous optimization. Empirical results confirm that summarization-based retrieval consistently yields the highest verification scores, highlighting the value of LLM synthesis when grounded in rich context. Score distributions and threshold analyses expose each engine's reliability profile, enabling adaptive strategies that balance precision, coverage, and scalability in LLM-driven reasoning.

Ethics Declaration: Ethical clearance was not required for this research as it did not involve human participants, animal subjects, or sensitive data.

AI Declaration: Large Language Model (LLM) tools, specifically OpenAI's ChatGPT, were used for Grammar and spelling check.

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Preliminary Study of TexAI: Where Adaptive AI Reimagines Law Enforcement Training

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Abstract: Law enforcement agencies today operate at the frontline of data-sensitive decision-making, yet their training systems remain alarmingly analog. This gap has far-reaching consequences: The Police Department unintentionally deleted over eight terabytes of digital evidence, affecting nearly 17,000 criminal cases and causing significant public backlash and judicial delays (NBC 5 Dallas-Fort Worth, 2019). The root of this crisis lies not in technology alone, but in an outdated training paradigm that fails to prepare officers for the ethical, operational, and procedural demands of an AI-driven society. This paper explores how adaptive, explainable AI (XAI) can reframe the relationship between law enforcement and digital governance. We present TEXAI (XAI-powered Knowledge Base for Texas Law Enforcement), an AI-powered prototype built to modernize cybersecurity training in policing. Developed through user interviews and field research, the app combines real-time regulation updates with personalized, scenario-based microlearning-targeting a key challenge: officers forgetting or misunderstanding complex, evolving legal protocols. Our research examines how integrating XAI principles into law enforcement workflows introduces not only technological efficiency but critical epistemological transparency, fostering institutional accountability. We situate this intervention in the broader context of AI's role in public-sector transformation, arguing that ethical deployment of adaptive systems is essential to restoring public trust and preventing catastrophic human error. TEXAI also functions as a case study for how context-aware, role-specific AI tools can evolve through participatory design-responding to both human vulnerability and structural inefficiency. We contrast our solution with existing national systems such as PoliceOne Academy and Axon Academy, highlighting a novel intersection between AI explainability, justice system integrity, and digital literacy. The implications extend beyond law enforcement: in demonstrating how adaptive AI can personalize and democratize professional training in real time, we propose a scalable model for AI's responsible integration into high-stakes, socially critical domains. This work contributes to growing discourse around ethical AI, resilience in digital infrastructure, and the future of labor in AI-mediated institutions.

Keywords: XAI, Law enforcement training, Texas policing, Adaptive AI, Digital governance

1. Introduction

If the financial cost of cybercrime were compared to global economies, it would rank third, behind only the United States and China. The growing scale of these losses reflects how limited defenses and fragmented oversight have encouraged malicious actors to exploit vulnerabilities in increasingly digitized systems. While cybersecurity is often framed as a technical issue, it also exposes a broader challenge: institutions remain unprepared to respond effectively to complex risks in real time. This lack of preparedness is not confined to cyberattacks but extends to many areas where regulation, training, and decision-making intersect.

Recent local incidents illustrate these vulnerabilities. In 2023, the Dallas Police Department lost twenty-two terabytes of critical case data due to a failed transfer, while the Texas Department of Transportation suffered a ransomware attack that disrupted essential operations. These failures revealed more than technological weaknesses; they highlighted a systemic gap in training and oversight that directly impacts public safety. Beyond technology, first responders and officials are often expected to make rapid decisions while navigating intricate legal and procedural frameworks. Under stress, even experienced professionals can make mistakes with severe consequences for civilians.

These realities underscore the need for adaptive systems that go beyond cybersecurity alone. TEXAI builds on lessons from digital vulnerabilities but applies them to a wider spectrum of regulatory, operational, and training challenges. By providing real-time guidance, context-sensitive decision support, and adaptive learning tools, the system addresses the broader issue of how to prepare officers for both routine and high-stakes scenarios in a rapidly evolving environment.

Given these challenges, the goal of this research is to create a modular AI-powered system called TEXAI that enhances resilience, streamlines access to critical protocols, and supports informed decision-making in high-pressure situations. TEXAI is designed to directly address the gaps exposed by the Dallas data loss, offering real-time guidance and secure access to procedures that officers can trust. For instance, during a ransomware

lockdown, TEXAI could provide step-by-step instructions to ensure correct responses, minimize operational disruption, and reduce potential harm. This research also aims to evaluate how effective an AI-based solution is compared to existing, traditional methods of protocol access and training. By measuring both efficiency and reliability across these approaches, the study not only develops and tests TEXAI as a practical tool but also gauges the broader role AI can play in improving officer preparedness and bridging the divide between complex systems and their end-users.

In a discussion with a local law enforcement officer, we discovered the legal and cybersecurity training the officers receive every year. The system utilized at the moment is an outdated, powerpoint presentation which is reviewed right before a standardized test held once a year. The officer interviewed mentioned how "...a trend in how officers learn is that we're very hands-on and work better in interactive environments. An app which allows us to discuss our questions and ask any the second a situation arises, would definitely be beneficial… there are so many legal codes we have to memorize for real life situations which makes it easy to make mistakes, so this would remove that risk in our career". We took this feedback in mind when designing our model, especially when it came to the AI chatbot and the way it communicated in different situations with an individual.

TEXAI will feature two tailored interaction modes: one optimized for real-time situations with speed and clarity, and another designed for educational settings with deeper, more detailed explanations. While officers can still toggle between these modes through a simple interface tab, the AI also uses on-device intelligence to automatically detect the nature of a request and respond in the most appropriate mode. The model's tone will be a balanced hybrid, concise and direct during emergencies while remaining professional and polite. Users can request elaboration at any point, ensuring critical information is always accessible without unnecessary delay.

2. Review of Literature

Several platforms provide cybersecurity or compliance-related training for government and enterprise users, including law enforcement, but most fall short in delivering context-specific, adaptive learning experiences suited to the operational realities of police work. Research on adaptive learning systems demonstrates that personalization significantly improves knowledge retention, particularly in professional development settings (Khosravi et al., 2022; Brusilovsky and Millán, 2007). Rafferty et al. (2016) further highlight that adaptive teaching using partially observable Markov decision processes (POMDPs) allows training systems to dynamically adjust to learner performance, though these approaches remain underutilized in policing contexts.

Explainable AI (XAI) frameworks have also been increasingly used in education and compliance systems to support transparency, fairness, and trust (Adadi and Berrada, 2018). Doshi-Velez and Kim (2017) emphasise that interpretability in machine learning is essential for accountability in high-stakes domains, while Lum and Isaac (2016) caution against the risks of opaque predictive policing tools. This suggests strong potential for combining adaptive learning with explainable AI to create training solutions that are both effective and accountable in public safety contexts.

Privacy and security are equally central to technology adoption in law enforcement. Cavoukian (2011) outlines the Privacy by Design framework, which embeds data protection into system architecture from the outset, a principle echoed in the CJIS Security Policy (CJIS Division, 2020). Similarly, national and federal standards such as the Federal Information Security Management Act (FISMA, n.d.), the Federal Risk and Authorization Management Program (FedRAMP, n.d.), and the National Institute of Standards and Technology s Cybersecurity Framework (NIST, n.d.) establish regulatory benchmarks for secure data handling in government systems. Integrating such standards into training technologies ensures compliance while also building trust among officers and the public.

From a systems design perspective, Chen et al. (2019) argue that modular architectures increase adaptability and maintainability in industrial platforms, insights directly applicable to training solutions requiring scalability across diverse law enforcement agencies. Kumar et al. (2025) likewise emphasise the link between cybersecurity maturity and government efficiency, underscoring the importance of resilient, adaptable platforms in the public sector.

Finally, funding and policy incentives shape the adoption of law enforcement technologies. Federal grant programs such as those from the Edward Byrne Justice Assistance Grant Program (n.d.) and the Office of Community Oriented Policing Services (COPS Office, n.d.) illustrate the government's role in supporting training and technology modernization efforts. Embedding adaptive and explainable systems within this policy and funding environment positions new solutions like TEXAI not only as technically innovative but also as aligned with broader institutional frameworks. In sum, existing literature demonstrates that adaptive learning and

explainable AI each contribute valuable mechanisms for enhancing training effectiveness and accountability, yet they remain underexplored in law enforcement contexts. Prior research on privacy, compliance, and modularity underscores the need for systems that are secure, transparent, and adaptable, while policy frameworks and funding mechanisms establish pathways for real-world deployment. This convergence highlights the research gap that TEXAI addresses: delivering an adaptive, explainable, and regulation-compliant training platform tailored to the unique demands of police work.

3. Related Work

PoliceOne Academy by Lexipol, widely used among U.S. law enforcement, offers general modules on legal updates, tactical skills, and situational awareness. Some content touches on cybersecurity, but it lacks structured, role-specific modules on data privacy, digital evidence handling, or cyber incident response. It also does not adapt content based on learner performance or evolving digital threats.

KnowBe4 provides comprehensive training on phishing, social engineering, and digital hygiene but is primarily designed for corporate environments. It does not incorporate public sector regulatory frameworks or simulate law enforcement-specific scenarios, such as unauthorized data access during investigations or breaches involving body-worn camera footage.

Similarly, Infosec IQ and Proofpoint Security Awareness provide robust training content but rely on linear, non-adaptive learning structures. These platforms often overlook operational pressures faced by officers and do not provide guidance on state-specific laws or constitutional privacy protections.

TEXAI addresses these gaps by combining adaptive learning technologies with XAI-driven explainability. It emphasizes real-world simulations, compliance with data privacy laws, and role-specific feedback, distinguishing it from existing law enforcement and general cybersecurity education platforms. Unlike traditional training tools, TEXAI is designed to assist officers beyond the classroom, offering real-time tactical guidance during high-pressure situations. For example, when an officer responds to a mugging or another urgent scenario, TEXAI can provide step-by-step procedural guidance, enabling faster, informed, and legally compliant decision-making. This transforms TEXAI into a trusted assistant in live operations, supporting officers with critical insights when it matters most.

4. Methodology

To develop TEXAI as an effective, context-aware AI solution for Texas law enforcement, we adopted a modular and adaptive design approach emphasizing regulatory alignment, real-time usability, and operational relevance. Our methodology integrated technical, educational, and procedural considerations, grounded in both field research and established AI practices (Goodfellow et al., 2016; Russell & Norvig, 2021).

The development process included user-centered research, involving interviews and surveys with law enforcement officers to understand their practical needs, analysis of common cybersecurity and procedural incidents, and iterative prototyping to ensure TEXAI aligned with real-world operational demands (Nielsen, 1993). Each stage was designed to bridge the gap between complex legal and procedural knowledge and the daily decision-making needs of frontline personnel.

A critical component of the methodology is the fine-tuned adapter, developed using Apple's Foundation Models Adapter framework. This adapter enhances the base AI model's domain-specific reasoning without retraining the full model (Houlsby et al., 2019). It is trained on a curated dataset that includes regulation-based queries, real-world law enforcement scenarios, and procedural decision points. To ensure security and compliance, adapters are evaluated on-device, never made public, and operate within a closed privacy-preserving loop, ensuring both responsiveness and cybersecurity integrity.

The methodology further includes the design of three core interaction modes, Informational, Quiz, and Simulation, each serving distinct pedagogical and operational purposes. Informational mode answers officer questions on laws and procedures. Quiz mode delivers multiple-choice and free-response assessments, evaluating responses against a verified dataset. Simulation mode engages users in realistic scenario-based training, assessing actions in accordance with departmental regulations (Salas et al., 2009). A keyword-based control allows concise or detailed responses as needed, improving interaction fluidity.

Conversational memory was selectively implemented for Informational and Simulation modes, allowing TEXAI to maintain context across multi-turn dialogues while conserving resources. A failsafe mechanism clears memory if usage exceeds system thresholds, notifying users without disrupting the interface. Additionally, a long-term

memory module is under development to generate session summaries, progress tracking, and training coverage analytics, reinforcing personalization and long-term learning continuity.

5. System Architecture

TEXAI is built with a modular architecture to support rapid updates, legal adaptability, and real-time operational awareness. At the core is the fine-tuned Foundation Model adapter, trained on curated datasets of Texas law enforcement regulations, procedural guidance, and real-world incident case studies. This adapter enables domain-specific learning without retraining the base model and is deployed dynamically through secure application updates.

An onboard controller manages the three primary interaction modes, directing queries to Informational, Quiz, or Simulation based on context and keywords. The keyword system prioritizes concise responses when prompts contain quick while defaulting to a more explanatory tone otherwise.

Conversational memory operates selectively to maintain context in Informational and Simulation modes while conserving system resources. The system discards irrelevant history and triggers a failsafe if memory thresholds are exceeded, notifying the officer while preserving on-screen content. Long-term memory will track learning progress, generating session summaries and checklists to improve training continuity.

Evaluation of TEXAI focuses on three main dimensions: effectiveness, adaptability, and user engagement. Effectiveness will be measured by the model's ability to provide accurate, context-specific responses to regulatory queries and procedural scenarios compared to traditional training methods. Key metrics include accuracy, response time, and comprehension.

Adaptability will be assessed through scenario-based testing in both controlled training environments and simulated field situations. Officers will interact with Informational, Quiz, and Simulation modes, and performance metrics will be collected for scenario completion, decision-making accuracy, and adherence to laws and procedures. The system's ability to integrate and deploy updated adapters will also be evaluated.

User engagement will be analyzed qualitatively through officer feedback and quantitatively through analytics, including mode-switching frequency, requests for expanded explanations, and interactions with long-term memory summaries. Evaluations will also consider the system's support for decision-making under high-pressure conditions and its ability to maintain compliance and procedural accuracy.

6. Design of TEXAI

The design of TEXAI integrates modular architecture, domain-specific adapters, and flexible interaction modes to meet law enforcement needs. The Informational mode allows officers to obtain immediate answers to regulatory queries. Quiz mode reinforces knowledge through structured exercises, while Simulation mode enables real-time scenario practice with context-aware evaluation. Interaction modes can adapt automatically based on the nature of the query using on-device intelligence. Concise or detailed responses are determined by keyword presence or operational context, ensuring that officers receive information appropriate to their current situation. The adapter system supports dynamic updates without retraining the base model, ensuring the system remains legally accurate and contextually relevant. Privacy is ensured through on-device evaluation of adapters and selective conversational memory.

7. Evaluations

Early models tested the AI's language capabilities and responsiveness. Initial results showed that the base model could manipulate language effectively but lacked specialization and context-awareness. Subsequent iterations added regulation-specific datasets, conversational memory, and structured modes, gradually improving accuracy, simulation capability, and adaptive response quality.

8. Testing and Results

To evaluate TEXAI's real-world performance, structured prompts were tested across Informational, Quiz, and Simulation modes. Responses were scored on a 10-point scale with four weighted criteria: relevance, accuracy, and compliance with Texas law (4 points), conciseness or detail depending on context (2 points), correct use of interaction mode (2 points), and effective use of conversational memory when applicable (2 points). There were 2 standalone prompts for informational style questions, 2 conversational prompts to track the bot’s

conversational memory and accuracy abilities, and 2 activity style prompts intended to activate quiz/simulation mode. The prompts, shown in Figure 1, were as follows:

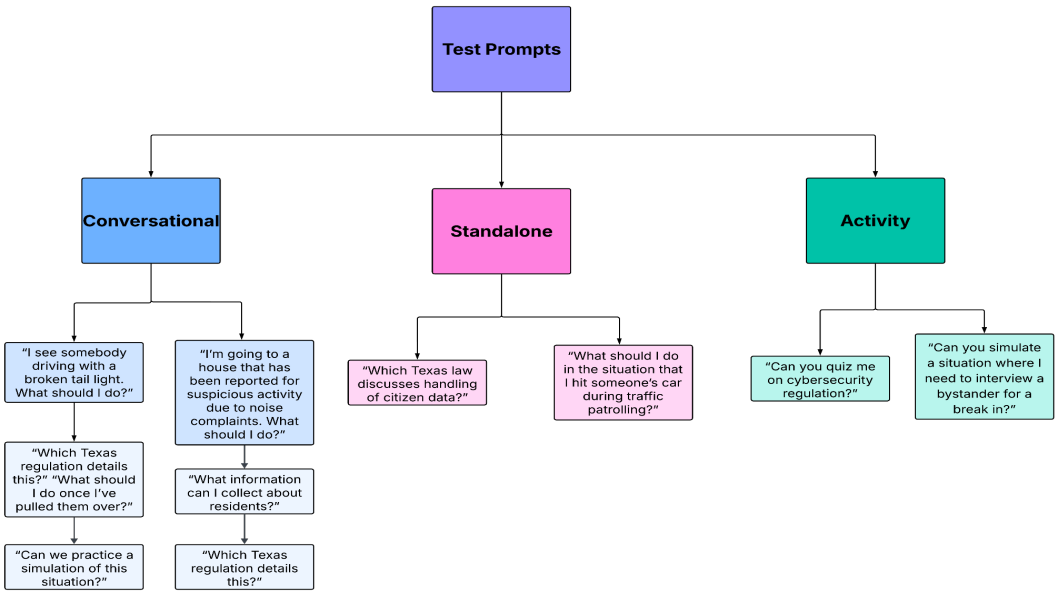

Figure 1: Prompts

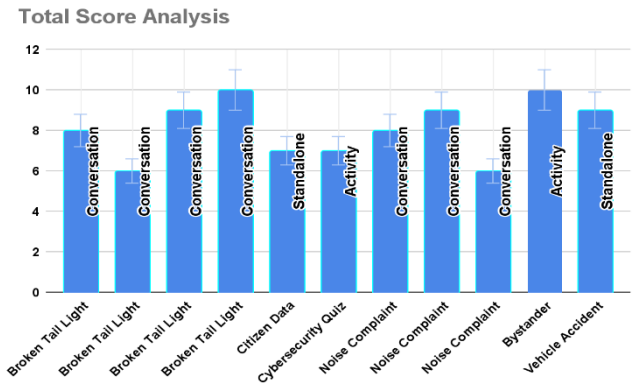

Figure 2: Total score analysis

Mode Score and Memory Score remained consistently strong across all scenarios, reflecting TEXAI's ability to switch modes correctly and maintain continuity during multi-step interactions. Conciseness and Detail varied more noticeably, performing better in activity-oriented and conversational tasks while showing occasional weaknesses in standalone informational prompts.

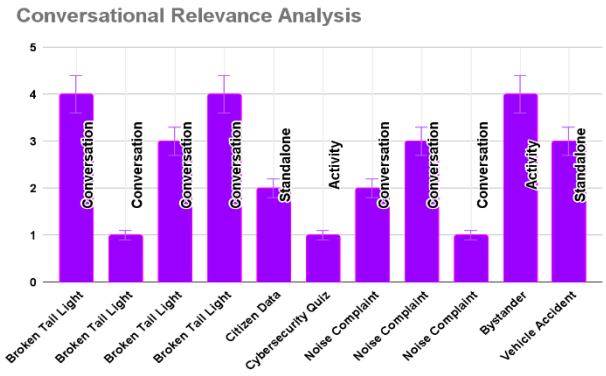

Figure 3: Conversational relevance Analysis

TEXAI generally maintained coherent and contextually appropriate dialogue, though performance was slightly weaker in scenarios requiring precise statutory grounding. This variation likely stems from the current absence of a fully integrated Texas law database, which limits the model's ability to cite legal code directly.

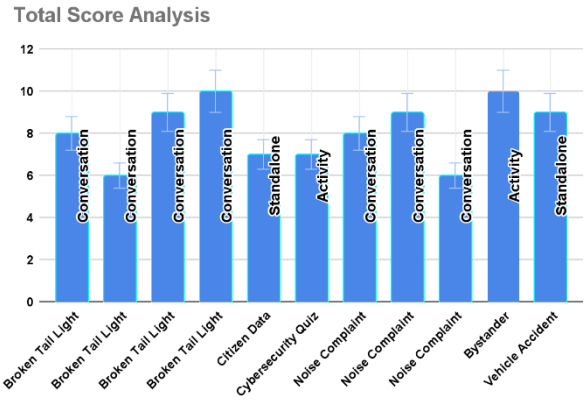

Figure 4: Total score analysis

The chatbot demonstrated strong practical guidance and simulation ability, particularly in roleplay scenarios such as traffic stops, noise complaints, and bystander interviews, where it emphasized officer professionalism, privacy, and safety. For example, in the broken tail light and noise complaint scenarios, the chatbot offered step-by-step

lawful guidance and effective context retention, but its legal referencing was often incomplete or imprecise. In contrast, simulation-based interactions such as interviewing a bystander produced excellent results, earning near-perfect scores due to structured feedback and context-appropriate professionalism. Standalone prompts, such as requests for Texas statutes on citizen data or cybersecurity regulation, highlighted the system's main weakness: statutes were either partially cited, misrepresented, or misapplied, resulting in lower accuracy scores. Overall, TEXAI consistently demonstrated high performance in adaptive coaching and situational practice but revealed clear limitations in legal citation reliability, suggesting the need for integration with more authoritative and structured legal databases.

9. Discussion

The results highlight TEXAI's dual strengths and limitations. Iterative design improved accuracy and context-awareness, while the modular adapter approach allowed legal updates without retraining the full model. Simulation testing confirmed TEXAI's potential as a real-time training and guidance tool: scenarios such as bystander interviews and noise complaints produced high-scoring outputs that emphasized professionalism, privacy, and officer safety. However, repeated testing also revealed a critical gap in legal referencing. In multiple cases, statutes were either incompletely cited or misapplied, reducing confidence in the system's regulatory precision. This weakness was traced to the informal nature of the prototype's training database rather than the model's reasoning process, suggesting that performance can be significantly improved through the integration of more comprehensive, structured legal datasets. Addressing this limitation will be central to TEXAI's future development and deployment in operational contexts.

Beyond this, the theoretical implications of TEXAI's design and performance point towards a new model of AI-mediated institutional learning. Traditional police training relies on static, uniform instructions that do not reflect the distributed, rapidly evolving nature of modern law enforcement. By contrast, TEXAI operationalizes theories of situated cognition and experimental learning (Lave & Wenger, 1991; Kolb, 1984) by embedding procedural knowledge within real-world contexts and dynamically adjusting feedback based on user input. This adaptive interactivity transforms training from a memorization exercise into a cognitive partnership, where human expertise and AI reasoning co-develop situational fluency.

The system's explainable AI foundation also aligns with theories of socio-technical accountability, which argue that transparency in algorithmic decision-making reinforces ethical behavior and public trust. From a theoretical standpoint, TEAI can also be understood as a prototype for adaptive governance infrastructure, a theory drawn from systems theory and public administration that emphasizes flexibility, resilience, and responsiveness in managing complex institutions. By allowing continuous adaptation to evolving laws, policies, and cyber threats,

modular AI systems can strengthen institutional learning capacity. This aligns with emerging literature on AI-driven public sector transformation, which asserts that intelligent systems can reduce bureaucratic friction and improve compliance through real-time knowledge dissemination.

10. Recommendations and Future Work

The successful performance of TEXAI in conversational memory and simulation modes suggests distinct areas for immediate pilot deployment. We recommend three core actions for law enforcement agencies and training leaders: First, Prioritize Simulation-Based Training by integrating the TEXAI Simulation Mode to replace passive training (e.g., PowerPoint lectures) for complex procedural scenarios, such as traffic stops and bystander interviews. Second, Utilize TEXAI as a Procedural Coach, not a Legal Authority. Given its limitation in precise statutory grounding, TEXAI should be used primarily as a context-aware procedural assistant and ethical guidance coach in the field, not as the sole source for confirming specific Texas legal statutes for court preparation. Third, Support Adaptive Deployment using a phased rollout strategy that leverages the system's adaptive nature to personalize learning and enhance institutional accountability based on identified training gaps.

The findings and limitations revealed during testing necessitate specific directions for future work and research. Development efforts will focus on enhancing long-term memory performance, simulation fidelity, and dynamic response adjustment. Key metrics will include response accuracy, scenario completion, user comprehension, and real-time decision-making support. (We are currently waiting for IRB approval to discuss and begin testing various models with individuals in law enforcement to further develop the app and AI model.) The primary research recommendation is to Integrate Structured Legal Datasets by linking the AI model with an authoritative, structured legal code database to eliminate the critical gap in legal citation reliability, which is essential for operational trust. Researchers should also Conduct Comparative Efficacy Studies (formal comparative studies must be performed to measure TEXAI's long-term impact against traditional training methods and procedural error reduction) and Generalize the Model by exploring adapting the core TEXAI architecture (XAI-powered, adaptive microlearning) to other high-stakes public service domains like emergency medical services (EMS) or fire compliance training, demonstrating its scalability.

11. Conclusion

TEXAI provides a scalable, adaptive AI assistant for Texas law enforcement, combining modular architecture, fine-tuned adapters, multiple interaction modes, and memory systems. The platform bridges the gap between complex legal knowledge and practical operational demands, supporting both training and high-pressure field scenarios. Continued evaluation and iteration will ensure TEXAI remains a reliable, legally compliant, and context-aware tool, enhancing officer preparedness, procedural accuracy, and decision-making in real-world applications.

Ethics Statement: A local police officer was consulted to provide professional insights into training practices. Participation was voluntary, informed consent was obtained, and no personal or identifying information was recorded. The discussion focused solely on professional practices relevant to this study. The anonymous police officer was aware that his answers would be utilized to develop this research paper.

AI Declaration: Portions of this report utilized OpenAI's ChatGPT (GPT-5), which was used to refine wording & suggest formatting.

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AI and Automation: Effects on Employment and Management

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Abstract: The rapid rise of Artificial Intelligence (AI) and automation is transforming industrial operations, reshaping job roles, and redefining management strategies, ultimately reshaping the structure of employment and redefining managerial practices across industries. This paper examines the nuanced impact of AI-driven automation on labor markets, workforce dynamics, and organizational management, drawing on interdisciplinary research from economics, computer science, and business studies. We examine three key dimensions: (1) the displacement and transformation of job roles due to intelligent systems, (2) the evolution of managerial decision-making empowered by AI-based analytics and predictive modeling, and (3) the emergence of hybrid human-AI collaboration paradigms within enterprises. Our analysis integrates case studies from sectors undergoing rapid AI integration, such as manufacturing, healthcare, and logistics, highlighting both job obsolescence and opportunities for upskilling and task augmentation. The paper also examines the ethical and strategic implications of managing an AI-enabled workforce. These include algorithmic transparency, bias mitigation, labor reallocation policies, and the design of AI governance frameworks. We identify managerial challenges in adapting to a dual-human-machine environment, including shifting leadership roles, redefining performance metrics, and maintaining employee trust amid technological change. Using empirical labor market data and organizational surveys, we propose a typology of employment impact, ranging from automation-intensive displacement to augmentation-driven productivity gains. We argue that the future of work depends not only on technological capability but on proactive policy, inclusive design, and agile management strategies. Our findings underscore the urgent need for interdisciplinary collaboration in crafting equitable AI transitions. We conclude with recommendations for policymakers, business leaders, and educators to ensure that AI serves as a catalyst for sustainable and inclusive growth, rather than as a force for division and dislocation.

Keywords: Artificial intelligence (AI), Automation, Workforce dynamics, Job displacement, Managerial decision-making, Human-AI collaboration, Upskilling, Ethical AI, Labor market transformation, AI governance

1. Introduction

1.1 Methods (Empirical Design)

This study integrates empirical analysis using cross-sectoral labor-market and organizational data. We draw on the EU Labour Force Survey (2019–2024) to capture occupational transitions and wage effects of automation, complemented by O*NET task-level data to quantify exposure to AI and automation. The key variables include task-exposure-to-automation (TEA), augmentation index (AIx), average wage trajectory, and transition-to-new-roles rate.

Our analytical framework applies task-exposure regressions and difference-in-differences (DiD) models to estimate employment outcomes across two sectors—manufacturing and healthcare. The empirical strategy follows a Human–AI Role Realignment (HARR) approach, distinguishing between displacement-driven and augmentation-driven transformations.

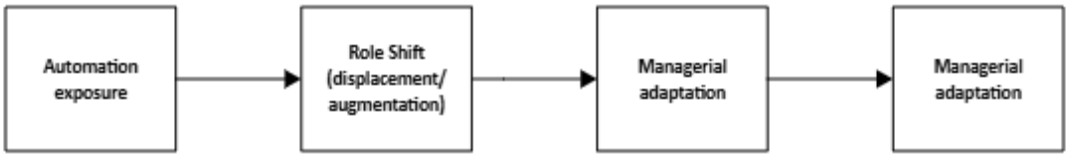

Figure 1: The Human–AI Role Realignment (HARR) Framework

Metrics such as time-to-insight, error-correction rate, and augmentation value measure productivity impacts. Figure 1 illustrates the analytical pipeline, from data collection and task classification to outcome modelling.

1.2 Background and Motivation

The technological landscape is reshaped by the rapid proliferation of automation technologies. AI systems reconfigure the operational core of industries, promising gains in productivity, efficiency, and data-driven precision. This wave extends automation from routine tasks to complex cognitive processes, reshaping both the nature of work and the structure of the workforce. The motivation for this paper is to provide a more nuanced,

empirically grounded understanding of AI's real-world impact. Stakeholders must assess how AI alters work and management to maximize benefits while minimizing disruption.

1.3 Scope and Objectives

The objective of this paper is to conduct a systematic and interdisciplinary examination of the effects of AI-driven automation on labor markets, management practices, and organizational dynamics. Drawing upon insights from computer science, economics, and business studies, we aim to provide a holistic analysis that captures the intersection between technological innovation and its human-centric consequences. The paper focuses on three dimensions:

Job Role Transformation: We will investigate the displacement of certain job roles and the augmentation of human capabilities, leading to the creation of new professional categories.

Evolution of Managerial Decision-Making: The paper will explore how AI-powered analytics are shifting management from an experience-based practice to a data-driven one, and examine the emergence of hybrid human-AI collaboration models.

Ethical and Strategic Implications: We will address the critical challenges accompanying this transition, including algorithmic transparency, mitigating biases in AI systems, and designing robust AI governance structures.

Through case studies, labor market data, and organizational surveys, this paper seeks to build a comprehensive typology of employment impacts. Our goal is to provide actionable strategies for corporate leaders, educators, and policymakers to ensure AI integration fosters sustainable and equitable growth.

2. Literature Review

2.1 AI and Automation in Industry

Over the past decade, the capabilities of Artificial Intelligence have greatly advanced, leading to its widespread integration in industries such as manufacturing and healthcare. This section reviews findings from literature on the effects of AI on manufacturing and healthcare.

The manufacturing industry has seen a large adoption of AI among many different sectors such as autonomous vehicles, renewable energy, and semiconductor production (Kim et al. 2021). Due to this widespread adoption, we are now entering the 4th industrial revolution, which emphasizes smart and efficient manufacturing at low costs (Vaidya et al. 2018). Plathottam et al. (2023) demonstrate that some key applications of AI are in quality control, finding that AI technologies can be utilized to detect defects in automotives and semiconductors, increasing the accuracy of workers by up to 6%. Additionally, a case study conducted by Thoben et al. (2016) finds that AI powered real time logistics systems in factories can lower inventory levels and reduce idle time by improving synchronizations between different departments. Similarly, Gao and Feng (2023) reveal that within the realm of manufacturing, AI is becoming increasingly involved in more complex tasks, bringing benefits to both productivity and economic sustainability.

However, despite these opportunities, the manufacturing industry faces many challenges. Dataset size, equilibrium, and quality of labels are extremely important when training an accurate deep learning model (He et al. 2019). However, reliable data storage is cost-intensive, and data preparation is very labor-intensive, so maintaining data quality is a large challenge for the integration of AI in manufacturing (Xu et al. 2022).

In contrast to manufacturing, the healthcare industry applies AI in a much more high-stakes environment, where the primary focus is not on efficiency, but also on clinical accuracy and improving patient outcomes. AI has shown considerable promise in the field of diagnostic imaging. Bajwa et al. (2021) find that in many specialties such as dermatology, pathology, and cardiology, AI technologies can often meet or surpass the capabilities of medical experts when identifying medical conditions from photos. In a different vein, Hirani et al. (2024) find that AI has enhanced telemedicine by improving accuracy of diagnostics and helping clinical decision-making through image analysis and chatbots. Bekbolatova et al. (2024) discuss how AI can assist in completing redundant administrative tasks. For example, a Japanese case study on the use of OpenAI's ChatGPT reveals that there is a high degree of similarity between medical summaries produced by AI and physicians (Kaneda et al. 2023).

However, many issues remain to be addressed before AI can be fully integrated into healthcare systems, such as those of data privacy. For instance, Yadav et al. (2023) find that even though data used to train AI can be de-identified, algorithms can be developed to re-identify patients. This is particularly impactful in fields such as dermatology, where it is impossible to de-identify patient photos. Murdoch (2021) explores policies to overcome

this challenge, such as providing the right for patients to withdraw their data and educating patients about how their data is utilized.

Across both healthcare and manufacturing, AI has demonstrated significant potential to improve decision making and productivity. While manufacturing benefits from process automation and logistics optimization, healthcare benefits from AI powered diagnostics and administrative tasks. However, despite these advances, numerous challenges still need to be overcome. The manufacturing industry struggles with maintaining good data, and the healthcare industry struggles with maintaining data privacy of patients.

2.2 Theoretical Frameworks: Economics and Computer Science

From an economic perspective, much research draws from theories of technological change and labor displacement. One foundational concept is skill-biased technological change (SBTC), which describes how technological advancements such as automation increase the demand for skilled labor relative to unskilled labor (Card & DiNardo 2002). Acemoglu and Restrepo (2019) present a task-based framework which distinguishes between the displacement effect and the reinstatement effect. They find that the displacement effect occurs when tasks previously performed by labor are taken over by capital, such as AI technology. Additionally, they find that the reinstatement effect occurs when these technologies generate new tasks better suited for labor, thereby reintegrating workers and increasing labor demand. Their work suggests that the adoption of AI will benefit firms and workers who can complement AI rather than be replaced by it. This aligns with findings from Bessen (2020) who emphasizes that new technologies rarely replace entire occupations but instead may force workers to make transitions to new roles and positions.

In computer science, much research revolves around how humans interact with AI systems. For example, human-in-the-loop (HITL) for machine learning, where AI models are continuously refined through human feedback, improving accuracy and transparency in AI decisions (Wu et al. 2021). Budd et al. (2023) analyzes the role of HITL in healthcare systems for medical image analysis. They note that three major issues that oppose the integration of AI in healthcare are: the time and effort required to annotate large datasets, the extreme level of accuracy and precision needed in the medical field, and the opaqueness of modern deep learning algorithms. HITL can assist in overcoming these challenges through the incorporation of human decision making into the AI training process.

2.3 Gaps in Current Research

Despite the growing body of literature on AI automation and its impact on the workforce, several gaps remain underexplored. One such area is the hybrid collaboration between AI and humans. While many studies discuss job displacement, few investigate how workers and intelligent systems can work together to perform tasks more effectively. Research that does exist often lacks insight into the dynamics involved in this, especially in sectors requiring empathy and human judgement.

Another overlooked area is the development and application of ethical management frameworks. Although algorithmic bias has received attention in computer science, there is limited work translating these findings into actionable strategies for business leaders. Questions of accountability, transparency, and employee autonomy are frequently raised, but rarely resolved.

These limitations suggest the need for more inclusive, evidence-based, and policy-oriented research that integrates innovation with organizational perspectives.

3. Evolution of Managerial Practices

The integration of Artificial Intelligence into the enterprise represents a fundamental shift in the practice of management. Due to the integration of AI, managerial roles are shifting from directing human labor to coordinating collaboration between employees and machines. This section examines this transformation with the shift towards AI-driven decision-making, the emergence of hybrid human-AI collaboration paradigms, and the consequent redefinition of leadership roles and performance metrics.

3.1 AI-Driven Decision-Making

Historically, managerial decision-making has been a 'bounded rationality' process, where leaders operate with incomplete information. AI-based analytics and predictive modeling address these limitations by augmenting cognitive capacity (Shrestha & Ben-Menahem, 2019). Machine learning models analyze complex data to identify patterns, forecast outcomes, and model decision impacts with unprecedented precision (Shrestha & Ben-

Menahem, 2019). This transforms decision-making from a reactive, experience-based art to a proactive, evidence-based science.

Business intelligence and predictive analytics tools are at the forefront of this change. For instance, in supply chain management, AI models can analyze real-time data from sales, weather patterns, and geopolitical events to predict demand fluctuations and optimize inventory levels, moving beyond static, rule-based systems to dynamic, self-learning models (Govindarajan & Ananthanpillai, 2023). Similarly, in finance, AI algorithms are used for credit scoring, fraud detection, and algorithmic trading, making decisions that are faster and often more accurate than those of human experts (Shrestha & Ben-Menahem, 2019). The key contribution of AI is its ability to dynamically process high-dimensional data and uncover relationships that would be opaque to human analysis, enhancing both the speed and quality of decisions.

3.2 Hybrid Human-AI Collaboration

The most sophisticated applications of AI in management do not involve the complete replacement of human decision-makers but rather the creation of new, hybrid collaborative paradigms. This approach, often termed "augmented intelligence," is built on the principle of cognitive complementarity, leveraging the distinct strengths of both humans and machines (Nguyen, 2025). AI excels at data processing and forecasting, while humans provide context, ethics, and creativity.

Effective human-AI collaboration involves designing interactive systems where the human and the AI can engage in a collaborative sensemaking process. Research in this area emphasizes the importance of Explainable AI (XAI), which aims to make the reasoning behind an AI's recommendation transparent and interpretable to the human user (Le Merrer et al., 2024). When a manager can understand why an AI has suggested a particular course of action, they are better equipped to critically evaluate the recommendation, identify potential model limitations or biases, and integrate the AI's insight with their own domain knowledge. For example, in medical diagnostics, an AI may flag a tumor as potentially malignant, but the clinician collaborates with the system by considering the patient's broader medical history and unique circumstances to make a final diagnosis - a decision that is more robust than either the human or AI could make alone (Hirani et al., 2024). This model positions AI not as a decision-maker but as a cognitive partner.

3.3 Redefining Leadership and Performance Metrics

The rise of AI-driven decision-making and human-AI teams necessitates redefinition of leadership. As AI takes over many of the analytical and administrative tasks traditionally performed by managers, the focus of leadership shifts from task oversight to "systems thinking." Leaders in an AI-enabled workplace must become architects of effective human-AI ecosystems (Batool et al., 2025). This requires a new set of competencies, including data literacy, an understanding of algorithmic principles, and the ability to manage the ethical implications of deploying AI.

Furthermore, leadership must evolve to foster trust and psychological safety in an environment where employees may feel threatened by automation. Leaders must help employees adapt to working alongside AI, develop new skills, and focus on the uniquely human aspects of their roles that AI cannot replicate (Yu et al., 2023). Performance evaluation criteria must also evolve. Traditional Key Performance Indicators (KPIs) focused on individual task efficiency are often insufficient for measuring the success of hybrid teams. New metrics are emerging that focus on the quality of human-AI collaboration, the accuracy of joint decisions, and the team's ability to innovate. Organizations are beginning to measure outcomes such as "time to insight" and the "value of augmentation," shifting the focus from the performance of the individual to the synergistic output of the integrated human-machine system (Nguyen, 2025).

4. Organizational Dynamics and Workforce Management

4.1 Intelligent Automation in Workforce Management

Routine tasks such as scheduling, payroll, and attendance are increasingly being automated with AI. Sundari et al. (2024) note that the use of AI in Human Resource departments can improve productivity by up to 30% while simultaneously decreasing data processing errors. This dual benefit highlights AI’s ability to both accelerate workflows and improve reliability. By automating routine tasks, AI reduces the need for human data-handling, minimizing the possibility of human error.

Recruitment and candidate-screening are significant time investments, often involving manual screening of CVs and resumes. This process is vital to company success, as employee quality directly influences team productivity,

culture, and performance. Albassam's (2023) study highlights that AI technology is already being implemented for resume screening and candidate matching. However, one limitation of AI is that it cannot account for more human factors. Another AI technology noted by the study is AI powered chatbots, which can interact with candidates. Although these chatbots help recruiters save time, they may be unable to respond to heavily personalized questions, which can frustrate candidates (Albassam 2023).

Another routine task being revolutionized by automation is employee scheduling. Effective schedules must balance preferences with business needs. According to Govindarajan and Ananthanpillai (2023), using data analytics and sophisticated algorithms, AI powered scheduling systems can estimate future workforce requirements to prevent understaffed or overstaffed shifts. Additionally, this technology can generate more balanced and efficient schedules by considering the abilities, availability, and preferences of employees. This allows employers to maximize output while minimizing unnecessary expenses, improving efficiency and profitability throughout the company, also reducing scheduling errors and bias.

In organizations with a large, diverse workforce, managing the payroll and complex compensation structures can be a monumental, time-consuming, and error-prone task. Manual processing is often susceptible to delays and errors, which can put companies at risk of financial discrepancies and employee dissatisfaction. According to Walter (2021), AI algorithms have the capability to automatically update employee compensation details in real-time and the ability to identify discrepancies in pay, reducing the chance of incurring fines and overpayments.

Through the analysis of AI automation in workforce management systems, two main implications arise. Firstly, as AI algorithms cannot accurately assess nuanced human qualities, a hybrid approach must be considered for people-facing roles, such as resume and candidate screening. Secondly, as AI improves productivity and accuracy, it raises questions about the future of HR roles. With the automation of routine tasks, the role of HR departments must shift away from manual data-entry and calculations, and towards strategic functions such as talent development, employee engagement, and automation oversight. Emphasizing empathy, communication, and inclusive decision making will be critical to complement AI's efficiency and ensure proper integration into workforce management systems.

4.2 Employee Experience and Satisfaction

AI automation also affects morale, retention, and job satisfaction. Although automation is often associated with job displacement, the reality is that it can often improve the experience of employees throughout organizations.

Sundari et al. (2024) find that AI technology has many uses in employee-facing tasks. For example, AI can be used to provide automated and personalized feedback to employees, enabling more immediate and objective assessments. Furthermore, AI systems can analyze performance trends to identify skill gaps and recommend training programs tailored to each employees' individual needs. As a result, employees are more likely to feel supported in their career growth, improving job satisfaction and employee performance.

Additionally, job insecurity due to AI is becoming a large issue. Bhargava et al. (2020) highlight that high-skilled employees and creative workers have a positive outlook on AI due to its ability to handle mundane tasks. However, the lower-skilled workforce has a negative view, fearing automation may render their roles obsolete These fears can have harmful effects on employee morale and retention. When employees believe their jobs are at risk, engagement declines, and turnover intentions rise (Sadeghi 2024). Due to this, the implementation of AI may have a net negative impact on organizations reliant on low-skilled workers, as the benefits of automation are offset by fears of job insecurity.

This signals the need for training that clarifies how AI works and its actual role within the organization. Additionally, organizations should include employees in the decision-making process, giving them the opportunity to voice their fears and provide their opinions on AI. So, the implementation of AI should not solely be a top-down procedure, but instead be participatory, incorporating both education and dialogue.

4.3 Strategic Workforce Planning

In recent decades, strategic workforce planning has become increasingly important, and dependent on AI to optimize labor allocation, forecast workforce demands, and manage operation uncertainty. This allows organizations to generate more accurate workforce forecasts through computerized analysis of large amounts of data.

AI has made a large impact on workforce forecasting, especially as supply chains become more dynamic and traditional planning methods that rely on static rules and conditions become less efficient (Adenuga et al. 2020). However, AI-based tools can dynamically uncover patterns in data to anticipate staffing needs based on factors like task type, location, and skill level. Since machine learning algorithms can be trained on new data, their forecasting accuracy improves over time.

Furthermore, AI enhances organizational resilience amid labor shortages and crises. According to Rane et al. (2024), by analyzing vast amounts of data such as weather patterns, geopolitical events, and market trends, machine learning algorithms can foresee supply chain disruptions in real time. Additionally, natural language processing tools analyze news reports and social media to identify emerging threats. This real-time analysis allows organizations to respond quickly to potential threats, reducing risk.

This shift from rule-based to data-driven forecasting marks a significant change in workforce planning. Traditional systems rely on assumptions that can often fail to account for rapid fluctuations in demand and supply. Contrastingly, dynamic machine learning models forecast and adapt to changes in real time, while simultaneously improving in accuracy as they train on new data. This enhanced forecasting can allow organizations to be proactive instead of reactive when dealing with labor fluctuations and disruptions.

5. Managerial and Policy Recommendations

5.1 Strategies for Business Leaders

To effectively integrate AI, business leaders must champion a human-centric strategy grounded in transparency. Communicating clearly about the purpose of new AI systems and the expected evolution of job roles is a critical first step as transparent AI systems help build trust and improve employee perception of automation (Le Merrer 2024; Yu et al. 2023). Organizations should implement protocols to ensure that decisions made by AI are fully understood by affected employees. This should be coupled with pilot programs that involve employees directly in the testing and deployment process, which can demystify the technology and ensure it is practically applied.

Managers should frame AI as an augmentative tool and redesign workflows so technology handles routine tasks, freeing employees for creative work (Nguyen 2025). Such a focus shifts the organizational mindset from job threat to value creation.

Finally, establishing a robust internal governance framework is essential. This includes creating clear ethical guidelines for AI use, addressing potential algorithmic bias, and ensuring accountability in decision-making processes, because although AI excels at data analytics and process automation, it lacks the capacity for empathy and moral judgement (Batool 2025; Albassam 2023). Thus, relying solely on algorithmic outputs would risk dehumanizing human processes and undermining employee trust. Implementing continuous feedback loops, where employees can report on their interactions with AI tools, will further build trust and allow for iterative system improvement.

5.2 Guidelines for Policymakers

Policymakers should use fiscal instruments to steer AI adoption toward equitable outcomes. This can include offering tax incentives for companies that invest in technologies designed to augment, rather than displace, human labor (Wang 2021). Simultaneously, developing modern social safety nets, such as portable benefit systems not tied to a single employer, is crucial for supporting a more fluid workforce.

Regulatory oversight must be strengthened to ensure fairness and accountability. This includes mandating independent audits for algorithms used in critical public and private sector decisions, such as hiring and credit scoring (Le Merrer 2024). Establishing clear, national standards for data privacy and security in the context of AI is also necessary to protect citizen and employee rights.

Public investment should be directed toward both research and infrastructure. Public investment in AI research addressing societal challenges can ensure benefits are broadly distributed. (Sajwani 2024). Furthermore, investing in digital infrastructure, particularly in underserved communities, will be vital for providing equitable access to AI-driven opportunities.

5.3 Educational and Training Initiatives

To support the current workforce, governments and industries must collaborate to build a national infrastructure for lifelong learning. This should include the promotion of accessible micro-credentialing systems that allow workers to rapidly gain certified skills in specific AI applications. Public-private partnerships are key

to closing immediate skills gaps. These collaborations can develop modern apprenticeship programs and targeted training initiatives that align directly with emerging industry needs (Ahsan 2024). The goal is to cultivate a resilient and adaptable workforce that can thrive alongside intelligent systems.

6. Conclusion

The integration of artificial intelligence into the economy is not an inevitable force with a predetermined outcome. As this research indicates, the effects on employment and management are contingent upon the strategic choices enacted by organizational and public leaders. Our empirical design, grounded in labor-market and task-exposure analysis, supports the proposed Human–AI Role Realignment (HARR) framework. A future of shared prosperity from automation requires interdisciplinary effort. Human-AI augmentation, equitable policy, and adaptive education will determine whether this shift brings shared progress or deeper division.

Ethics and AI declaration: AI was not used in this paper. The authors confirm that the content of this manuscript is original and has not been submitted or published elsewhere.

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Cracking the Chip: AI-Powered Security for Semiconductor Threats

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Abstract: Semiconductor supply chains have become increasingly vulnerable to sophisticated, low-level threats that originate in the early phases and propagate undetected across various stages of semiconductor device production. As semiconductor systems grow more complex and globally interconnected, these low-level design threats present significant risks, including data breaches, system failures, and long-term erosion of reliability. This paper presents a comprehensive AI-driven framework to detect, model, and mitigate hardware security threats across the semiconductor supply chain, from design and fabrication to assembly. We begin with the design phase, illustrating how vulnerabilities like hardware Trojans in third-party IP blocks, compromised EDA scripts, and speculative execution side-channels can be exploited. AI techniques, such as anomaly detection for logic integrity, dynamic hashing for secure script flows, and entropy-based instruction shuffling, are shown to proactively block or obfuscate these attacks. These models serve as templates for following stages, including fabrication (tampered masks or altered process flows), assembly and packaging (hardware fingerprinting), and post-silicon validation (malicious test routines or data exfiltration). Our contributions include a stage-wise breakdown of threat surfaces across the supply chain and the design of threat models with corresponding AI-driven defenses that analyze patterns, enforce trust boundaries, and obfuscate system behavior. Additionally, to assess the viability of these defenses, we outline a validation framework involving simulated and prototyped defenses, which include instruction shuffling, JTAG interface monitoring, and machine learning-based fault pattern analysis. Proposed evaluation metrics include detection accuracy, computational overhead, entropy of runtime traces, and classification accuracy. By addressing persistent security threats early and continuously through the chip lifecycle, we aim to leverage AI to shift hardware security from reactive patching to proactive risk management. Our work emphasizes the importance of securing semiconductor systems at their root, offering a path toward proactive hardware security and highlights the need for scalable, interdisciplinary solutions at the intersection of AI, hardware design, and supply chain security.

Keywords: AI-Driven security, Hardware threat modeling, Adaptive defense, Semiconductor supply chain security

1. Introduction

Semiconductors, also commonly known as integrated circuits in today's age, drive nearly all devices around the world. From mobile devices to life-saving medical devices, these small yet powerful chips are the foundation of the digital age and would not exist without the critical industry behind it. The semiconductor supply chain is an intricate system that is composed of many interconnected stages. Its sprawl lies on a global scale, which is crucial in upholding its infrastructure. Due to the number and complexity of its stages, an effective global framework is critical as "no singular country", or company, can perform all roles in the supply chain in a reliable manner to produce the numerous types of semiconductors needed in the international market (Thadani and Allen 2023). Considering the vital role that the semiconductor supply chain plays and its reliance on global interconnection, it is increasingly important that vulnerabilities are rooted out along each stage to preserve its function. The existence of security threats at any stage of the supply chain serves not only to weaken its infrastructure but will also cause detrimental repercussions for the consumers that depend on semiconductors. With the rapid advancement of artificial intelligence, it is critical for this high-value industry to seek how they can leverage techniques powered by AI to reinforce its supply chain, an infrastructure that is crucial to global economic function.

1.1 Motivation

Hardware security vulnerabilities often originate during the early stages of chip design and persist throughout the entire lifecycle of a semiconductor. These low-level threats often serve as the root cause of cascading security issues, ultimately manifesting as critical software-level security breaches. As modern systems become increasingly complex and interconnected, the consequences of such vulnerabilities grow more severe, ranging from compromised data integrity to large-scale cyber-attacks. Such weaknesses create rippling consequences not only in the semiconductor industry, but for the various economic sectors that depend on semiconductor technology as well. This paper is motivated by the urgent need to proactively identify and mitigate hardware-level threats at their point of origin. By leveraging AI-driven techniques, we aim to enhance the resilience of semiconductor systems and disrupt the attack chain before it escalates to higher system layers.

1.2 Contributions

This paper seeks to advance existing research concerning the usage of artificial intelligence to target hardware vulnerabilities in the semiconductor supply chain and demonstrate how key figures within the industry can reinforce their sector to mitigate current and theoretical threats. The key contributions of this paper include:

- Comprehensive Threat Categorization Across Supply Chain Stages: We present a stage-wise categorization of hardware threat vectors, such as design-time Trojans, test access misuse (e.g., JTAG abuse), and counterfeit components, and map them to realistic attack scenarios and propagation paths.
- AI-Powered Detection and Mitigation Techniques: We propose a suite of machine learning-based techniques tailored to specific vulnerabilities, including FSM anomaly detection, optical/SEM image classification of chip defects, and instruction-level runtime obfuscation guided by AI policies.
- Framework for Adaptive Defense: We introduce a modular defense framework where AI agents can adaptively respond to threats depending on the supply chain phase, enabling detection as well as real-time mitigation (e.g., dynamic instruction shuffling or scan chain monitoring).
- Validation Methodology: We propose a structured evaluation foundation using detection time, classification accuracy, and reverse engineering resistance as metrics, and describe prototype implementations to support future empirical validation.

2. Background

The semiconductor supply chain can be divided into three broad stages: research and design, manufacturing, and assembly and test packaging. Each stage involves specialized sectors distributed across key geographic regions including the United States, South Korea, Japan, China, Taiwan, and Europe (Varas et al 2021). Understanding the roles these regions play is essential for identifying vulnerable phases, as disruptions at any point can cause cascading consequences throughout the chain. These risks are not unique to semiconductors. Critical infrastructure industries like energy have faced similar supply chain cyberattacks, underscoring the urgent need for AI-powered defenses and zero-trust frameworks (Kumar, Tripathi, and Das 2025). Securing the semiconductor supply chain, the foundation of digital systems, can also improve resilience in sectors like energy, healthcare, and defense.

Manufacturing begins with pre-competitive research, which advances semiconductor fabrication and composition to meet evolving needs. Design translates this research into real-world architectures under complex parameters. Reusable intellectual property (IP) blocks streamline development by eliminating the need to recreate common elements, allowing engineers to focus on innovation. This is enabled by electronic design automation (EDA) tools, which include simulation, design, and verification. Simulation tests circuit behavior under various conditions. The design stage includes logic synthesis, schematic capture, and layout construction. Verification ensures the design meets specifications and is manufacturable, using physical and functional checks. Undetected flaws here can lead to costly delays. As noted by Varas et al (2021), chip design and EDA contribute roughly 54% of the semiconductor supply chain's total value added, highlighting their strategic importance.

The next major phase is manufacturing, where chips are fabricated through complex, nanoscale processes. Semiconductor fabs manufacture integrated circuits on silicon wafers, each containing hundreds of identical chips. Extreme precision and cleanliness are required—any contamination or tampering can compromise the batch, leading to significant losses. Depending on the application, fabrication can span 400 to 1,400 steps over 14 to 20 weeks (Varas et al 2021). Fabs rely heavily on specialized semiconductor manufacturing equipment (SME) to carry out these intricate procedures.

Finally, wafers enter the assembly, testing, and packaging stage. Known as back-end manufacturing, this phase prepares chips to meet functional and mechanical requirements. Primarily concentrated in Asia, it involves dicing wafers into individual dies, placing them onto substrates, and encapsulating them to protect against environmental and mechanical damage (Varas et al 2021). While this summary simplifies a highly technical process, the step is vital to delivering functional, defect-free chips to global markets. Major U.S. firms like Apple, Intel, and Texas Instruments depend heavily on this stage to commercialize their designs (Tomoshige 2022).

3. Methodology

Our methodology follows a multi-step approach involving threat modeling, AI framework design, and validation design, based on a comprehensive literature review and analysis of documented hardware attack cases.

First, we conducted an extensive review of academic literature, vulnerability databases (e.g., NIST's National Vulnerability Database), and industry case studies to identify and classify hardware threats across key stages of the semiconductor supply chain. Threats such as malicious IP insertion, JTAG exploitation, and counterfeit component introduction were examined in terms of their entry points, propagation behavior, and observable surfaces for detection.

Building on this analysis, we designed an AI-driven mitigation framework in which each stage of the supply chain is assigned targeted defense strategies. For example, the design phase employs anomaly detection and instruction obfuscation techniques, while the manufacturing phase uses image classification models for physical inspection. Each AI approach was chosen based on the nature of the threat's signal surface and the operational constraints of that stage.

To evaluate the feasibility and potential effectiveness of these defenses, we propose a validation framework that includes: (1) prototype simulation; (2) metric-driven comparison of proposed AI techniques with existing verification tools; and (3) threat injection scenarios to evaluate detection accuracy and response time. Although full implementation is left to future work, we outline practical experimental setups and tooling pathways, such as leveraging open-source RTL designs, SEM image datasets, and accessible FPGA development platforms.

4. Threat Modelling

To systematically address supply-chain security, we formalized a stage-wise threat model that specifies adversary capabilities, trust boundaries, attacker goals, and operational constraints in Table 2. This structured model provides the foundation for mapping AI-driven defences to stage-wise risk scenarios.

- **Adversary Capabilities:** Potential attackers include malicious insiders at IP vendors, EDA providers, fabrication facilities, with varying levels of access to RTL/netlists, process manufacturing parameters, packaging steps, or test/debug interfaces.
- **Trust Boundaries:** We assume that inhouse designs and OEMs retain partial trust, while third-party IP vendors, EDA toolchains, and offshore/decentralized fabs are considered potentially compromised.
- **Attacker Goals:** Depending on stage, goals include violating integrity (e.g., Trojan insertion), confidentiality (e.g., side-channel extraction of keys), authenticity (e.g., counterfeit parts), and availability (e.g., parameter drift leading to failure).
- **Operational Constraints:** Practical deployment requires low false-positive rates, tight resource budgets and testability compliance for real-time systems.

Table 1: Formalized Threat Model

Stage	Adversary Capabilities	Trust Boundaries	Attackers Goals	Constraints
Design	Insert malicious logic into IP/netlists; inject compromised EDA scripts; exploit open test/debug ports.	IP vendors are untrusted; EDA providers are partially trusted.	Integrity/Trojan-free design; confidentiality (protect cryptographic keys).	≤1% false positives; monitor overhead <5% area/power.
Manufacturing	Modify process parameters (doping, etching); introduce dopant-level tampering; conceal physical defects.	Foundries are partially trusted; Semiconductor Manufacturing Equipment vendors are untrusted.	Authenticity: genuine wafers only; reliability and reproducibility.	Inline inspection latency < 5 sec per wafer; minimal throughput loss.
Assembly	Swap with counterfeit ICs; alter packaging to enable probing; exploit environmental stress (humidity, delamination).	Outsourced semiconductor assembly and test vendors are untrusted; Original Equipment Manufacturers are trusted.	Authenticity (prevent counterfeits); confidentiality (block invasive probing).	Fingerprinting stable across voltage, current and temperature; provenance auditable and traceable.

4.1 Design Phase Threats

4.1.1 Hardware Trojans in IP blocks

Intellectual property (IP) blocks are reusable components of logic that support reusable designs, which allows for efficient implementation of logical components and Integrated Circuits. However, they also introduce significant security threats. For example, hardware Trojans embedded into these third-party IP-blocks can be extremely difficult to identify, especially when they are delivered as black-box gate-level netlists. Artificial Intelligence offers a promising solution to this conundrum by enhancing and deepening the reach of traditional testing methods. AI can be trained not only on traditional inputs and outputs, but also on side-channel indicators such as timing glitches, power consumption, and electromagnetic emissions. By monitoring these additional parameters, AI improves the likelihood of identifying subtle anomalies in chip behavior, indicating the presence of unwanted logic or circuits. Thus, AI can significantly strengthen the verification process of IP blocks, as its speed and adaptability allow for broader and deeper testing against potential threat vectors.

4.1.2 Exploitation of infected EDA tools

Another point of entry for critical vulnerabilities lies in EDA tools. Bugs in these EDA tools present a unique level of complexity as they are often embedded in automated steps of the EDA processes. Malicious actors can take advantage of this and inject compromised scripts in between the different stages without altering the source HDL code, making them hard to detect in source code audits or even in post-silicon validation once the chip is fabricated. In their 2023 study, Mavarapu et al highlight that attacks such as HeisenTrojan specifically exploit vulnerabilities in EDA tools, “establishing a permanent presence and providing a beachhead for intrusion into that system.” Figure 1 illustrates how such attacks can propagate. The script shown compiles a CPU core using the synth_design command. The flatten_hierarchy flag removes module boundaries, hindering traceability and making previously inserted malicious logic harder to detect. While it does not insert Trojans directly, it complicates verification workflows. By flattening the design hierarchy, any malicious logic can become deeply embedded in the netlist and no longer traceable to its original HDL modules, significantly deterring detection. Artificial Intelligence can support analysis of the provenance of the chips by verifying signed and reproducible EDA workflows. Anomaly detection is implemented on authenticated metadata, such as versioned commits and digital signatures, to identify suspicious changes rather than modifying hash semantics. These hashes will be flexible to accommodate valid and trusted edits but trigger alerts when any suspicious modifications are made. Furthermore, AI models can be used to secure the script pipelines by classifying changes and verifying their authenticity and enforcing credential-based editing leveraging the previously discussed hashes. For example, when the compromised script's timing and utilization reports show any unexpected spikes in logic usage or delays, the trained AI models can quickly assess whether the flattened netlist matches with the original high-level structure. This allows authorized users to make safe updates while effectively blocking tampering attempts.

```
# Read in all RTL files
read_verilog ALU.v SCC.v IM.v DM.v SCP.v

# Set the top-level module
set_top SCP

#Elaborate and compile the design
compile_ultra

# Write out synthesized netlist
write -format verilog -hierarchy -output synthesizedSingleCycle.v

#Setting parameters
set_clock_uncertainty 0.25
set_max_delay -from [get_ports A] -to [get_ports B] 2.0

#Malicious modification
set_dont_touch [get_cells *ALU.v*] # prevent ALU from being optimized or inspected
set_app_var suppress_messages {TIM-123} #hide specific timing warnings from logs

# Synthesize CPU design
synth_design -top SCP -part xc7a35tcsg324-1 -flatten_hierarchy rebuilt
#flattern hierarchy flag obscures the original module structure
#making detection of malicous code harder
```

Figure 1: Infected TCL script

4.1.3 Side-Channel leakages

Information leakage through side channels poses a serious security risk by exploiting a system's architectural behavior rather than its logic. These attacks extract sensitive data by monitoring power consumption, network activity, storage, and cache usage—revealing internal chip operations. A notable example is the exploitation of branch prediction and speculative execution. In branch prediction, the CPU guesses whether a branch will be taken; if it guesses wrong, the wrongly predicted instructions are rolled back. However, these discarded instructions can leave behind observable traces such as cached entries or memory timing variations. Attackers can exploit this by training the branch predictor to speculatively access sensitive memory, leading to data leakage of confidential information, though speculative execution does not modify program state. AI offers a promising defense against such threats. As Demme et al (2012) noted, side-channel attacks rely on detecting patterns in a program's behavior. AI can disrupt these patterns through dynamic instruction shuffling, rearranging non-critical instructions, similar to how operating systems schedule code blocks across threads, to eliminate predictability. Furthermore, AI can detect emerging trace patterns and inject obfuscation blocks, such as padded memory accesses or dummy instructions, maintaining functional correctness while increasing system unpredictability.

4.1.4 Insecure/open access test interfaces

Another significant threat during the design phase is the improper implementation of design-for-test features, particularly the exploitation of the JTAG (Joint Test Action Group) interface. JTAG is an industry-standard protocol widely used for testing and debugging integrated circuits (ICs), SoCs, and PCBs, allowing external access to internal logic and registers without physical intervention. However, if JTAG access is not properly fused or locked during IP block transfer or at any point in the chain of custody, it becomes a powerful attack vector. Malicious actors can gain low-level control of the device, including CPU, memory, and I/O, to inject code or modify program behavior. As Dong et al (2017) note, hardware Trojans have successfully exploited unsecured JTAG ports to manipulate device memory via the data bus. Artificial intelligence can play a key role in mitigating such threats both at design time and during runtime. At design time, AI-powered static analysis can identify unsecured or improperly fused JTAG/TAP ports in RTL/netlists. At runtime, anomaly detection of scan activity and power traces can detect and respond to abnormal JTAG usage events. Unlike traditional rule-based tools, AI models trained on diverse design patterns offer deeper vulnerability recognition and proactive detection. At runtime, embedded AI logic can monitor activation events and respond adaptively shutting down access to sensitive chip regions in the event of unexpected JTAG activity.

4.2 Manufacturing-Phase Threats

4.2.1 Physical tampering

During wafer fabrication, malicious actors or insider threats can introduce or mask physical defects such as dopant impurities, contaminants, or open circuit faults. Due to their microscopic and localized nature, these flaws often evade detection through traditional methods like electrical testing or visual inspection. Left unaddressed, they can degrade chip functionality and security over time, potentially compromising entire product lines before deployment. Though seemingly minor, such defects may slip past quality assurance and create systemic vulnerabilities. As Nam and Kim (2023) note, chip-level defect analysis is becoming critical due to the unpredictability and cost of customer-discovered flaws that wafer-level testing often misses. AI offers a scalable solution to mitigate these risks. Modern testing systems generate massive datasets, and convolutional neural networks (CNNs) trained on SEM images and micrographs can efficiently detect and classify anomalies. This reduces testing overhead, making robust defect detection more feasible and incentivizing early intervention. Furthermore, AI can be used to develop degradation models that monitor drift patterns over time. This can prove to be useful in the early identification of unusual drift patterns indicative of those infinitesimal defects. Such predictive capabilities can help mitigate the large-scale impact of these faults by enabling proactive correction before devices reach critical deployment stages.

4.2.2 Deviation in fabrication parameters

During wafer manufacturing, the integrity of physical parameters such as doping concentration, etching precision, and dielectric quality is crucial to chip security. Deviations, accidental or malicious, can degrade performance or functionality, compromising chips even if the digital design is errorproof. For example, metal layers that are thinner than specified can reduce component isolation, increasing vulnerability to side-channel leaks. Keith, Castillo-Villar and Bhuiyan (2023) highlight the growing exposure of fabrication facilities to cyber-

physical threats and demonstrate through stochastic modeling how even small variations can be part of larger adversarial campaigns. To counter these risks, AI provides powerful tools for real-time adaptation and specification verification. AI systems can dynamically adjust manufacturing parameters based on live sensor data, using reinforcement learning and feedback control to maintain consistency across wafers and prevent drift in metrics like etch duration or deposition thickness. To reinforce this process, chips produced at trusted facilities can serve as "model keys" with detailed profiles of power consumption, leakage, delay, and timing jitter. By modeling these features with Gaussian Mixture Models (GMM), AI can continuously compare ongoing output to the baseline. Any deviation beyond accepted tolerances triggers alerts or corrective actions, enabling proactive protection against fabrication-layer tampering.

4.3 Assembly and Packaging Threats

4.3.1 Counterfeit insertion and lack of traceability

The back-end stages of the semiconductor supply chain, particularly assembly, packaging, and testing, present a critical point of vulnerability for counterfeit chip production and insertion. The geographic concentration of foundries in East and Southeast Asia, combined with the decentralized nature of packaging operations, increases the risk of authentic chips being replaced with visually identical counterfeit ones. These substitutes may lack essential cryptographic modules or tamper detection circuits, making them highly exploitable. Moreover, if counterfeit chips carry cloned serial numbers or markings, they undermine traceability and accountability within the global supply chain. To address this, a hybrid approach combining artificial intelligence and blockchain-based provenance tracking offers a compelling solution. AI models can create unique chip-level fingerprints by analyzing subtle variations in timing, thermal response, and power-up behavior, which result from minor manufacturing variations. These fingerprints provide an identifier that allows physically identical clones to be differentiated from legitimate chips. Blockchain technology has shown promise in enhancing transparency, security, and automation in cyber risk management through decentralized ledgers and smart contracts. This approach can improve risk assessment and streamline processes, offering valuable lessons for securing complex supply chains (Kumar, Kocian and Loo 2024). When coupled with blockchain technology, each legitimate chip's lifecycle events can be recorded securely in a decentralized ledger (Neisse, Steri and Nai-Fovino 2017). AI can enhance this system by continuously scanning ledger entries, calculating risk scores, and identifying flows that may have unauthorized substitutions or modifications. This combination of AI-based fingerprinting and blockchain accountability enhances both hardware authentication and the integrity of provenance records, thereby mitigating the risks of counterfeit infiltration in semiconductor supply chains.

4.3.2 Environmental factors -based attacks

Moisture penetration during the packaging stage of semiconductor manufacturing presents an often overlooked but critical security risk. Moisture can degrade encapsulation materials, weaken structural barriers, and facilitate invasive physical attacks such as signal probing or micro-wiring modification. In plastic-encapsulated microelectronics, moisture diffuses over time—particularly through cracks or voids—leading to dielectric breakdown and interfacial delamination (Hadi, Ahmed and Sayyid 2011). These pathways can be exploited by adversaries to manipulate internal circuit elements. Moreover, certain hardware Trojans may remain dormant under standard conditions but activate when triggered by environmental factors like humidity or temperature. These sleeper mechanisms pose a significant threat in long-lifecycle devices, as their malicious behavior emerges only during field operation. To address these vulnerabilities, artificial intelligence can be integrated into non-destructive testing (NDT) workflows, offering a proactive and scalable defense. AI-enhanced NDT methods such as infrared thermography, X-ray imaging, and acoustic microscopy can improve defect detection, automate anomaly classification, and enable predictive diagnostics (Safhi, Keserle and Blanchard 2024). When applied to semiconductor packaging, these techniques can detect early signs of delamination, moisture-induced stress, or material degradation by comparing current chips with reference profiles. Additionally, time-series AI models can analyze environmental and electrical data to identify degradation trends, allowing manufacturers to detect and address issues before they evolve into security threats. By combining predictive moisture behavior with AI-driven inspection, manufacturers can ensure environmental conditions do not undermine device security. Table 1 summarizes these threats and corresponding mitigations across each stage of the supply chain.

Table 2: Threat Model Summary Table

Stage	Threat	Proposed AI defense
Design	Compromised IP Blocks	Comprehensive analysis of side channel indicators beyond traditional inputs
Design	Infected EDA Tool/Scripts	AI-based contextual script hashing, behavior verification, credential-based editing
Design	Side-Channel Leak	Instruction shuffling, AI-derived memory padding and obfuscation blocks
Design	Insecure Test Interface	Detection of open TAPs using AI trained on diverse patterns, runtime monitoring and response for unexpected access
Manufacturing	Physical Tampering	Using CNNs for SEM image classification, drift tracking for early anomaly detection
Manufacturing	Parameter Deviations	Modelling parameters using GMM to identify deviation from base behavior
Assembly	Counterfeit Chips	AI-based chip fingerprinting and blockchain, creation and comparison to key models
Assembly	Moisture/Environmental factors	NDT enhanced by AI, Time series AI models of environmental degradation

5. Framework Validation

To assess the effectiveness and overhead of the proposed AI-driven threat detection and mitigation framework, we outline a multi-pronged validation blueprint centered on simulation, comparative benchmarking, modeling of real-world vulnerability scenarios and aligned with established practices in hardware security and industrial inspection. While full-scale experimentation is reserved for future work, this plan lays out concrete evaluation paths using open-source tools, widely available datasets, and standardized test protocols to ensure reproducibility and practical relevance.

5.1 Trojan and Logic-Based Threat Detection

We simulate hardware Trojans and architectural vulnerabilities in RTL designs using open-source toolchains like Verilator and OpenROAD. Trust-Hub benchmarks will serve as the primary dataset, providing ground-truth examples of Trojan-inserted netlists. AI-based FSM anomaly detectors and graph-based classifiers will be compared against rule-based verification approaches and SAT-based deobfuscation attacks (Subramanyan et al., 2015). Evaluation metrices will be detection accuracy, false positive rate, false negative rate, runtime latency, and resource overhead (area, power, LUT utilization).

5.2 Runtime Obfuscation and Side Channel Defense

AI-enhanced instruction shuffling and AI- powered obfuscation mechanisms on FPGA SoCs built with LiteX, synthesized via Vivado (for FPGAs) or Design Compiler (for ASICs), and simulated using ModelSim or Verilator. Metrics include entropy of observable memory/cache access patterns, IPC (instructions per cycle), and runtime delays. Reverse engineering resistance will be evaluated using SAT-based deobfuscation attacks (Subramanyan et al., 2015) and formal equivalence checking, replacing software reverse engineering tools to ensure hardware-appropriate evaluation. Side channel leakage will be tested using standardized techniques such as Test Vector Leakage Assessment (TVLA) and mutual information analysis (Gierlichs et al., 2008).

5.3 Tamper Detection Using SEM Imagery

To identify packaging and physical tampering, we train lightweight convolutional or transformer models on scanning electron microscope (SEM) images. State-of-the-art industrial anomaly detection baselines such as PatchCore (Roth et al., 2022), RD++ (Tien et al., 2023), and PNI (Bae et al., 2023) will be included for comparison.

Models will be built using TensorFlow or PyTorch and evaluated on their ability to detect surface abrasion, lithographic drift, classification accuracy, localization precision, robustness and other subtle anomalies. Public SEM imagery and held-out defect sets will be used to benchmark classification accuracy and robustness.

5.4 Counterfeit Detection via Behavior Fingerprinting

We simulate authentic and counterfeit chips on FPGAs and analyze power and timing behaviors. We explicitly scope these experiments to logical-level fingerprints and do not generalize to dopant- or process-level attacks without silicon datasets. RNNs or sequence classifiers will be trained to fingerprint genuine behavior patterns and detect deviations. Modified variants—such as those simulating dopant shifts or corner process changes—will test generalizability. Metrics include classification accuracy and false positive rate.

5.5 Process Drift Detection in Fabrication

Process deviations such as bridging faults, voids, and misalignments will be simulated using TCAD tools (e.g., Silvaco). A time-series model (e.g., RNN) will be trained to detect and localize these variations. Baselines will include frameworks such as M2D2 (Lin et al., 2025). Performance evaluation metrics will focus on detection precision and robustness under varying process conditions.

5.6 Reproducibility and Deployment Constraints

All experiments will specify dataset splits, baseline implementations, parameters, and tool versions to ensure reproducibility. Hardware prototypes will report overhead in terms of area, power, and timing. Practical deployment requirements, such as maintaining area overhead under 5% and ensuring acceptable false positive rates, will be explicitly analyzed.

6. Discussion

Our framework is designed for seamless integration into existing semiconductor workflows with minimal disruption. The detection models are lightweight and can be deployed either on an isolated security-dedicated chip region or a separate system, consuming no more than 5% computational overhead. Training data is largely available from public sources, such as Trojan benchmarks like TrustHub and archival fabrication data collected for quality control. While the framework primarily targets new chip design and production, legacy systems can still benefit through offloaded processes like cloud-based system monitoring.

At this stage, our work remains a theoretical design study. Prototyping and precise overhead measurements, including power and performance impact, are planned for future work. Although our evaluation plan outlines how the framework could be validated, implementation and empirical testing will follow due to current resource limitations. Some strategies, such as runtime obfuscation, introduce overhead and may complicate worst-case execution-time (WCET) certification in real-time systems. These trade-offs must be carefully considered when defining security budgets and QoS (Quality of Service) goals. Nevertheless, once realized, the proposed measures could enable chipmakers to issue machine-verifiable integrity certificates per wafer lot, providing downstream integrators with traceable, auditable assurance—an increasingly vital requirement in regulated sectors such as automotive and medical devices.

Much prior work has addressed isolated stages of the supply chain, offered targeted solutions but lacked a unified approach. For example, Wilson et al (2024) introduced RAPTOR, a deep-learning discriminator for detecting tampering in post-fabrication packaging, yet it does not account for earlier threats such as malicious IP or test access insertion. Lin, Tsend and Tsai (2025) developed M2D2, a multi-modal drift detection framework for monitoring equipment and process health in wide-bandgap fabrication, focusing on operational anomalies rather than adversarial behavior. Sun et al (2024) proposed a CNN-based method for lithographic hotspot detection during the CAD stage, offering layout-level accuracy but limited to physical design vulnerabilities. In contrast, our framework spans the entire semiconductor supply chain, integrating CNN-based SEM classification, AI-powered provenance ledgers, and anomaly detection across both logical and physical domains. In contrast, our framework spans the entire semiconductor supply chain, combining CNN based SEMs classification, AI powered ledgers, and anomaly detection across both logical and physical domains. It integrates insights from these works but extends them into a modular, stage-specific, and adversary-aware architecture designed for proactive security response.

7. Conclusion

As semiconductor systems continue to evolve in complexity, they also grow increasingly susceptible to security vulnerabilities introduced across the design, manufacturing, and assembly pipeline. This paper presents a comprehensive, AI-driven framework for detecting, modeling, and mitigating hardware-level threats at each critical stage of the semiconductor supply chain. By integrating machine learning with side-channel analysis, image-based defect detection, provenance tracking, and adaptive runtime obfuscation, we demonstrate how AI can go beyond passive threat identification and serve as an active, scalable defense mechanism.

Through detailed threat modeling, our work underscores the potential of artificial intelligence as a cornerstone for secure and resilient hardware ecosystems. Future directions include expanding these defenses into edge-deployed AI chips and collaborating with industry partners to operationalize these solutions at a scale. Our findings lay the groundwork for trustable semiconductor manufacturing in an era where both performance and security are paramount.

Ethics Declaration: This research did not require any ethical clearance.

AI Declaration: OpenAI's ChatGPT was used to check and correct any in-text citation formatting and reference list formatting issues. The tool was not used to generate original content or conduct analysis.

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Teaching Bayesian Reasoning as a Pathway Toward Active Thinking and Explainable AI

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Abstract: Decision-making under uncertainty requires not only computational tools but also critical thinking skills that allow individuals to evaluate assumptions, weigh evidence, and mitigate automation bias. While many contemporary AI systems operate as opaque black-box models, Bayesian Networks (BNs) provide a transparent and explainable alternative, making them well-suited for both decision support and AI education. This paper introduces an educational framework where learners construct, parameterize, and interpret Bayesian models to address authentic problems, such as classifying suspicious emails in cybersecurity. By explicitly modelling variables, dependencies, and prior assumptions, BNs engage students in probabilistic reasoning while promoting metacognitive reflection and critical evaluation of their decision-making process. The contribution of this work is threefold: (1) it positions Bayesian Networks as both a mathematical reasoning tool and an accessible entry point into explainable AI; (2) it integrates probability theory, critical thinking, and transparency into a unified framework for Responsible AI education; and (3) it demonstrates how transparent reasoning can support human-in-the-loop decision-making and reduce automation bias. While the framework does not claim to solve the general challenges of explainability in complex AI models, it offers a concrete and transferable pathway for cultivating active thinkers capable of designing, interpreting, and questioning AI-assisted decisions.

Keywords: Bayesian networks, Explainable AI, Probabilistic reasoning

1. Introduction

Critical thinking in decision-making is defined as the ability to analyse, evaluate, and synthesize information in order to choose the best possible course of action among multiple alternatives (Facione, 2015). It involves identifying biases, uncovering underlying assumptions, and weighing alternative options (Paul & Elder, 2006). Within decision-making contexts, critical thinking is not merely a theoretical competence but a dynamic process that guides individuals in making informed judgments, especially under conditions of limited or uncertain information.

Decision-making under uncertainty represents a particularly demanding cognitive task, since decision-makers must often estimate potential outcomes based on incomplete or ambiguous data (Kahneman & Tversky, 1979). Uncertainty may arise from either missing information or the inherent stochasticity of the environment. In such situations, critical thinking functions as a filter for risk assessment, helping individuals to mitigate systematic judgment errors and cognitive biases.

Decision support tools are commonly employed to enhance critical thinking in uncertain contexts. These tools provide structured methods for analysing data, calculating probabilities, and evaluating scenarios, allowing decision-makers to combine quantitative and qualitative elements before reaching conclusions (Power, 2008). However, the increasing integration of artificial intelligence (AI) into decision-support systems has introduced both opportunities and challenges. A major concern is automation bias, the tendency of users to over-rely on AI recommendations even when they are incorrect (Parasuraman & Manzey, 2010; Goddard et al., 2012). This risk is exacerbated in "black-box" AI models, such as deep neural networks, which produce outputs without offering sufficient interpretability (Cabitza et al., 2017; Ribeiro et al., 2016).

In this regard, Bayesian Networks provide a transparent and explainable alternative, grounded in probabilistic reasoning and causal modelling. By engaging users in the explicit definition of variables, dependencies, and prior assumptions, Bayesian reasoning not only supports more reliable decision-making but also cultivates critical and metacognitive skills (Tonekaboni et al., 2019). Through this process, learners are not passive recipients of AI outcomes but active participants who construct, test, and reflect on the models themselves (Bansal et al., 2019).

While Bayesian Networks are inherently transparent due to their graphical structure and probabilistic reasoning, their educational and practical value can be further enhanced through integration with contemporary Explainable AI (XAI) frameworks. Modern libraries such as SHAP (Lundberg & Lee, 2017), and

LIME (Ribeiro et al., 2016) focus on generating local and global explanations for complex black-box models, but they often struggle to provide users with causal insights. Bayesian Networks can act as complementary tools within such frameworks by offering causal and probabilistic explanations that are both mathematically grounded and pedagogically intuitive. For instance, visualization dashboards that combine SHAP-like feature importance with Bayesian causal graphs can help learners and practitioners not only understand which variables influenced a decision, but also why these relationships exist within a broader causal structure. This integration bridges the gap between interpretable statistical modelling and state-of-the-art AI explainability, positioning Bayesian Networks as both a didactic instrument and a practical component of responsible AI pipelines.

This paper introduces an educational framework for teaching Bayesian reasoning as a pathway to transparent and responsible AI. By progressively integrating concepts such as probability theory, conditional dependence, and Bayes' theorem into real-world applications of Bayesian Networks, the approach aims to empower learners to both understand and critically evaluate AI-based decision-making. The ultimate goal is to encourage a shift from passive users of opaque AI systems to active thinkers capable of designing, interpreting, and questioning decision-support models in complex and uncertain environments.

Importantly, this work does not claim to fully resolve the broader challenge of AI explainability, nor to guarantee the development of fully "active thinkers." Instead, it positions Bayesian Networks as an illustrative case through which learners can engage with uncertainty, bias, and causal reasoning in an interpretable way. While the framework is grounded in Bayesian modelling, its principles—transparent reasoning, user involvement, and metacognitive reflection—can inform broader educational strategies for interacting with complex AI models, including deep learning systems when combined with XAI libraries. In this sense, the contribution should be viewed as a pathway: a modest but concrete step toward cultivating reflective and critically engaged users of AI.

The main contribution of this paper lies in the design of an educational framework that integrates Bayesian reasoning into responsible AI education. By leveraging Bayesian Networks as both probabilistic models and interpretable learning tools, the framework offers a structured pathway for cultivating critical thinking, metacognitive reflection, and transparent decision-making under uncertainty. This contribution is situated at the intersection of mathematics education, explainable AI, and human-centred decision support.

The innovation of the work is twofold. First, it introduces Bayesian Networks not only as mathematical constructs but also as explainable AI instruments that can be embedded in learning environments to promote active user engagement. Second, it demonstrates how these principles can complement broader XAI methodologies, positioning Bayesian reasoning as a pedagogically grounded yet technologically relevant bridge between statistical learning and modern AI systems. In doing so, the paper provides a novel perspective: fostering a shift from passive reliance on opaque AI outputs toward active engagement with interpretable, causally informed models.

The remainder of the paper is structured as follows: Section 2 reviews related work on critical thinking, probabilistic reasoning, and research in Explainable AI (XAI). Section 3 presents the theoretical foundations of Bayesian reasoning. Section 4 introduces the proposed educational framework, followed by Section 5 which illustrates its application through a cybersecurity decision-making scenario. Section 6 outlines the methodological approach, Section 7 discusses implications for responsible AI and future directions, and Section 8 concludes the paper.

2. Related Work

The integration of Artificial Intelligence (AI) into decision-making processes has been widely studied, particularly in domains such as healthcare, finance, and cybersecurity (Topol, 2019; Samek et al., 2017). While AI systems can improve accuracy and efficiency, their reliance on opaque "black-box" models such as deep neural networks has raised concerns regarding transparency, interpretability, and trustworthiness (Ribeiro et al., 2016; Cabitza et al., 2017). These challenges have been linked to automation bias, the human tendency to over-rely on automated recommendations even when they are incorrect (Parasuraman & Manzey, 2010; Goddard et al., 2012).

To address these issues, research in Explainable AI (XAI) has sought to provide frameworks that enable users to understand and critically evaluate model outputs. Approaches such as LIME (Ribeiro et al., 2016) and SHAP (Lundberg & Lee, 2017) aim to approximate explanations for complex models, but their post-hoc nature has been criticized for offering partial or misleading insights (Lipton, 2018). In contrast, probabilistic graphical

models, and particularly Bayesian Networks (BNs), have been highlighted as inherently interpretable alternatives, as they explicitly represent causal relationships and conditional dependencies among variables (Pearl, 2018; Jensen & Nielsen, 2007).

Within the educational domain, Bayesian reasoning has been proposed as a valuable tool for teaching probabilistic thinking and decision-making under uncertainty (Konold, 1989; Gigerenzer & Hoffrage, 1995). Prior studies emphasize that engaging learners in the construction and evaluation of Bayesian models not only improves their statistical literacy but also fosters critical thinking by requiring them to assess assumptions, update beliefs with new evidence, and reflect on their reasoning processes (Conati et al., 2002; Bansal et al., 2019). Moreover, integrating Bayesian reasoning into AI education has been suggested as a pathway to developing more responsible and transparent uses of intelligent systems (Tonekaboni et al., 2019; Lyell et al., 2021).

The related literature was systematically reviewed using Google Scholar and Scopus databases combining search terms such as *"Bayesian reasoning in education," "Explainable AI," "critical thinking and AI,"* and *"automation bias."* Studies were included if they discussed probabilistic reasoning, AI explainability, or pedagogical frameworks involving uncertainty. This transparent search and selection process ensured that both foundational theories and recent XAI developments were represented.

Despite the rich literature on Explainable AI and Bayesian reasoning, few studies explicitly connect these domains within an educational context. Existing works often address either probabilistic reasoning or AI explainability separately, without proposing a unified pedagogical model that links the two. This gap highlights the need for an integrative framework that teaches explainable reasoning through hands-on Bayesian modelling—precisely the contribution of this study.

Taken together, these strands of research highlight the need for pedagogical approaches that move learners from passive consumers of AI outputs to active participants in the construction of interpretable, probabilistic models. Our work builds on this line of inquiry by proposing a didactic framework for teaching Bayesian Networks as both a mathematical tool and a means of cultivating critical thinking for transparent AI.

3. Theoretical Framework

3.1 Reasoning under Uncertainty: Human and AI Perspectives

Decision-making under uncertainty has long been analyzed through two complementary perspectives. The first is the intuitive and heuristic approach (Agor, 1986), which emphasizes how humans rely on mental shortcuts, intuition, and biases when probabilities are unclear. Classical studies by Tversky and Kahneman (1974) demonstrated that under uncertain conditions, individuals often deviate from rational models and adopt heuristics such as availability, representativeness, or anchoring. While these strategies enable fast judgments, they also introduce systematic errors. Interestingly, similar biases can be observed in the use of automated AI systems, where users may over-trust model outputs without scrutinizing underlying assumptions (Parasuraman & Manzey, 2010).

The second perspective is the probabilistic approach (Selvin, 1975), which treats uncertainty through formal probability models. Within this approach two dominant schools emerge: the frequentist view, where probability reflects long-run frequencies, and the Bayesian view, where probability encodes the degree of belief about a hypothesis given available evidence. The Bayesian framework is particularly relevant to AI, since it provides a formal mechanism for updating prior beliefs with new data, enabling dynamic inference rather than static prediction (Pearl, 1988; Fenton & Neil, 2013).

In the context of artificial intelligence, this theoretical distinction mirrors the contrast between black-box machine learning models, which often replicate heuristic reasoning without transparency, and Bayesian reasoning, which offers an explainable and statistically grounded methodology for handling uncertainty. Thus, understanding Bayesian inference is not only a matter of mathematical education but also a cornerstone for developing AI systems that promote transparency, accountability, and critical engagement.

3.2 Cultivating Probabilistic Reasoning in Education and AI

Developing probabilistic reasoning is widely recognized as a critical educational objective, particularly in data-driven societies where uncertainty permeates decision-making (Fenton & Neil, 2011; Garfield et al., 2008; Batanero et al., 2016). Traditional instruction often emphasizes formulaic computation of probabilities, but

research suggests that fostering deeper understanding requires engaging learners in the cognitive process of reasoning under uncertainty rather than in mechanical calculation alone (Zieffler et al., 2008).

From an AI perspective, this pedagogical insight parallels current debates in explainable AI (XAI). Just as students must move beyond rote learning of probability rules, AI users must move beyond passive acceptance of black-box predictions. Tools such as Bayesian Networks can serve both as computational models for inference and as didactic instruments that make reasoning under uncertainty visible and interpretable (Salter-Townshend et al., 2012; Khuda et al., 2024).

Inquiry-based and discovery-oriented approaches (Bruner, 2004) align well with this goal. By constructing Bayesian models, learners not only simulate uncertainty but also observe how new evidence reshapes prior beliefs in real time. This mirrors the way transparent AI systems should allow end-users to interrogate, adjust, and reflect on model assumptions. In addition, realistic case studies — such as cybersecurity or medical diagnosis — situate probabilistic reasoning in authentic AI-driven decision contexts, reinforcing both statistical logic and metacognitive awareness (Biehler et al., 2015).

Ultimately, Bayesian reasoning bridges the gap between mathematics education and responsible AI design. It transforms uncertainty from an obstacle into a structured problem-solving process, equipping both learners and AI users with the capacity to critically evaluate assumptions, revise judgments, and resist automation bias. In this sense, the theoretical framework of Bayesian reasoning serves a dual role: as a cognitive scaffold for human learners and as a paradigm for building AI systems that are inherently explainable, transparent, and trustworthy**.**

3.3 Theoretical Foundation of Bayesian Networks

At the core of Bayesian Networks lies Bayes' theorem, which formalizes how beliefs about the probability of a hypothesis are updated in light of new evidence. Formally:

$$P(H|E) = \frac{P(E|H)P(H)}{P(E)}$$

where P(H) is the prior probability of a hypothesis, P(E|H) is the likelihood of observing evidence E given H, and P(H|E) is the posterior probability once new information is incorporated. This updating mechanism positions Bayesian reasoning as a dynamic learning process, rather than a static estimation of probabilities (Pearl, 1988; Fenton & Neil, 2013).

Bayesian Networks extend this principle by structuring conditional dependencies among multiple variables through a directed acyclic graph (DAG). Each node represents a random variable, while edges denote causal or probabilistic relationships. Crucially, each node is equipped with a conditional probability table (CPT) that quantifies how its value depends on its parents in the graph. This compact representation allows for efficient reasoning in complex domains where uncertainty is pervasive.

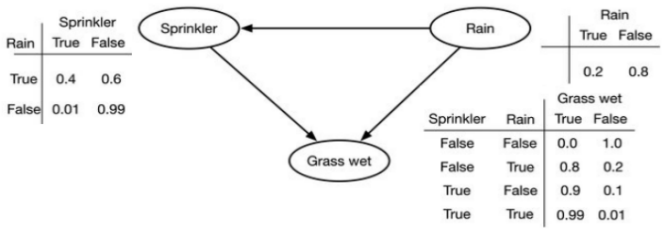

Figure 1: Example of a Bayesian network with conditional probabilities (Zhang et. al., 2021)

From an artificial intelligence perspective, Bayesian Networks are particularly valuable because they bridge two traditionally separate areas:

- Statistical inference, by enabling robust probabilistic reasoning under uncertainty.
- Causal modeling, by making explicit assumptions about how variables influence one another (Pearl, 2009).

This dual role makes Bayesian Networks central to the current movement toward explainable and responsible AI. Unlike neural networks or other black-box models, Bayesian Networks allow users to trace the reasoning process: one can examine which variables drive the outcome, how evidence updates prior assumptions, and

where uncertainty remains. This transparency fosters user trust and mitigates automation bias by encouraging critical engagement with model outputs (Tonekaboni et al., 2019).

Furthermore, Bayesian Networks have been successfully applied in domains where both accuracy and interpretability are essential, including medical diagnosis, cybersecurity, environmental management, and decision-support systems (Fenton & Neil, 2013; Bansal et al., 2019). Their theoretical foundation thus provides not only a mathematical framework but also a paradigm for AI that is both transparent and pedagogically powerful, making them ideal for contexts where human decision-makers must remain active evaluators rather than passive recipients of algorithmic outputs.

3.4 Problem Statement

Despite the rapid progress of Artificial Intelligence in decision-support systems, a persistent challenge remains: the opacity of black-box models. Neural networks and other complex architectures often deliver accurate outputs but provide limited insight into their reasoning processes. This lack of transparency fosters automation bias, where users over-rely on algorithmic recommendations without questioning their validity (Parasuraman & Manzey, 2010; Goddard et al., 2012). Such dependence weakens critical thinking and undermines responsible AI adoption, particularly in high-stakes domains such as cybersecurity, healthcare, and environmental management.

While Explainable AI (XAI) research has advanced significantly, most approaches focus on post-hoc explanations, attempts to justify or approximate the reasoning of opaque models (Ribeiro et al., 2016; Cabitza et al., 2017). These explanations, however, often remain abstract and insufficient for cultivating users' ability to critically evaluate AI outputs. What is missing is a systematic pedagogical framework that trains decision-makers not only to interpret explanations but also to construct and reason with transparent models themselves.

Bayesian Networks (BNs) offer a promising foundation for bridging this gap. By explicitly encoding variables, dependencies, and conditional probabilities, BNs provide a transparent mechanism for probabilistic reasoning (Pearl, 1988; Fenton & Neil, 2013). Unlike black-box models, they allow users to inspect assumptions, update beliefs with new evidence, and trace causal pathways. Yet, their potential as an educational tool for teaching explainability and fostering critical thinking in AI contexts remains underexplored.

This paper addresses this gap by proposing an innovative instructional intervention that employs Bayesian Networks not only as a statistical tool but also as a didactic framework for Responsible AI education. By engaging learners in building and testing their own BN models, the approach shifts them from passive users of opaque systems to active thinkers capable of transparent reasoning and informed decision-making.

Figure 2 illustrates the overall research design and process, outlining the methodological steps from theoretical foundation to data interpretation.

Figure 2: Research Design and Process Flow

4. Educational Framework: Bayesian Reasoning as a Pathway to XAI

The proposed educational framework positions Bayesian Networks not only as a statistical tool but as a structured pathway toward cultivating explainable reasoning in Artificial Intelligence (AI). While traditional probability instruction often focuses on abstract formulas and mechanical calculations, this framework emphasizes the progressive development of critical and metacognitive skills through authentic problem-solving. The core innovation lies in explicitly linking Bayesian reasoning with the principles of transparency and interpretability that underpin Explainable AI (XAI).

The framework is organized into seven interconnected stages (table 1), each designed to build upon the previous one and guide learners from foundational probability concepts toward the construction and reflection on Bayesian models in real-world contexts. This staged progression ensures that learners move step by step from understanding uncertainty mathematically to practicing transparent reasoning in applied scenarios.

Table 1: Pedagogical structure of the intervention

Stage	Description	Student Activity	Learning Objective
Introduction to Probability	Basic concepts, definitions, and computations	Solving simple probability problems	Establishing a common mathematical foundation
Independent & Dependent Events	Relationships between events	Identifying event relations in real-world scenarios	Connecting abstract concepts with empirical observations
Conditional Probability	Updating probabilities with new information	Analysing examples	Understanding the influence of observations
Bayes' Theorem	Application in belief revision	Calculating simple Bayesian problems	Introducing the logic of Bayesian updating
Bayesian Networks – Theory	Nodes, causal links, conditional probability tables	Designing structures in software	Linking theory with practical model building
Application to Authentic Problems	Case studies (e.g., cybersecurity, environment, diagnosis)	Constructing and analysing Bayesian models	Developing modelling and decision-making skills
Presentation & Reflection	Interpretation and discussion of results	Presenting models to peers	Fostering metacognitive awareness and communication skills

Figure 3 presents the internal flow of the proposed educational framework, describing the sequential learning stages through which participants engage with Bayesian reasoning and explainable AI concepts.

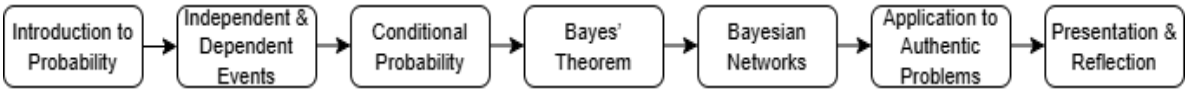

Figure 3: Educational Flow within the Framework

At each stage, learners are encouraged to not only compute probabilities but also to make their reasoning explicit. This emphasis on transparency mirrors the goals of XAI: making decision processes visible, interpretable, and open to critique. For example, when students update beliefs using Bayes' theorem, they practice a transparent form of reasoning where assumptions (priors), evidence (likelihood), and updated conclusions (posterior) are all explicitly represented. Similarly, the graphical structure of Bayesian Networks allows learners to see how evidence propagates through causal dependencies, offering a direct analogy to the explanatory mechanisms that AI researchers aim to achieve in complex machine learning models.

Thus, the educational framework goes beyond teaching probability theory. It instills an *explainable mindset*, a way of thinking where learners not only generate outputs but also understand and articulate the reasoning that leads to them. This dual orientation, combining mathematical rigor with explainability, prepares learners to engage critically with AI systems and provides a didactic microcosm of XAI principles. In this way, Bayesian reasoning becomes both a pedagogical bridge and a conceptual foundation for building responsible, transparent AI practices.

5. Application: Bayesian Networks in Cybersecurity Decision-MakingProblem Setting

To demonstrate the practical and pedagogical value of the proposed framework, this section presents a hands-on example situated in the domain of cybersecurity. Decision-making under uncertainty is a daily challenge for security analysts, who must evaluate large volumes of incoming data—such as emails, logs, and network activity—in order to determine whether a potential incident is benign or malicious. This scenario provides a fertile context for engaging learners with Bayesian reasoning, since it requires combining incomplete and often ambiguous evidence while avoiding systematic cognitive biases.

5.1 Problem Setup

Using GeNIe Academic software, learners are asked to build a Bayesian network for email triage with one parent node and three evidence nodes:

- Spam (parent; states: *Yes*, *No*)
- Suspicious Sender (child of *Spam*; *Yes/No*)

- Unsafe Link (child of *Spam*; *Yes/No*)
- Unusual Language (child of *Spam*; *Yes/No*)

The model assumes conditional independence of the three evidences given *Spam*.

Learners are also given the following probabilities (table 2)

Table 2: Probabilities extracted from historical data

Evidence node	Condition	P(Yes)	P(No)
Spam email		0.16	0.84
Suspicious Sender	given **Spam=Yes**	0.70	0.30
	given **Spam=No**	0.05	0.95
Unsafe Link	given **Spam=Yes**	0.65	0.35
	given **Spam=No**	0.10	0.90
Unusual Language	given **Spam=Yes**	0.80	0.20
	given **Spam=No**	0.15	0.85

Learners must then compute the probability that a message is spam if it shows a suspicious sender and unusual language, but does not contain a link. Using the Bayesian network they developed, it turns out that the probability of an email with the above characteristics being spam is 0.85 (figure 4).

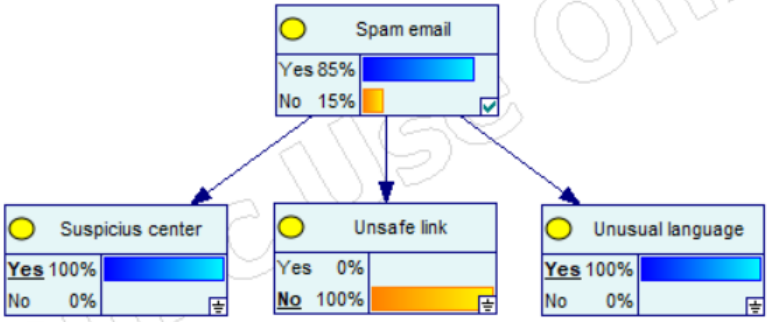

Figure 4: The Bayesian network that the trainees are asked to build

Through the constructed network, students apply Bayes' theorem to update prior beliefs in light of new observations. For example, the absence of an unsafe link reduces the posterior probability of spam, but the co-occurrence of a suspicious sender and unusual language significantly increases it. This dynamic revision illustrates how Bayesian reasoning handles uncertainty in a structured, interpretable way.

The exercise also highlights how small changes in observed features can drastically shift decision outcomes, reinforcing the importance of data quality and feature evaluation in AI-driven decision support.

5.2 Transparent Reasoning vs. Black-Box AI

The strength of this activity lies not only in its mathematical rigor but also in its alignment with the principles of Explainable AI. Unlike opaque neural networks, Bayesian Networks make the reasoning process explicit. Students can clearly observe how each piece of evidence (e.g., unusual language) modifies the posterior probability of spam. The transparency of priors, likelihoods, and causal dependencies fosters metacognitive reflection, allowing learners to question their assumptions, identify potential biases, and understand why certain outcomes emerge.

This transparency directly addresses the problem of automation bias: rather than blindly trusting algorithmic outputs, students learn to interrogate the decision-making process itself. In this way, the exercise not only enhances statistical literacy but also cultivates an explainable mindset, equipping learners with the ability to critically evaluate AI-driven decision-support systems.

5.3 Pedagogical and AI Implications

From an educational perspective, this example reinforces the framework presented in Section 4 by bridging abstract probability theory with authentic, high-stakes decision-making scenarios. From an AI perspective, it highlights how Bayesian reasoning serves as a microcosm of XAI, demonstrating the value of transparent, causal, and interpretable modelling. By engaging in this process, students are not passive users of opaque algorithms but active thinkers who construct, test, and explain their models—mirroring the broader goals of responsible AI.

6. Discussion

This study highlights the pedagogical potential of Bayesian reasoning as both a method for structured decision-making under uncertainty and as a model of explainable AI. By engaging learners in the explicit construction of Bayesian Networks, the framework reduces automation bias and emphasizes human-in-the-loop decision-making. Rather than relying uncritically on opaque algorithmic outputs, students learn to interpret causal structures, evaluate assumptions, and iteratively update beliefs in response to new data.

The contribution of this approach is therefore twofold. First, it empowers learners to become active thinkers, capable of questioning, testing, and refining models instead of acting as passive recipients of AI-generated outputs. Second, it provides a concrete example of explainable AI, where the reasoning process is transparent and interpretable. In contrast to black-box models, Bayesian Networks show how evidence combines to shape conclusions, fostering not only mathematical understanding but also a mindset of reflective and responsible decision-making.

Nevertheless, some limitations must be acknowledged. The proposed framework currently focuses on Bayesian reasoning and does not directly extend to more complex models such as deep neural networks, which dominate many AI applications. While Bayesian Networks are uniquely suited for illustrating explainability through causal modelling, the generalizability of this approach requires further investigation. Future work should explore how similar pedagogical principles can be applied to other AI paradigms, for instance by integrating Bayesian explanations with post-hoc XAI tools such as SHAP or LIME, or by developing hybrid teaching modules where Bayesian reasoning complements the interpretability of more complex architectures.

In this sense, teaching Bayesian reasoning acts as a bridge: it cultivates learners' ability to critically reason under uncertainty ("active thinkers") while simultaneously introducing them to transparent models that exemplify the principles of explainable AI. This dual orientation situates the intervention at the intersection of education, decision science, and responsible AI.

7. Conclusion

This paper introduced a pedagogical framework for teaching Bayesian reasoning as a pathway toward active thinking and explainable AI. By guiding learners through the progressive construction of Bayesian Networks, from probability fundamentals to real-world applications, the framework enables them to move beyond passive use of AI tools and toward active engagement with the reasoning process itself.

The educational value lies not only in enhancing probabilistic literacy but also in cultivating critical and metacognitive skills that reduce automation bias and strengthen responsible decision-making. At the same time, the framework positions Bayesian reasoning as a paradigmatic example of explainable AI, demonstrating how transparent and causal models can complement modern AI practices.

By positioning Bayesian reasoning as both a cognitive tool and an AI paradigm, the proposed framework illustrates how education can simultaneously nurture active thinkers and advance the goals of explainable and responsible AI.

Ethics Declaration: No ethical clearance was required for this study.

AI Declaration: AI tools were used solely for English language editing.

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Undergraduate Business Curricula and AI in the Workplace

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Abstract: As AI adoption accelerates in organizations and business operations, it is important that higher education continue to study its impact on teaching and learning. Following the formal introduction of two AI applications at a 23-campus university system, this work-in-progress research aimed to understand business faculty pedagogic response to AI and employer needs at one institution. Given that curricula design involves multifactorial thinking, this report is part of a larger study involving a sequenced set of data analyses. On the higher education side, for this study, current syllabi of courses in the General Management concentration in the undergraduate business program were analyzed. General Management appeared to be the most popular business concentration last year. As the technology continues to evolve, any study provides only a snapshot in time. Given higher education's role in the economic sector, at this transformative juncture, modernizing academic understanding of the workplace needs to examine pedagogical practice relating to graduate preparation for new opportunities and challenges.

Keywords*:* Graduate preparedness, AI-Readiness, Business education

1. Introduction

The knowledge gap between labor market demands and graduate preparedness for Industry 5.0 is undergoing intensive academic and industry research. Meanwhile increasing AI certification programs offered by IT companies to meet the demand from across industries to upskill or reskill their employees is a reminder of the need in higher education. The study reported here is a sub-set of a larger research that will examine how business education curricula needs rethinking by exploring labor market demands and faculty adaptation to employer requirements.

Recent academic research mostly relates to students' views and experience of AI in higher education and educators' perceptions of the impact of AI on teaching and learning. A 2017 McKinsey report estimated that 47% of American jobs are at high risk of automation by 2030 (Manyika, et al, 2017). A recent report by Microsoft (June 2025) studied the overlap between AI capabilities and job tasks, highlighting where AI might change how work is done. The researchers wrote ""Our research shows that AI supports many tasks, particularly those involving research, writing, and communication, but does not indicate it can fully perform any single occupation. … As AI adoption accelerates, it's important that we *continue to study* its societal and economic impact."

As the technology continues to evolve, any study provides only a snapshot in time. How old jobs are reconstituted, or discontinued, and what new jobs emerge need to be an ongoing research topic, because modernizing our understanding of workplace activities will be crucial as generative AI continues to change how work is done and how it impacts business, society and the economy. Given higher education's role in the economic sector, at this transformative juncture, modernizing our understanding of the workplace needs to examine graduate preparation for new opportunities and challenges.

2. Context

The goal of this research category work-in-progress study is to investigate how undergraduate business education curricula at one campus of a 23-campus public university aligns with the AI needs and expectations of employers who hire new 'general management' business graduates. Certainly, business schools will continue to prepare students for gainful employment as an outcome of their business education. However, some business schools also aim to achieve positive societal impact through their business education. Society in this context refers to external stakeholders of relevance to the business school. Societal impact refers to how a school makes a positive impact on the betterment of society, as identified in the school's mission. Societal impact can be at a local, regional, national, or international level. Therefore, 'to prepare career-ready students and to assist regional businesses be successful', a question arises in the context of the impact of AI on industries and jobs, how does the education curriculum align with the transformations? For this paper, briefly, do our program curricula respond to new expectations and standards in labor and markets and how?

It is therefore timely that our business programs review the new required competencies that have emerged because of advancements in AI technologies affecting both labor and industries. And to identify where existing programs need re-thinking to respond to the changing work environment. It is imperative to identify what are transferable skills and knowledge that can be applied across different situations, environments and fields while

maintaining both their relevance and impact. Early informal review of my college program indicates a somewhat episodic approach to responding to AI innovations.

Our research methodology involves a sequenced set of data analyses. For this study, on the higher education side, current syllabi of courses in the General Management program were content-analyzed. General Management appeared to be the most popular business concentration in the last year. Another study layer will survey faculty relating to their perceptions of the AI-driven workplace, and their own preparation and pedagogic adaptation. Another data set of job postings for general management positions will be analyzed. Contrasting all data sets will help us to understand better how the business curricula needs redesign to respond to the changing work environment.

3. Methodology

Content analysis is a research method used to determine the presence of certain words, themes, or concepts within some given qualitative data (i.e. text). In this paper, using content analysis via a secured AI platform, we determined and analyzed the presence, meanings, and relationships of AI-related course policy-tool use-and-skills development in current syllabi of all courses in the General Management concentration in the undergraduate Business Administration program. 'Current' refers to the last academic year. This timeline is important because it is book-ended by the commercial introduction of ChatGPT free version in November 2022 and the home campus-wide introduction of Co-Pilot in Fall 2024 followed by the CSU system-wide surprise launch of ChatGPT earlier this year (January 2025). Since ChatGPT's consumer launch in late 2022, the intervening two years saw rapid acceleration in the use of AI tools - generally speaking - including among students and faculty. Microsoft's Co-Pilot was formally offered for all-campus use in the system to ensure equity, so that no student is at a disadvantage regarding learning resources.

While not a complete indicator, course syllabi may be viewed as one reasonable window into how faculty are responding and adapting to the introduction of AI in higher education. Syllabi were analyzed for possibly including AI use policy and integrating AI tool use or AI fluency development. Assuming students' 'digital native' orientation and the availability of freely available AI software, this study is premised on advancing students AI fluency. In all 35 sample syllabi offered by different instructors - covering core/required, and elective courses - were analyzed using ChatGPT edu V5. This version of ChatGPT enables the researcher to keep the data, which AI uses, private and secure. Two sections of the same course taught by the same instructor were considered one course. Two sections of the same course taught by different instructors were considered separately to reflect instructor differences. Only syllabi that explicitly state AI use policy or/and directly integrate AI tool use or AI fluency development are analyzed further. Additionally, the syllabi and results were reviewed manually for accuracy.

Following a review of the academic literature and recent business reports from publicly-listed companies on the fore-front of AI development, AI adoption, and general business consulting-education, the following questions were selected and queried for analysis in this study. The questions address some core AI knowledge and skills that employers are seeking of undergraduate students studying "general business management"; and attempt to understand where undergraduate business academic preparation currently stands in relation to the AI-changed work environment.

- a. Which course syllabi state an AI use policy?
- b . Identify the courses whose learning outcomes integrate AI tools use or AI fluency development'
- c. Identify the courses or learning outcomes, assignments, or tasks where the student are introduced to, or learn to use AI-powered analytics to interpret datasets.
- d. Identify the courses or learning outcomes or assignments or tasks where the student are introduced to, or learn to use AI-tools to discover market trends, learn customer behavior, or improve operational performance, to help attain business goals.
- e. Identify the courses or learning outcomes or assignments where the student is alerted to be vigilant about inherent biases or errors in AI algorithms

4. Results

- a. Course syllabi which explicitly state an AI use policy

Only 5 of the 35 sample syllabi examined allow or encourage AI use. The syllabi for Principles of Microeconomics (ECON 200 - core course) and Principles of Macroeconomics (ECON 205 - core course) explicitly have statements that *allow and encourage AI use as a tool, provided students take full responsibility for the accuracy and*

appropriateness of AI-generated content. Syllabi for Human Resources Management (HRM 312-elective) and Leadership and Management (MGMT 314-elective) taught by the same instructor contain a section titled "Generative AI (Gen-AI) Integration." It references the CSU-system AI Commons initiative and explains that AI tools may be used to brainstorm, draft, edit, organize research, and generate practice scenarios, and emphasize that students remain responsible for their own work. Similarly, Managerial Economics & Business Strategy (ECON 380-core) includes a detailed *"AI Policy"* section that allows AI tools for research purposes (e.g., brainstorming, gathering sources) but prohibits their use for completing assignments, exams, or quizzes. Disclosure of AI use is required.

At the other end of the spectrum, 5 course syllabi expressly prohibit use of AI. The syllabus for Employee Relations & Employment Law (MGMT 318-elective) specifies: "*AI tools may not be used for graded assignments unless I explicitly state otherwise*." Violations result in no credit and a resubmission opportunity. Similarly, Business Ethics (core) states a strict prohibition on generative AI: "*The use of generative AI, including ChatGPT, is expressly prohibited. Use of these tools will be considered a violation of the CSUEB Academic Dishonesty Policy*." Likewise, Business, Government and Society (core) and International Business (core) syllabi – two different courses offered by the same instructor – states, ""*If you turn in a paper that has been plagiarized in any way, including use of artificial intelligence, you will automatically receive an F on the assignment*. The same courses taught by another instructor outline a detailed plagiarism policy and do not reference artificial intelligence. In one section of Marketing Principles (core), the *"Artificial Intelligence Statement"* explicitly states that all graded work must be student-generated; AI tools cannot be used and any use constitutes violation of academic honesty. The parenthetical clause 'unless the instructor explicitly allows it' seems a nod to possible approved AI use in some instances but that is unclear.

Thus, at the time of this report, 25 out of 35 sample course syllabi do not have any explicit AI use policy. Only 5 of the 35 syllabi examined allow or encourage AI use and 5 course syllabi expressly prohibit use of AI. See Figure 1.

			Courses (Examples)
AI Policy	*Clear Policy Statement*	Explicitly allow or encourage responsible AI use	- Principles of Microeconomics (ECON 200 - core) - Principles of Macroeconomics (ECON 205-core) - HR Management (MGMT 312 -elective) - Leadership & Management (MGMT 314 -elective) - Managerial Economics & Business Strategy (ECON 380 - core)
	Ambivalent Statement / No Explicit Policy	Neither prohibit nor mention AI	25 courses (majority of sample)
	Prohibitive AI Policy Statement	Strict ban or classify AI use as plagiarism	- Employment Law (MGMT 318 - elective) - Business Ethics (MGMT 300 - core) - Business, Government & Society (MGMT 370-core)) - International Business (MGMT 385 – core option) - Marketing Principles (MKTG 300 - core)

Figure 1: Research Question

- b. Courses whose learning outcomes or content integrate AI tools use or AI fluency development

Principles of Microeconomics (ECON 200-core) includes a learning module and an essay assignment centering on *"AI and the Future of Work".* There is also a discussion task designed around using microeconomic reasoning to better understand the impact of AI on industries and jobs. Cumulatively, students learn to apply microeconomic principles to analyze AI's role in markets, labor, and productivity. In Principles of Macroeconomics (ECON 205-core), students use a required learning assistant Edvisor (an ai platform); and applying fundamental analytical methods, learn to interpret economic variables and events based in real-world issues. Consequently, the two courses develop AI literacy and critical evaluation skills, not just conceptual economics understanding.

Syllabi of Information Technology Management (ITM 300-core) sections taught by two different instructors indicate that the course outcomes and modules explicitly teach data mining, machine learning, and AI

visualization, giving students hands-on experience analyzing and interpreting data with AI tools. For example, syllabi mention explicit topics that develop AI fluency: *"Introduction to Data Mining and Machine Learning", "Data Visualization with Generative AI (DVGAI)", "Generative AI – Prompt Engineering", and "Personal Productivity Using AI".* Students learn prompt engineering, data visualization using AI, and applied AI in business technology contexts. Assignments in both sections also integrate direct AI skill-building. Students gain hands-on experience with applied AI tools within Excel, cloud computing, and analytics environments.

		Courses (Examples)
AI Literacy - Fluency goals	Literacy-Fluency learning outcome statement or reference	- Principles of Microeconomics (core): Develops AI literacy through tasks and "AI and the Future of Work" module. - Principles of Macroeconomics (core): required Edvisor platform - Information Technology Management (core): Hands-on AI analytics training. - Decision Science (core): foundational data-driven decision-making & technologies
	Some implicit exposure through data analytics or Excel-based modeling	- Introduction to Managerial Accounting (core) - Financial Management (core) - Managerial Economics & Business Strategy (core)
	No AI literacy or fluency goals; learning outcomes do not mention AI tools or skills.	Majority of sample

Figure 2: Research Question

In Decision Science (MGMT 350-core), students are required to use Excel spreadsheet software and quantitative modeling tools that align with data-driven decision-making frameworks that are foundational in AI analytics technologies. While not named as "AI," the course outcomes and content focus on *"Decision analysis, optimization, simulation, and forecasting"* explicitly links to *"data-driven decision-making technologies"* and *"quantitative techniques in data-driven decision-making"* -- skills related to AI fluency that employers are seeking in new college business graduates.

In summary (Figure 2*)*, only 3 courses out of 35 sample course syllabi *explicitly* integrate AI tools use and AI fluency development in its learning outcomes and instructional content. Information Technology Manage (core) explicitly teaches data mining, machine learning, and AI visualization, giving students hands-on experience analyzing and interpreting data with AI tools. Decision Science (core) develops foundational quantitative and software-based data modeling skills, which are essential for AI tool use and interpreting AI-driven analytics; but the syllabus examined at this time does not mention AI literacy or skills in outcomes or content.

- c. Course content, learning outcomes or assignments where students are introduced to or learn to use AI-powered analytics to interpret datasets

Among the 35 sample syllabi examined, only 2 course syllabi - Information Technology Management (ITM 300) and Decision Science (MGMT 350) - explicitly introduce students to and train them in the use of AI-powered analytics for interpreting datasets. In one section of ITM 300, students learn to analyze business data using Excel and similar technologies, and apply those skills to business problems. The inclusion of *Generative AI* and *machine learning* modules explicitly introduces students to AI-based data analytics, visualization, and decision-making tools. In another section of ITM 300, the course objectives and modules include understanding how AI and data analytics support managerial decision-making and interpreting data ethically in a global IT context. Students engage with Excel and cybersecurity labs while learning about how AI and analytics provide competitive advantage. In both sections, AI and analytics modules position students to address the important tasks of interpreting and managing data tasks to derive data-driven business insights.

Syllabi for both sections of MGMT 350 indicate a focus on quantitative reasoning, optimization, simulation, and forecasting using spreadsheet and software tools. Using Excel, students perform statistical analyses to model real-world problems, a precursor to AI-based analysis. In this course, students learn computational and data analysis methods that align with and prepare them to use newer AI-supported decision tools, especially those produced by the same company. Introduction to Financial Accounting (core course) and Introduction to Managerial Accounting (core course) include *data analytics* assignments through an external but these are rule-based, not AI-driven.

Briefly, Information Technology Management explicitly introduces student to data mining, machine learning, and AI visualization, giving students hands-on experience analyzing and interpreting data with select AI tools. Decision Science develops foundational quantitative and software-based data modeling skills, essential for interpreting AI-driven analytics. Given that the courses use Excel, a Microsoft product, to analyze datasets, it may not be premature to state that the Excel exposure and training may help the students quickly learn to use Microsoft's data visualization AI tool.

- d. According to a PWC report, employers hiring for general management are increasingly prioritizing candidates who can strategically integrate AI into core business functions (June 2025). Therefore, an important question framing this study is in which courses, or learning outcomes, or assignments, are students introduced to or learn to use AI-tools to discover market trends, learn customer behavior, and improve operational performance, and help attain business goals?

Learning outcomes in ITM 300 emphasize using information systems and analytical tools to "improve business processes and enhance competitiveness". The learning modules teach how gen AI can detect market trends and customer behavior patterns through data mining and visualization. Topics on CRM (Customer Relationship Management) and Enterprise Resource Planning (ERP) systems, introduce students to how businesses may use AI to understand and anticipate customer needs and market shifts. The modules on productivity and process improvement connect directly to operational optimization and strategic decision-making. Students use Excel for data analytics to solve problems related to organizational efficiency and market insight generation. Assignments and readings explicitly connect data analytics and AI to achieving strategic business goals.

Although not explicitly labeled "AI," Decision Science (MGMT 350) course provides the statistical and modeling foundation for understanding how AI can help analyze market data, predict consumer behavior, and optimize operations - core components of AI-powered business analysis. As two required courses (ITM 300 and MGMT 350) for students pursuing the General Management concentration, these courses form a technical-strategic learning continuum. While ITM 300 introduces *hands-on AI tools* (machine learning, data visualization, productivity AI), MGMT 350 develops *quantitative reasoning* needed to interpret and act on analytics results. Together, they prepare students to apply AI to conduct market analysis, improve operational efficiency, and plan-implement strategic performance.

Briefly, at the time of this writing, only 2 core courses out of 16 core/required courses explicitly introduce and require students to use AI tools and concepts (such as machine learning analytics, chatbots, or AI-driven operations systems) to discover market trends, customer behavior, operational performance, to help attain business goals.

The capstone course (MGMT 499), which all undergraduate students in the Business Administration program are required to take, uses the CAPSIM package (comprising a textbook, simulation, and simulation exam). Students practice strategic planning and performance analysis in a virtual business. At the time of this study, CAPSIM is a decision-support learning tool; and does not explicitly integrate AI-tools or AI-fluency development. It is surmised that in their graduating year capstone course, students may not develop AI fluency because AI trend or forecasting tools are not introduced or AI-related skills and lessons from ITM 300 reinforced. Briefly, in the CAPSIM package, students use case studies and simulations to assess competitiveness, conceptually learning data-informed strategy, and AI is not part of the instruction

- e. "Businesses using AI responsibly are focused on fairness and mitigating any biases in the technology" (Short, 2025). Several reports this year highlight a core employer need - for managers to ensure AI is used responsibly and fairly. This includes being vigilant about possible errors and inherent biases in AI algorithms that could lead to discrimination, especially in hiring and performance reviews. Therefore, an important question framing this study is in which courses or learning outcomes or assignments are students alerted to be vigilant about inherent biases or errors in AI algorithms?

Except for three course syllabi, none of the other syllabi include learning that address biases, ethical risks, or accuracy issues in AI algorithms. The syllabus of one section of Information Technology Management (core) explicitly addresses the potential errors in AI algorithms. This course covers modules including "Artificial Intelligence: the Tech Impacting Nearly Every Industry," "Databases, Analytics, AI and Machine Learning," and "Information Security." The modules include applied learning about ethical, security, and globalization issues in information technology, where bias in algorithms and ethical AI use are explicitly acknowledged as managerial responsibilities. The syllabus of the other section includes topics relating to algorithmic outputs, prompting students to engage critically with AI-driven data interpretation and visualization - areas where bias and error

awareness may arise to become an important principle of responsible AI use. In Principles of Microeconomics (core) and Managerial Economics & Business Strategy (core), detailed course policy statements alert students to *review AI output* and to be responsible for verifying AI data. Both Human Resources Management and Leadership and Management syllabi permit AI use, but they do not frame it in a critical-awareness or bias-mitigation context.

However, there are courses in which students learn and are alerted generally to be vigilant about inherent biases or errors in data analytic results, not specifically to AI-analytics. Syllabi of at least 5 out of 16 core course and 1 elective course actively cultivate student vigilance toward bias, error, and misinterpretation in data analytics and quantitative reasoning, often embedding the quality-assurance check within data-driven assignments, analytical projects, or ethical learning outcomes.

In Introduction to Managerial Accounting (core), students complete chapter-based *Data Analytics Assignments* that require a publisher-supplied learning platform and the use of Excel to interpret cost data and managerial performance metrics. The course integrates explicit learning outcomes on *ethical decision-making*, emphasizing that students must not only apply technical procedures correctly but also recognize and correct potential data classification errors, irregularities, or misleading analytic results. Syllabi of both sections of Financial Management (core) reinforce this analytical vigilance through applied financial modeling and project work. Students are required to think critically about computational results, underlying assumptions, and sources of potential error.

Similarly, both Managerial Economics and Business Strategy (core; ECON 380) and Global Economic Analysis (core option; ECON 385) further advance students' awareness of data bias through structured analytical assignments. ECON 380 emphasizes distinguishing relevant from irrelevant data in economic decision-making, developing student competence in scrutinizing the assumptions underlying quantitative models. ECON 385 extends this practice to global datasets and international policy analysis, requiring students to critically evaluate macroeconomic data. These exercises familiarize students with the limitations of real-world data sources and the interpretive biases that can emerge in economic modeling.

Altogether, students are expected not only to perform quantitative analyses but also to question the reliability, validity, and ethical implications of the data and models they employ.

5. Limitations of Study

Many core and elective courses have multiple sections. As such, often times there are different instructors for the same course. Thus, for instance, two different instructors of the same course may include considerably similar syllabi content; but their methodology and/or pedagogical approach may be different. This study examined in-depth two sections of Information Technology Management (core) focusing on their stated learning outcomes and content. Examining output and impact would enrich the study.

While some courses (e.g. Managerial Economics & Business Strategy, Human Resources Management, and Leadership and Management) allow AI-tool use and even encourage AI skill development as course policy, their course content modules do not incorporate where or in which course topic contexts such use or skill development may occur. Further, while syllabi content may not mention actual or possible AI-tool use, the instructor may highlight in class discussions, their prevalent use and impact on the course topics and student learning.

This report is part of a larger study involving a sequenced set of data analyses. We looked at only one aspect of pedagogic practice – the syllabus. Another study layer will survey faculty relating to their perceptions of and any pedagogic adaptions to the AI-impacted workplace. To understand the labor market, a set of job postings will be content analyzed. Contrasting the data sets will help us to understand better graduate AI-readiness and how the business curricula needs redesign to stay relevant.

6. Discussion

At the time of this writing, only 5 of the total 35 syllabi examined allow or encourage AI use, 5 course syllabi expressly prohibit use of AI, and 25 out of 35 sample course syllabi do not have any explicit AI use policy. Examining syllabi content, learning outcomes and assignments, only 3 courses (Principles of Microeconomics, Principles of Macroeconomics, and Information Technology Management), directly integrate *both* AI fluency development and AI-tools use.

The above-mentioned 3 courses are also core courses; thus, 3 out of 16 core/required courses explicitly introduce or require students to use AI tools and concepts (such as machine learning analytics) to discover market trends, improve operational performance, and learn other factors that help attain business goals. In the required capstone course, using the CAPSIM package, students use case studies and simulations to assess competitiveness, conceptually learning data-informed strategy; but AI is not part of the instruction. Therefore, it may be conjectured that in their graduating year capstone course, students may not further develop AI fluency (Bloom's taxonomy) because AI trend or forecasting tools are not introduced nor AI-related skills and lessons from learned from the aforementioned 3 core courses reinforced.

While syllabi of both Information Technology Management (core) and - Decision Science (core) courses specifically mention using Excel, this software may improve to include enhanced beta AI features. It is also likely that Microsoft's (MS) data visualization tool Power BI may be available to be explored to a limit by students using the school-licensed MS suite. Furthermore, it may be noted the Excel's data visualization does not work in Macbooks. Therefore, the College may need to consider developing AI fluency in one particular set of AI tools.

While not including specific potential biases, ethical risks, or accuracy issues in AI algorithms, at least 5 out of 16 core course and 1 elective course actively cultivate student vigilance toward bias, error, and misinterpretation in data analytics and quantitative reasoning. Collectively, at least 8 course syllabi out of 35 examined, demonstrates that the undergraduate general management concentration aims to teach students to interpret data critically. Might there be a need to intentionally increase students' attention to potential errors in AI-analytics as AI-features and stand-alone AI-analytics tools become widely available and used in industry?

Clearly, at the College-level, business faculty response to the introduction of AI tools has been mixed, perhaps more on the cautious side. Even at institution-level, an uncertain and cautious outlook is evident. Upon faculty requests, MS Co-Pilot's proposed launch in Fall 2024 was delayed until January 2025. Some key concerns included addressing student needs relating to AI use, to have a curriculum-course policy in place, environmental costs, etc. While some faculty and community members explored ChatGPT early on, it was only this year – late January 2025 – that CSU system-wide announced ChatGPT availability in March to all 23 campuses. At the time of writing this work-in-progress research paper, Senate is deliberating an AI-use policy for faculty in their courses.

Faculty continue to be divided; and many remain skeptical about the benefits of this learning resource. This work-in-progress is only a snap-shot of how faculty generally are responding to the transformations occurring in the AI-driven higher education workplace. The concerns and optimism are normal when a disruptive innovative technology appears to be transforming work and human enterprise. To conclude on an optimistic note, an observation is noteworthy. According to Harland (2025):

> *AI may be growing in importance, but that doesn't mean uniquely human skills are getting any less important. In fact, 83 percent of employees and leaders globally agree that the rising use of AI will make human skills even more vital. The future isn't AI; it's human-directed AI.*

Ethics Statement: This research did not require IRB approval because no human subjects were involved. Copies of documents examined were anonymized and data privacy ensured in both analysis and writing.

AI Declaration: ChatGPT edu version available to our university was used to only analyze the study documents. Yet, given known errors in AI-analytics, the results were manually verified as well. The creation of the paper from concept to production is the faculty-author's own work.

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Rethinking Holistic AI Development Through Social Diversity, Interdisciplinary Collaboration and Integrative Knowledge Production

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Abstract: The rapid deployment of AI reveals persistent socio-technical and data-driven biases that reflect profound epistemic limitations in knowledge production. These biases are not accidental, but symptomatic of deeper epistemic limitations in the way AI knowledge is produced — often by homogeneous teams within technocentric paradigms that exclude alternative perspectives. This paper argues that the underrepresentation of diverse social actors in AI development not only perpetuates inequality, but also severely limits the epistemic and ethical robustness of AI systems. The focus of this paper arises in particular from the preliminary findings obtained in the Horizon Europe project STEP, which highlight the potential of the framework to improve the inclusivity and trustworthiness of AI. The central thesis is that social diversity must be considered as an epistemic condition and not just an ethical or demographic ideal. Drawing on sociology, psychology and educational science, the authors show how integrating plural forms of knowledge, lived experiences and cultural perspectives into the design and development process can lead to AI systems that are more context-sensitive, equitable and trustworthy. Rather than proposing inclusion as an external corrective, this paper discusses a paradigm shift in AI development - a paradigm shift that embeds diversity into the infrastructure of knowledge production itself. The contribution of this paper is twofold. First, it proposes a theoretical model of integrative knowledge production that identifies mechanisms through which interdisciplinary collaboration can challenge dominant epistemologies and promote systemic reflexivity. Second, a participatory design framework is outlined to operationalise this model through concrete methodological tools, including dialogic co-design workshops, ethnographic participation in data selection and cross-functional team structuring. These practises aim to break through technocratic compartmentalisation by creating space for social critique and situated intelligence within AI development cycles. Finally, the authors reflect on the transformative potential of this approach and suggest that rethinking who is involved in AI knowledge production will not only change the outcomes of AI systems, but also the normative foundations of the technological future. From this perspective, ethical AI is not just explainable or compliant — it is structurally inclusive, responsive to different lifeworlds and open to critical reinvention.

Keywords: Epistemic diversity, Algorithmic justice, Participatory AI, Interdisciplinary design, Sociology of technology, Inclusive innovation, Knowledge infrastructures, Human-centred AI, Bias

1. AI and Biases: Introduction and Background

AI systems that collect and process data on humans and human behaviour often become a mirror of social inequality (Ferrara, 2024). This bias is not only encoded in the data sets, but also results from the cultural, institutional and professional environment in which AI tools are designed and developed. This is often due to the lack of diversity of people involved in the development of AI systems and tools, as well as biases within science and culture/humanities. As Snow (1969) warned, the growing divide between the sciences and the humanities hinders the solution of complex problems and a gap that is still evident in AI knowledge production. He also argued that this growing divide is a significant obstacle to effectively tackling the complex challenges of the modern world. Indeed, even today we can observe that the process of knowledge production in the field of AI is dominated by homogeneous teams and technocentric worldviews and tends to exclude alternative knowledge systems, reinforcing existing hierarchies (Ferrara, 2024). These rely too heavily on data sets that favour, for example, the Western perspective and stereotypical assessments of the validity of information (Nersessian & Mancha, 2020; Zowghi & da Rimini, 2023). AI harbours the risk of perpetuating existing biases by reinforcing the perspectives and interests of dominant groups, while holistic, interdisciplinary knowledge and different cultural values fade into the background (Ahrweiler et al., 2025; Gichoya et al., 2023). This dynamic can lead to an overrepresentation of dominant cultural norms and an underrepresentation of minority identities and alternative perspectives or diversity (Roche et al., 2023). In this way, AI models become biassed tools that reflect and reproduce historical inequalities since their inception. This is particularly evident in biometric technologies, predictive policing, recruitment algorithms and health

diagnostics - where AI often fails marginalised groups. The profound epistemic limitation reflects the societies and dominant group that create, implement and govern AI, in a vicious cycle that has proven flawed in recent years (De Sousa Santos, 2024).

Considering the aftermath of the rapid development of AI and the challenge of keeping up with its technological, scientific and substantive advances (Jungherr, 2023), this paper identifies specific scientific gaps. Indeed, this paper presents a fundamental response to this challenge: it proposes to invert the traditional model of AI development by integrating diverse voices - those that speak different (social) languages and have different worldviews and scientific backgrounds. This approach encourages developers and engineers to redesign tools through the lived experiences of their communities, moving from a model of technological imposition to a model of participatory co-creation and co-design, in a conscientious, reliable and human-centred design and development of the upcoming research and development of AI (Bencivenga et al., 2025).

The authors believe that this will help train a new generation of interdisciplinary researchers who are able to conceptualise and use AI to design and shape more inclusive and equitable societies by considering the opportunities and challenges related to gender, diversity and inclusion and shaping future planning and decision-making in a way that incorporates diverse perspectives and promotes equality (Ferrara, 2024). Capitalising on the synergy of diverse disciplines such as computer science, engineering, economics, sociology, law, pedagogy and education, this new AI development approach will tailor not only educational systems but entire social ecosystems to the dynamics of the future, while working towards integrity in scientific research, which would lead to more complete, consistent and holistic outcomes.

In response to the growing concern, the European Union has been at the forefront of regulation. The provisional agreement on the Artificial Intelligence Act (December 2023) (European Parliament, 2023) introduces a comprehensive framework of safeguards, restrictions and prohibitions, coupled with sanctions for non-compliance. The AI Act is the first of its kind in the world and sets a precedent for the regulatory framework worldwide. It was complemented by the *Ethics Guidelines for Trustworthy AI* (European Commission, 2019), issued by the High-Level Expert Group, which include the key principles of acting humanely, transparency, accountability and non-discrimination. At the same time, the European Commission has made significant progress in establishing ethical guidelines for AI researchers and the topic of AI ethics has been a focus of various projects and initiatives. The guidelines were a decisive step in this direction. Following an open consultation that received more than 500 comments, these guidelines have been thoroughly revised since their first draft was published in December 2018. However, they often remain abstract and offer limited practical tools for implementing diversity and inclusion. There is still a gap between the high-level ethical obligations and the daily reality of AI research and application (Floridi et al., 2018). Furthermore, legal restrictions, although necessary in some cases, can unintentionally stifle innovation (Aghion et al., 2023) - especially in socially sensitive areas of research where nuanced understanding is essential (Nersessian & Mancha, 2020). Moreover, it should be emphasised that there is little concrete practical advice to date on how to ensure that diversity and inclusion considerations are embedded in both specific AI systems and the broader global AI ecosystem (Zowghi, da Rimini, 2023). In addition, AI's reliance on historical data poses a challenge due to inherent biases, particularly in relation to gender equality and other equality, diversity and inclusion (EDI) approaches. Dealing with these biases is crucial for the integral and fair application of AI.

Today, the future appears not as a deterministic tool, but as part of a broader ecosystem of interventions that together bring about meaningful change. While the linear approaches of 20th century social sciences provide insights, today we recognise the complex interplay of numerous interacting variables and think it is time to explore the transformative role of new knowledge guided by both AI and components of EDI. Our framework operationalises these high-level ethical commitments by embedding diversity into AI development practises at the design stage.

2. From Epistemic Blind Spots to Participatory Knowledge

To address the persistent systemic problems that underlie the production of knowledge and AI-related tools today and reproduce the inherent biases of the society that produces them, we propose to rethink the foundations of AI knowledge production. This requires a move away from ethics as compliance and towards epistemic diversity as a fundamental principle. Particularly in recent decades, the ethical principle has become increasingly established as a principle that underpins the production of knowledge but also serves as a check in case of discrepancies, inconsistencies or misuse (Anderljung et al., 2025; Brundage et al., 2018). In this approach, biases or prejudices were often only identified after knowledge had been created, i.e. through a retrospective intervention after the knowledge had been produced (Brundage et al., 2018).

We propose a paradigm shift in which inclusion is not an afterthought or a subsequent parameter, but an embedded property of AI infrastructures - a property that influences every phase from design to implementation.

We draw on three interrelated areas:

- The sociology of technology, which explores how power relations shape scientific and technological practises.
- Educational science, which investigates how knowledge is co-constructed and passed on in different populations.
- Psychology, which explores how cognitive biases and group dynamics influence decision-making and creativity.

Together, these fields offer insights into how plural perspectives can be mobilised as epistemic enrichment rather than treated as marginal additions.

Drawing on the sociology of knowledge (Berger & Luckmann, 1966) and critical pedagogy (Freire, 1970), we define epistemic diversity as the integration of diverse perspectives, cultural narratives and experiential knowledge into the AI knowledge production system. Rather than assuming objectivity through abstraction, this perspective emphasises contextual, lived realities as sources of innovation and critical insight. As Pragya affirms,

> *Supposed neutrality and distance created by technology makes it harder to bring the power imbalance and inequalities to light. The manner in which the use of such tools has caught on in the research and academic sector makes it crucial to talk about who makes knowledge (Pragya, 2025: 2341).*

We are aware that this is a controversial topic that can be analysed from many different angles (Marti & Recupero, 2021; Friedman, & Nissenbaum, 1996). We are dealing here with an evolving science that requires the interpenetration and cross-fertilisation of different fields of knowledge and disciplines, and we certainly do not claim to be exhaustive in this paper. But we are definitely interested in asking the question of where knowledge originates and develops so that we can better analyse the biases and biases that very often underlie it (Jungherr, 2023; Jasanoff, 2004).

At the same time, we do not want to give too general an answer to a specific and precise problem. We are aware that it is not a question of proposing a black and white alternative to the ethical issues surrounding the development of artificial intelligence. Nor is the proposal of the EDI approach a simple or easy solution, precisely because of the complexity of the question we are trying to answer. We also recognise that the concepts associated with an inclusive approach that embraces equality and diversity are themselves under scrutiny (Stinson & Vlaad, 2024; Noble, 2018), and the debate remains open and evolving (Benjamin, 2019).

It is therefore essential to anchor any ethical framework in a reflexive and interdisciplinary dialogue that is sensitive to context, power dynamics and historical inequalities — rather than applying universal or standardised models that run the risk of reproducing the same biases they are supposed to mitigate. Such a shift requires a deep epistemological engagement with the question of what inclusion in AI development really means and who is involved in its definition (Costanza-Chock, 2020; Stinson & Vlaad, 2024).

3. Participatory Design and Implementation Framework

In order to operationalise epistemic diversity and further develop the above, we propose a participatory framework (Ahrweiler et al. 2025, Özer, 2024), which has already experimented in the ongoing Horizon Europe STEP project - *STEM and Equality, Diversity and Inclusion: an open dialogue for research enhancement in Portugal* (2023-2025), G.A. N. 101078933, with three methodological pillars:

1) Dialogic co-design workshops: These would bring together interdisciplinary teams with community representatives to collaboratively develop design goals, evaluate modelling assumptions and define success metrics. These workshops follow a dialogue-based pedagogy (Freire, 1970) and are based on theories of co-production (Jasanoff, 2004).

Each workshop consists of three iterative phases:

- Pre-workshop: community representatives and developers jointly select use cases through participatory mapping (e.g. Miro boards with 20+ stakeholders[1]).
- Implementation: 2-day sessions with role-playing bias scenarios (e.g. simulating how a hiring algorithm could exclude non-native speakers).
- Post-workshop: Voting on design priorities using the Delphi method (Özer, 2024), with anonymised feedback integrated into Jira/GitHub tickets[2].

Selection criteria: at least 40% participants from marginalised groups (as per UN SDG 10 indicators), with gender-balanced facilitation teams.

2) Ethnographic data practises: Rather than simply extracting data or using pre-existing databases, researchers from different scientific fields and disciplines collaborate where possible to understand how data is contextualised and interpreted within communities. This avoids epistemic extractivism (Medina, 2013; De Sousa Santos, 2024) and promotes relational accountability.

Data collection combines:

- Immersion: Researchers spend more than 15 days in the target communities and use dense description (Geertz, 1973) to document contextual factors (e.g., how older users interact with voice AI in a noisy environment).
- Tools: open-source platforms such as Open Ethnographer for semantically analysing field notes validated by member checking.
- Quality control: annotations of datasets must achieve 0.8+ Krippendorff's alpha for intercoder reliability of bias labels (Nili et al., 2017).

3) Cross-competence teaming: structuring of AI development teams must involve various experts from the social sciences and humanities (SSH) from the outset (Marti & Recupero, 2021).

The effective implementation of the framework requires consciously assembled teams that reflect epistemic diversity. One possible configuration envisages different but interdependent roles, including technical developers who integrate fairness specifications and translate participatory insights into concrete technical changes. Complementing this are social scientists who monitor societal impact through intersectional approaches, and community liaisons who reconcile lived experiences with technical design by collaboratively developing culturally appropriate testing protocols and shared deployment decisions. While hypothetical, this configuration is based on emerging principles in the literature and can serve as a blueprint for further empirical research. These teams are trained in EDI principles alongside core AI competences and are tasked with continuous critical evaluation of development trajectories.

Effective implementation of the proposed framework requires not only teams that reflect epistemic diversity, but also mechanisms to manage potential disagreements, particularly on contentious issues. While the framework emphasises full participation and engagement, it recognises that not all concerns can be addressed simultaneously. To overcome this challenge, the inclusion of a facilitator role is essential, acting as a transversal mediator throughout the development process. This role, akin to a facilitator or coordinator, would ensure that different perspectives are constructively integrated and that, where necessary, adjustments are made to maintain a co-operative and inclusive environment. Such a role is critical to managing conflict and fostering productive dialogue, ensuring that development remains focused and aligned with the overall goals of the project.

To ensure reproducibility, each pillar follows a standardised protocol based on the principles of participatory action research (PAR) (Cornwall & Jewkes, 1995; Chevalier & Buckles, 2019). The overarching goal is to elucidate PAR's efficacy as a collaborative, inclusive, and empowering research paradigm that actively involves

[1] Miro Boards are collaborative online whiteboards that allow multiple users to work together in real time, regardless of location. In the context of your project, using Miro Boards with more than 30 stakeholders means that more than thirty participants— - e.g. community representatives, developers, social scientists, and moderators — work together in the same virtual space to capture use cases, share ideas, and visually organise priorities.

[2] After the workshops, participants provide anonymous feedback, which is systematically recorded and integrated into the technical development process with the help of tools such as Jira or GitHub. "Jira" is a project management tool to track tasks, bugs, and features. "GitHub" is a platform for collaborative programming where issues and feature requests are logged along with code repositories. By converting the anonymous workshop feedback into Jira/GitHub tickets, the community members' insights are translated directly into realisable technical tasks. This ensures that participants' contributions are not lost, but become a visible part of the development pipeline, subject to accountability and follow-up.

stakeholders in the knowledge co-creation process (Kemp et al., 2019). Originating from critical social theory and adult education, PAR distinguishes itself through its commitment to social justice and democratic principles, fostering a research environment where affected communities are not merely subjects but co-investigators and agents of change, thereby shifting research control to those most impacted by its outcomes (Torre et al., 2015). The participatory framework (Figure 1) integrates iterative co-design, ethnographic engagement and structured evaluation to ensure that societal considerations are embedded throughout the AI development lifecycle. The model emphasises cyclical exchanges between technical teams and community stakeholders, supporting both the identification of potential biases and the refinement of system requirements. It can be deduced that the three concepts are intertwined, cross-fertilise each other and have common intersections that can contribute even more to the advancement of knowledge from its initial production, based on a methodology that is as innovative as it is simple.

Figure 1: Participatory framework concept

From a qualitative perspective, the preliminary results from the experiences of the above-mentioned EU project underline the value of dialogue-based and participatory approaches in the design of responsible AI development. The co-design workshops have shown that structured dialogue, participatory mapping, and iterative feedback mechanisms can effectively translate diverse community perspectives — especially from marginalised/rejected groups — into actionable design goals. Complementing this, ethnographic data practises offered rich insights into the contextual dynamics of data use, and emphasised the importance of relational accountability and validation of annotations through member checking and intercoder reliability measures. Furthermore, early experiments with cross-competency teams demonstrated the potential of epistemically diverse teams to embed fairness constraints and cultural sensitivity into technical processes. Taken together, these experiences show that inclusive methods not only broaden the range of design priorities, but also promote trust and inclusivity in AI practise. However, it is important to point out that these findings are still preliminary, as they come from a single implementation within the project and will be the subject of further research and publication. The following section therefore critically analyses limitations and outlines future research opportunities.

The ultimate goal of participatory design is to cultivate researchers who are both technically proficient and EDI-aware and ethically conscious. Taken together, these practises aim to break through the technocratic compartmentalisation that often characterises AI development and create space for social critique, situated intelligence and pluralistic values (Avellan et al., 2020). Rather than seeing ethics as a constraint or add-on, the proposed model understands ethical engagement as a form of epistemological intervention - one that is integral to the innovation process itself (Bencivenga et al., 2025). The result is a more holistic, adaptive and equitable approach to AI development that recognises the socio-technical nature of intelligent systems and

the multiplicity of people they affect. In this way, the degree of innovation can be measured not only with the well-known Technological Readiness Level (TRL, Figure 1) (Yfanti & Sakkas, 2024), but it is also possible to extend the application to the Societal Readiness Level (SRL, Figure 2) (Innovation Fund Denmark, 2019; Leone et al., 2024) and embody its critical and active role in the design and adoption of inclusive technologies (Bernstein et al., 2022). We therefore propose a value scale, as shown in the figure below, that considers the value of innovation based on its acceptability at the societal level (Obrien et al., 2024).

Phase	TRL	Description
Research	1	Basic principles observed and described
Research	2	Technology concept and/or applications formulated
Research	3	Analytical or experimental proof of principal functions and/or concept characteristics
Development	4	Validation of components and/or mock-ups in laboratory
Development	5	Validation of components and/or mock-ups in representative environment
Development	6	Demonstration of a prototype or system/subsystem model in a representative environment
Deployment	7	Demonstration of a system prototype in an operational environment
Deployment	8	Actual system completed and qualified through tests and demonstrations
Deployment	9	Actual system completed and qualified through successful operational missions

Figure 1: TRL scale

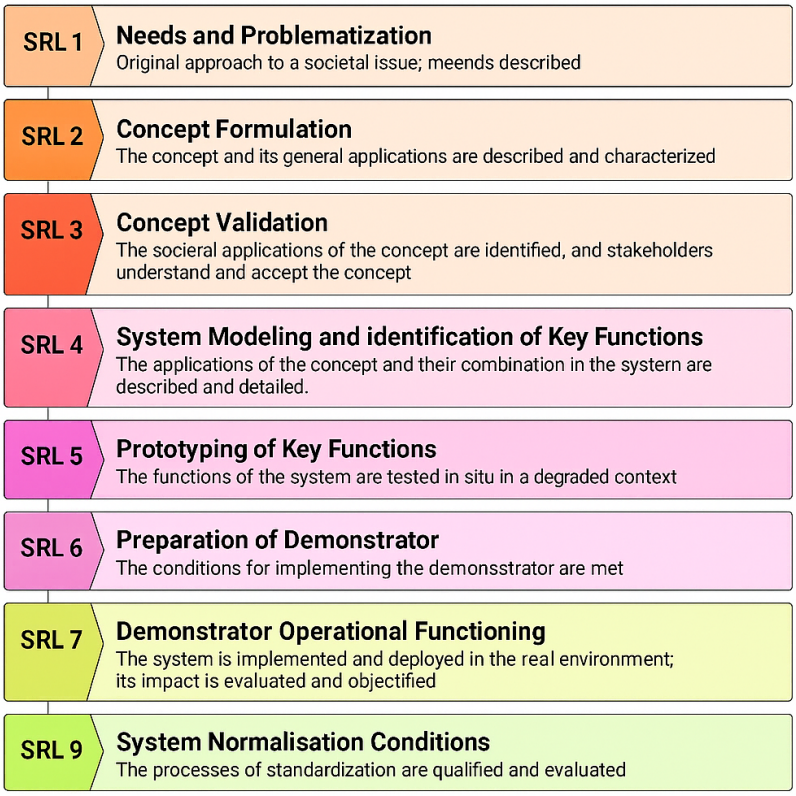

Figure 2: SRL scale

The SRL scale (Verma & Allen, 2024; Owen et al., 2012) assesses the social acceptability of innovation across 9 levels, ranging from problem recognition (level 1) to cultural integration (level 9) (Bruno et al., 2020). The scale is now used internationally and has several variants. Our intervention plan within the STEP project aimed to increase the SRL from 3 to 7, which represents a significant improvement in societal acceptance. By linking SRL and TRL, developers can assess both technical readiness and societal acceptance, mitigating the risks of socially misguided innovation.

4. Limitations and Future Implementation

The proposed framework opens up several critical avenues for future research and practical development at the intersection of AI and social inclusion and equality. While the STEP project demonstrates its potential to improve societal readiness and reduce bias, further work is needed to consolidate its methodological robustness, ensure its scalability and support its adaptation to diverse global contexts.

A first priority is the development of standardised metrics that can be used to assess the actual impact of participatory processes on model performance and bias reduction. Future research should explore the use of fairness metrics such as the Disparate Impact Ratio across large data sets and introduce sub-indices of SRL, including a Gender Bias Index and a Cultural Sensitivity Score, to capture intersectional inequalities that aggregate SRL levels cannot fully uncover. In addition to these tools, the concept of return on investment for inclusion (ROI) (Hoffman et al., 2011) could help quantify the long-term benefits of early participatory design, such as lower mitigation costs and higher social acceptability relative to the upfront investment required.

The here proposed framework offers a transformative approach to inclusive AI development, but several limitations and challenges are recognised. Firstly, the approach is very resource intensive. Dialogic co-design workshops and ethnographic dives require a significant investment of time and human input, which can limit scalability - especially for small projects or underfunded public initiatives. Secondly, persistent power asymmetries can undermine participatory processes. Even in an inclusive environment, community participants or junior contributors may self-censor when experienced developers or researchers are present.

Thirdly, while the SRL metric is innovative in terms of assessing social acceptability, it lacks the granularity to capture intersectional differences in highly heterogeneous social contexts. Several mitigation strategies are currently being developed to remedy this. In addition, the possible development of SRL sub-indices — such as a Gender Bias Index and a Cultural Sensitivity Score and others — should allow for a more nuanced assessment of inclusion outcomes.

Despite these efforts, there remains a fundamental tension between the depth of participatory inclusion and the efficiency of technical development. Applications where the stakes are high, such as AI in healthcare, may warrant extended and longer participatory phases, even if this results in delayed adoption, while commercial applications may require lighter but more frequent bias audits. Future implementations will likely rely on configurable levels of participation that calibrate this trade-off according to sectoral and contextual needs.

Taken together, these future implementations point to the evolution of the proposed framework into a globally adaptable model for inclusive AI. By combining rigorous metrics, decolonised practises, sustainable participation strategies and scalable design methods, the approach can ensure that AI systems are not only technically robust, but also socially legitimate, culturally responsive and sustainable in the long term, bridging the persistent gap between technological innovation and societal trust.

5. Conclusions

This paper proposes a participatory framework for the development of AI that incorporates epistemic diversity in the design phase and builds a bridge between technical and societal readiness. This is necessary to find breakthrough solutions to the current gaps in dealing with algorithmic biases and the design, production and implementation of AI. While much of the research focuses on identifying biases in AI systems and trying to avoid biases in post-production, we believe that we should take a broader action-oriented approach by developing tools and methods to avoid, prevent and mitigate these biases, especially those related to EDI. Including diverse voices and cultural perspectives in AI development from the design stage represents a significant step forward in creating equitable and inclusive technologies that can thus certify integrity (Almufareh, 2025). Incorporating EDI principles and gender-sensitive design principles into AI from the outset therefore requires developers to change the system of data collection and represents a fundamental shift in knowledge: finding and incorporating sources that are not biassed is a challenge, but it can and should still be done. While it is undeniable that, especially in recent years, powerful players — whether in companies or at government level — have often resisted EDI frameworks or dismissed the urgency of the debate with algorithmic bias, it is precisely this resistance that emphasises the need for systemic reflexivity in AI development. The reluctance of influential stakeholders to recognise structural gaps highlights the asymmetry between those who benefit from current technological trajectories and those who are disproportionately exposed to their risks. This divergence of interest illustrates why integrative knowledge production, based on interdisciplinary collaboration and participatory approaches, is so important: it creates mechanisms through

which alternative epistemologies and lived experiences can exert influence, even when political or market incentives are misaligned. While supranational organisations such as the European Union may have stronger regulatory influence to counterbalance these power dynamics, other contexts demonstrate the vulnerability of smaller governments to industry capture. Therefore, the proposed framework not only addresses the technical challenges, but also situates AI development within the broader struggles of governance, legitimacy, and societal accountability.

In contemporary innovation processes, it is becoming increasingly essential to assess not only the technical feasibility of a particular technology, but also its potential for social acceptance, adoption and integration within the specific communities or social groups for which it is intended. The success of an innovation depends not only on its technological maturity, but also on its fit with the cultural, ethical and contextual realities of its users. Consequently, the integration of TRL with SRL becomes an important analytical and strategic framework. Such integration enables researchers, developers and policy makers to assess both the technical development and the societal viability of innovations simultaneously. This dual consideration helps to minimise the risk of technological failure due to social resistance, misalignment with user needs or a lack of contextual awareness. Ultimately, aligning TRL and SRL increases the likelihood that innovations are both technically robust and socially meaningful, contributing to more sustainable and responsible innovation outcomes.

In this regard, it is crucial that the development of innovation — especially in the field of artificial intelligence — is guided from the outset by considerations of social readiness and participatory engagement. Rather than treating SRL, EDI and participatory approaches as secondary or downstream concerns, they should be embedded from the conceptualisation and design phase of technological development. This means that various stakeholders — including end users, civil society actors, representatives of marginalised groups and others — are actively involved from the earliest stages of ideation and prototyping. Such participatory approaches not only increase the social legitimacy and relevance of AI systems, but also help to recognise potential ethical, cultural and structural impacts before deployment. The early inclusion of societal concerns in the innovation process ensures that AI solutions are not only technically advanced, but also context-sensitive and in line with collective values and long-term societal goals.

Incorporating SRL-driven participatory methods from the earliest stages of AI development strengthens societal trust and supports ethically robust innovation.

Acknowledgements

This work was partly funded by the Horizon Europe STEP Project, under Grant Agreement No. 101078933.

Ethical statement: The research presented in this article did not involve human participants, collection of personal data, or interventions requiring formal ethical approval according to the authors' institutional guidelines. Therefore, no ethical approval was required. The authors confirm that the study was conducted in accordance with the principles of research integrity and the applicable ethical standards of their respective institutions.

Statement on the use of artificial intelligence tools: The authors declare that they have not used any artificial intelligence tools to generate, modify, or revise the content of this article, with the exception of the title. All texts, analyses, and conclusions are the exclusive result of the authors' work.

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A Gamified Phishing Simulator Using Reinforcement Learning

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Abstract: An organisation's security is fundamentally reliant on its people. Regardless of the sophistication of its cybersecurity infrastructure, the absence of comprehensive training and awareness can lead to vulnerabilities. Traditional phishing awareness training typically involves sending simulated phishing emails to employees, allowing organisations to monitor actions such as link clicks, email reporting, and responses. While this method offers valuable insights into employee behaviour, it often struggles to engage users effectively. This conventional approach may not create a dynamic learning environment conducive to better retention of vital security practices. Furthermore, users generally do not receive immediate feedback regarding their interactions with phishing links, leaving organisations more susceptible to social engineering attacks. This research seeks to address the issue by developing an interactive gamified phishing simulator that employs reinforcement learning (RL). The methodology for this study consists of two key components. First, a literature review was conducted to assess existing phishing awareness techniques and explore how RL can be applied effectively. This review examined the integration of RL within cybersecurity education and explored the impact of gamification on user behaviour. For the RL agent, a dataset comprising both phishing and legitimate emails was compiled. The agent was then trained to discern phishing emails from legitimate ones based on various email features. Then the agent presents users with email challenges and delivers real-time feedback on their selections. The simulator incorporates a reward and badge system that promotes active participation and ongoing learning. This approach aims to overcome the limitations traditionally associated with static phishing training by fostering continuous learning, ultimately reducing user susceptibility. The effectiveness of the proposed simulator was evaluated based on its classification accuracy of phishing and legitimate emails.

Keywords: Reinforcement learning, Gamified phishing, Phishing simulator, Artificial intelligence

1. Introduction

Phishing is executed through various channels, including email, SMS, and voice calls. Email phishing is the most common method, where the victim receives an email that looks like it is from a legitimate source (Alkhalil et al., 2021). These emails often contain manipulative language to encourage users to click on links, download attachments, or provide personal information under the threat of consequences. Smishing involves sending fraudulent text messages that appear legitimate, asking for personal details or prompting the download of an app. Vishing occurs when attackers make phone calls, posing as representatives of legitimate organisations, like banks, to extract sensitive information from victims (Salahdine, Mrabet and Kaabouch, 2021). From an organisational perspective, a single mistake, such as opening a phishing link, can expose an organisation to serious risks such as data breaches, ransomware infections, and Distributed Denial-of-Service (DDoS) attacks. Likewise, at an individual level, attackers can use sensitive information for malicious intent such as identity theft, financial fraud, or gaining access to personal applications (Ravi et al., 2021; Alkhalil et al., 2021). Many users assess the legitimacy of emails based on their overall look and feel, such as formatting, branding, logos, and language used. A poorly designed email with spelling errors or missing elements may raise suspicion, but a well-thought-out phishing email convinces users that it is from a legitimate source. As a result, relying solely on visual cues is an unreliable strategy to detect phishing and thus the reason users are still susceptible to phishing. People are amongst the weakest links for being victims of phishing attacks; organisations must invest resources and time to train staff to identify phishing attacks (Alkhalil et al., 2021; Alsharnouby, Alaca & Chiasson, 2015).

In South Africa (SA), the average data breach is estimated to cost more than R50 million per incident as cybercrimes become more frequent and complex; this cost will increase (Ngejane et al., 2024). SA has experienced substantial financial and data losses due to phishing incidents. Traditional phishing awareness training typically involves sending simulated phishing emails to employees and tracking their responses, such as clicks, reports, and ignored emails. While this provides some insights into behavior, it often lacks engagement and effectiveness. Employees' perception towards simulated phishing training is linked to lower productivity, increased feelings of boredom, anxiety and stress, thus resulting in a lack of user participation and employees not giving the training their full attention (Wannenburg, 2023). This approach fails to create an engaging learning experience, which could lead to better retention of critical security practices. Additionally, users do not receive immediate feedback that they have interacted with a phishing link, increasing the organisation’s vulnerability to social engineering attacks. This delay in feedback prevents employees from learning from their mistakes in real-time, making it harder to improve their ability to recognize phishing attempts in the future (Ngejane et al., 2024). Atemkeng and Wabo (2020) stated that 46% of cybersecurity cases were due to careless or uninformed staff.

Several studies have suggested that awareness training is the most effective approach in preventing attacks, as users are the final line of defence against many cyber-threats.

Although organisations strive to improve user awareness and training in phishing emails, many users still struggle to recognise phishing emails (Alsharnouby, Alaca & Chiasson, 2015). The same phishing simulations are used within the organisation, thus not incorporating dynamic and updated phishing tactics to simulate sophisticated phishing attacks, making the training less effective. Most research focuses on users' responses to internet phishing attempts; however, there is a lack of research on how employees within an organisational space handle phishing scams (Yeoh, 2022; Alkhalil et al., 2021). This study seeks to close this gap by creating an interactive gamification phishing simulator using intelligent agents to improve cybersecurity awareness through an engaging gamified environment. The simulator challenges users to identify phishing threats while providing real-time feedback. To ensure that users remain engaged, it includes a reward and badge system that encourages user participation and continuous learning. Unlike traditional static training methods, this approach offers a dynamic, direct learning experience tailored to real-world scenarios. The primary beneficiaries will be workplace industries aiming to strengthen phishing awareness and reduce user susceptibility. By including a gamified approach into realistic phishing simulations, the application aims to provide users with hands-on experience that better prepares them to recognise real-world phishing attacks for personal and organisational security thus mitigating user susceptibility to being phished (Ariyadasa & Fernando, 2024; Karim, 2019). Increased awareness directly contributes to reducing the various phishing techniques (as mentioned previously) as well as credential and identity theft and financial fraud. For the organisation, this means fewer successful social engineering attacks, thus mitigating against potential data breaches and hackers gaining unauthorised access to the organisation's system. As a result, social engineering becomes more difficult for hackers to exploit the weakest link in cybersecurity defence - the human element.

This research asserts the necessity of developing and implementing a gamified awareness solution to address the limitations associated with traditional static phishing training by fostering continuous learning, ultimately reducing user susceptibility. The remainder of the paper is as follows: Section 2 presents a literature review that was conducted to assess existing phishing awareness techniques and explore how RL can be applied effectively. This review examined the integration of RL within cybersecurity education and explored the impact of gamification on user behaviour. Section 3 presents the design and implementation of the proposed solution. For the RL agent, a dataset comprising both phishing and legitimate emails was compiled. The agent was then trained to discern phishing emails from legitimate ones based on various email features. Section 4 offers an evaluation of the solution, discussions, and future work. While Section 5 concludes the paper.

2. Literature Review

This section delves into the evolution of email phishing detection techniques, beginning with traditional rule-based filters and progressing to machine learning approaches. It is included to establish a basic understanding of how email threats have been managed, the limitations of traditional methods, and the need for adaptive intelligent systems as phishing techniques become more sophisticated. This gap has prompted the integration of machine learning, which brings flexibility, pattern recognition, and improved detection accuracy.

2.1 Phishing Awareness Techniques

Ho et al. (2025) from UC San Diego and the University of Chicago conducted a study for 8 months using a randomised controlled trial to assess two forms of phishing training: Annual security awareness training and embedded phishing training at UC San Diego Health involving 19 500 real world users to determine if employee training through simulated phishing exercises and cybersecurity awareness programs assists organisations as a defence mechanism. Employees received one of several simulated phishing emails covering themes like: account security warnings, shared documents, benefits policy changes and social protocol updates; these simulated phishing emails mimicked real-world scams. Each phishing simulation tracked the following: Click rate of the user, time spent on training if the employee failed and whether training was completed. These researchers found that the annual cybersecurity awareness training that organisations rely on has no impact on phishing defences. Employees who completed the training more recently were just as likely to fall for phishing attempts as those who completed the training over 12 months ago. Additionally, the practice of sending fake phishing emails and training employees who fall for them also showed very little benefit, with training reducing failure rates by only 1.7%. Upon further investigation, they found that engagement with training content was low, with more than 50% of employees closing the training page within 10 seconds of opening it. The employees who completed their interactive training were 19% less susceptible to falling for phishing scams in the future

Khairallah and Abu-Naseer (2024) conducted a study and developed a tool called *EmailAware* that was used to enhance email phishing awareness among university students through gamification. Their goal was to see which training method (gamified learning or traditional video-based education) better improves phishing detection skills. The study consisted of two groups of 30 participants, one group watched video-based phishing training, and the other group used *EmailAware,* which is a gamified platform. To measure the effectiveness of their study, they used Jigsaw Online Phishing Quiz to assess phishing awareness and detection skills and a qualitative survey to gather participant feedback on the gamified approach. Based on their findings, it was revealed that the gamified group outperformed the traditional group by 59%, with more engagement and motivation from this group. The traditional group improved by 41% thus the study suggests the use of gamification to improve cybersecurity training.

Traditional cybersecurity awareness training programs have several weaknesses that limit their effectiveness (Shakya, Pillai, & Chakrabarty, 2023). A major issue is the lack of personalisation; many programs adopt a uniform approach that fails to account for individual learning styles and existing knowledge levels. This generic design reduces learner engagement and comprehension. Studies also highlight that traditional training often lacks interactivity and dynamic elements, making it difficult to maintain participant interest or promote active learning (Salloum et al., 2022). Another significant gap is the absence of standardised metrics to assess training effectiveness or track long-term behavioural change. To address these deficiencies, future training must integrate personalised learning paths, real-time threat simulations, and measurable outcomes. Programs should move toward more interactive, adaptive models that engage users meaningfully and reflect the realities of the cybersecurity landscape (Shakya, Pillai, & Chakrabarty, 2023).

2.2 Machine Learning Techniques

Machine learning (ML) techniques applied to cybersecurity awareness phishing detection are categorised into supervised and unsupervised learning. Supervised learning trains a model on a labelled dataset, where each input is paired with an output label. The goal is for the model to accurately predict the label of new, unseen data once it has learned the mapping between inputs and outputs. Conversely, in unsupervised learning, the model is given a dataset with only input features and no labels, and from this data, the model is to determine the best outcome (Salloum et al., 2022; Dada et al., 2019).

Ahmed et al. (2022) conducted a rigorous investigation aimed at developing a machine learning-based model for detecting phishing emails, addressing both technical limitations and user-specific vulnerabilities. The objective of the study was to propose an optimised ML framework for phishing detection. Data preprocessing included deduplication, removal of missing values, and a standard 70:30 train-test split. Performance metrics used for evaluation included accuracy, precision, recall, and F1-score. The results revealed three major findings. First, a strong correlation between feature richness and detection accuracy was observed, with the 50-feature dataset achieving 100% accuracy using Boosted Decision Trees. Weiss (1999) conducted a comprehensive review of machine learning (ML) and deep learning (DL) techniques applied to spam detection in both email and Internet of Things (IoT) environments. The study aimed to systematically survey existing detection methods, categorising them into supervised, unsupervised, and reinforcement learning approaches, while comparing their performance based on accuracy, precision, recall, and other key metrics. The findings underscored the effectiveness of supervised learning models, with SVM and Naïve Bayes achieving high accuracy rates, up to 99.5% and approximately 89%, respectively, while Random Forests demonstrated performance levels reaching 95.2%.

Taherdoost (2024) emphasises that although machine learning techniques are effective in detecting phishing emails, they face several limitations. For example, Decision Trees (DT) can overfit the training data if not pruned correctly, which reduces the classification accuracy. Misclassifying spam as legitimate is usually harmless, but incorrectly labelling a legitimate email as spam can lead to the loss of valuable information. Additional challenges include the need for large volumes of training data and the constant evolution of attacker strategies, such as using images, synonyms, and intentional misspellings to bypass filters. Furthermore, obtaining high-quality email datasets is difficult, and machine learning models often rely on many features to perform well. These systems also tend to work best when tailored to individual users, and their accuracy drops significantly when applied in general scenarios. Lastly, they require high processing power, which may limit their practicality in resource-constrained environments (Taherdoost, 2024; Thakur et al., 2023).

2.3 Reinforcement Learning (RL)

Reinforcement Learning (RL) is a learning technique within the field of machine learning. It consists of an Artificial Intelligence (AI) agent that interacts with its environment through trial and error, perfecting its choices based on rewards received from past actions (Shakya, Pillai and Chakrabarty, 2023). RL is a new area of study in the literature and its significance within cybersecurity is increasing, it is being widely studied in various disciplines such as robotics, control systems, advertising, video games, autonomous vehicles and autonomous surgeries (Cengiz and Gök, 2023). In the cybersecurity space, it plays a vital role as it can adapt to dynamic and unpredictable environments without the use of predefined models. The use of RL to combat cybersecurity threats can provide security solutions to intrusion detection systems, penetration testing, cyberattacks through Denial of Service and Distributed Denial of Service attacks (DoS and DDoS) and assist with mitigating spoofing and phishing attacks (Oh et al., 2023).

Salahdine, Mrabet and Kaabouch (2021) proposed an innovative intrusion detection algorithm known as Adversarial Environment using Reinforcement Learning. The approach uses Double Deep Q-Network (DDQN), integrating RL with supervised learning. MAGPIE was proposed by Heartfield, which is an anomaly classification architecture that combines unsupervised anomaly detection in real-time with a Multi-Armed Bandit RL algorithm. This approach allows a system to dynamically select models based on human presence inference within a smart home space. Oh et al. (2023) implemented an adversarial cyber-attack simulator used to strengthen cybersecurity using the Deep Reinforcement Learning (DRL) framework. Their approach used an agent-based model that continuously learnt and adapted, making it suitable for an unpredictable nature as network security. Through RL, cybersecurity allows various domains to become more adaptive and automated in their threat detection. In phishing detection, RL agents interact with an email-based environment, refining their ability to classify emails by strategically balancing learning from past experiences and exploring new patterns.

3. Design and Implementation

The initial implementation involved a reflex agent that was developed to classify emails based on a set of predefined rules and patterns, such as the presence of suspicious keywords, URLs, or sender domains. While this approach was straightforward and provided quick results, it quickly became obvious that the reflex agent was limited in its ability to adapt (Salahdine, Mrabet and Kaabouch, 2021). This limitation led to the exploration and eventual adoption of a hybrid approach using a supervised Machine Learning (Random Forest) classifier and Reinforcement Learning agent for personalised awareness training.

This paper focuses on supervised ML algorithms, which have shown high accuracy in classifying emails as legitimate or phishing such as, decision tree, which is used for both classification and regression tasks and is able to manage categorical and numerical inputs. It splits data by checking distinctive features based on how well they separate the categories, by using measures like Gini Index (measuring misclassification risk) and Entropy (measuring information gain) (Salahdine, Mrabet and Kaabouch, 2021). This helps the model determine which features to use at each node in the tree. Random forest (RF) uses multiple decision trees built from random subsets of the data and features. Each tree makes a prediction by looking at a different part of the data and the result is based on the most voted class (phishing or legitimate). This approach improves accuracy and manages noisy or imbalanced data better than a single decision tree.

3.1 Random Forest Design

The primary responsibility of the Random Forest Agent is to accurately classify incoming emails, determining whether they are phishing attempts or legitimate correspondence. Utilising a complex ensemble learning technique, the agent analyses various features of each email, such as sender information, subject lines, and the content within the message. By aggregating the predictions made by multiple decision trees, the Random Forest Agent enhances accuracy and reduces the likelihood of misclassification. This sophisticated approach not only helps in identifying potential threats to user security but also minimises false positives, ensuring that legitimate emails are not mistakenly flagged as harmful.

Dataset: A dataset obtained from Rokibulroni (2023) included 3,650 phishing emails and 2,183 legitimate emails, which comprises 333 LLM-generated spear-phishing emails, 3,317 traditional phishing emails collected from public datasets spanning 1998–2022. There are 1,781 emails from the Enron email corpus, and 402 SpamAssassin marketing emails.

Feature Extraction: The system uses the extract_features function (from email_features.py) to convert each email into a set of numerical features. The features used are presented in Table 1 below:

Table 1: Feature Extractions

has_url	Whether the email body contains a URL (One if yes, zero if no).
sender_has_suspicious_domain	Whether the sender's domain looks suspicious (e.g., too many dashes, numbers, or unusual patterns).
has_urgency	Whether the subject or body contains urgent language (e.g., "urgent", "immediately").
subject_length	The length of the email subject. body_length: The length of the email body.
has_phishing_keyword	Whether the email contains common phishing keywords (e.g., "verify", "password", "security").
has_malicious_attachment	Whether the body mentions a file with a suspicious extension (e.g., .exe, .zip).

Data Preparation: Emails and their labels (*1* for phishing, *0* for legitimate) were loaded from a CSV file. Each email was processed to extract the above features, resulting in a feature matrix (X) and a label vector (y).

Model Training: The data was split into training and test sets (70% training, 30% testing). The Random Forest was then used to train a model. The forest contained twenty-five decision trees. Each tree was trained on a random bootstrap sample of data. At each split in a tree, a random subset of features was considered (to increase diversity among trees). The best split was chosen based on the Gini impurity, which measured how well a feature separates the classes. Trees grew until a maximum depth or until further splits were not meaningful.

Prediction: To classify a new email, its features were extracted and passed to each tree in the forest. Each tree made a prediction, and the final class was determined by majority vote across all trees.

Model Storage and Use: The trained Random Forest model was saved as a pickle file (random_forest_model.pkl). When needed, it was loaded and used to classify new emails in real time.

Integration with RL Agent: When the RL agent presents an email scenario to the user, the Random Forest model was used to determine the correct label (phishing or legitimate) for that email. The user's response was compared to the model's prediction: If the user's answer matches the model, the RL agent receives a positive reward. If not, the agent receives a negative reward. This feedback is used to update the RL agent's Q-table and policy.

3.2 Reinforcement Learning Design

Reinforcement Learning was chosen to enhance adaptability and personalise the training experience, beyond traditional and static ML approaches. The RL agent operates in a gamified phishing simulator, selecting email scenarios and adjusting difficulty dynamically using a Q-table that tracks the effectiveness of past interactions. To choose the next email, the agent uses an epsilon-greedy strategy: it sometimes explores by picking a random difficulty but usually exploits by selecting the difficulty with the highest Q-value for the current state. After the user responds to an email, the agent receives a reward (+5 for a correct answer, -1 for an incorrect one) and updates the Q-table. Table 2 below presents an overview of the agent's environment that was deployed:

Table 2: Reinforcement Learning Agent Environment

Inaccessible	The RL agent does not have access to all information about the environment (e.g., it cannot see future emails or the true intent behind an email). It learns from observed features and past experiences stored in the Q-table.
Non-deterministic	The outcome of the agent's actions (classifying an email) can vary due to the probabilistic nature of user behaviour and the randomness in email content. The same action in the same state may not always yield the same reward.
Episodic	Each email scenario is treated as a separate episode. The agent receives a reward or penalty after each classification, and the Q-table is updated accordingly. The outcome of one episode does not directly affect the next.
Static	The environment (the email being classified) does not change while the agent is deciding. The agent's policy (derived from the Q-table) is updated after each episode, but the email content remains fixed during classification.
Discrete	The state space (features of emails), action space (classify as phishing or legitimate), and rewards are all discrete.

The RL agent was implemented as a simple tabular Q-learning model. An epsilon-greedy policy balanced exploration with exploitation, while updates followed the standard temporal difference learning rule. The use of tabular Q-learning, although basic, provided a fast and functional baseline that made it possible to observe improvements without heavy computational requirements. In the gamified phishing simulator, the environment is a simulated interface where the agent interacts with phishing and legitimate emails. This feedback loop enables the agent to identify which email types and difficulty levels best support user learning, thus improving phishing detection and optimising personalised training outcomes.

4. Evaluation, Discussion and Future Work

4.1 Evaluation and Discussion

The web application supports registration, login, profile management, a leaderboard, and the simulation module. In the proposed system, each user has their personalised training, logging into their profile, able to track their progress. Through gamified elements such as a point system and badges, users feel encouraged to learn and improve their learning in an environment that keeps them engaged. If a user is not able to pass basic levels, which consist of obvious phishing clues, then the system will provide other tasks that are basic till the user can progress to the next level. By doing this, the user is supported on their learning journey and engaged with the content without feeling overwhelmed if a mistake is made.

In comparison to similar systems, the proposed gamified phishing simulator incorporates several novel features that enhance the user learning experience of phishing awareness training in an organisation. The system differs by including gamification with RL; this combination allows a dynamic, engaging, and adaptive training experience. This system gives instant feedback if users fail to spot phishing; through providing immediate feedback, users learn on the spot and this assists with recognising phishing attacks.

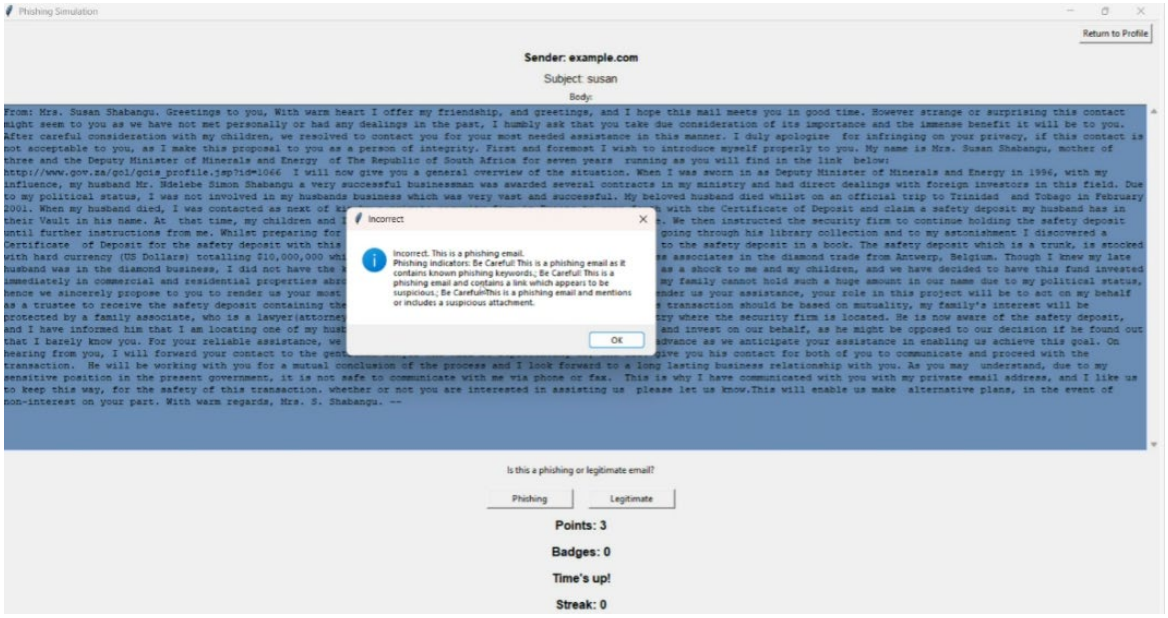

Figure 1: Phishing Simulator

When the RL agent presents an email scenario to the user, the Random Forest model is used to determine the correct label (phishing or legitimate) for that email. The user's response is compared to the model's prediction: If the user's answer matches the model, the RL agent receives a positive reward. If not, the agent receives a negative reward. This feedback is used to update the RL agent's Q-table and policy. The proposed phishing simulator solves problems found in current systems by making learning more interactive, engaging, and adaptable. By using reinforcement learning and gamification, the system keeps users interested and helps them improve their ability to spot and handle phishing attacks. This approach ensures that users are better prepared to deal with real phishing threats, improving the overall cybersecurity of the organisation.

4.2 Future Work

The proposed solution already integrates cutting-edge techniques like Reinforcement Learning and Random Forests for adaptive phishing awareness training. From here, several future research directions could deepen its

impact, broaden its scope, and enhance its effectiveness. Future research could focus on using Explainable AI (XAI) for user feedback and extend training beyond text-based phishing to include image-based, voice-based, and video-based phishing scenarios. Also, studies focusing on Human-Computer Interaction could be conducted to validate the hypothesis that gamification improves awareness and engagement.

5. Conclusions

This study addresses a critical gap by developing an interactive gamification phishing simulator powered by intelligent agents to enhance cybersecurity awareness in a gamified environment. The simulator empowers users to effectively identify phishing threats while delivering real-time feedback. To maximise engagement, it incorporates a robust reward and badge system that motivates active participation and continuous learning. Unlike outdated static training methods, this innovative approach provides a dynamic, immersive learning experience that mirrors real-world scenarios. The primary beneficiaries of this initiative are workplace industries focused on bolstering phishing awareness and lowering user susceptibility. By integrating a gamified strategy into realistic phishing simulations, the application equips users with invaluable hands-on experience that prepares them to recognise and combat actual phishing attacks, ultimately safeguarding both personal and organisational security. This heightened awareness plays a vital role in diminishing various phishing techniques, as well as preventing credential and identity theft and financial fraud. For organisations, this translates to a significant reduction in successful social engineering attacks, which mitigates potential data breaches and prevents unauthorised access to critical systems.

Ethics Declaration: Ethical clearance was not necessary for this study.

AI Declaration: Grammarly has been utilised for editing purposes and for enhancing overall writing quality.

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Improving Online Learning via VARK Learning Styles and Machine Learning-Driven Personalisation

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Abstract: Understanding student engagement and academic performance is crucial in online learning environments. However, many learning management systems (LMS) lack mechanisms to adapt to diverse learning styles and support meaningful collaboration. This study addresses these challenges by proposing a Personalised and Collaborative Learning Experience (PCLE) framework that integrates the Visual, Auditory, Reading/Writing, and Kinaesthetic (VARK) learning style model with collaborative filtering techniques. Unlike existing approaches that rely only on rating data, PCLE incorporates personalised learning styles into the recommendation process to create learner-centred outcomes. To overcome the lack of publicly available datasets containing personalised learning style data, a self-collected dataset was developed to reflect authentic learner preferences. Benchmark datasets from Coursera and Udemy were also used to validate baseline collaborative filtering performance. Three machine learning models—K-Nearest Neighbours (KNN), Singular Value Decomposition (SVD), and Neural Collaborative Filtering (NCF)—were applied and evaluated using Mean Absolute Error (MAE), Hit Rate (HR), and Average Reciprocal Hit Ranking (ARHR). Results from the benchmark datasets confirmed earlier findings that KNN performs well on structured review data, while the self-collected dataset demonstrated the added value of integrating learning styles. The self-collected dataset was evaluated separately, incorporating personalised learning styles into the recommendation process. This dataset represents the main contribution of the study, as VARK preferences were embedded alongside course interactions to extend recommendations beyond standard rating-based methods. This study highlights how personalisation and collaboration can be integrated into one framework to enhance learner engagement. While the same models were applied, embedding learning preferences into the self-collected dataset represents a methodological enhancement rather than a direct comparison with existing datasets. Findings highlight the role of dataset characteristics in shaping both accuracy and ranking quality and show how the PCLE framework balances personalisation with collaboration to support learner-centred outcomes. Future research should expand dataset diversity, include additional learner attributes, and explore advanced recommendation models to further optimise adaptability and performance.

Keywords: Personalised learning, Collaborative filtering, KNN model, SVD model, NCF model

1. Introduction

Online learning systems have become increasingly essential, especially after the COVID-19 pandemic (Khalaf, et al., 2022), driving demand for effective learning management systems (LMS) that offer adaptive and personalised learning to improve student engagement and academic success. Artificial Intelligence (AI) driven approaches (Ayouni, et al., 2021; Kanchon, et al., 2024) and personalised learning technologies (Essa, et al., 2023) improve engagement by tailoring content to learning preferences. Integration of AI-driven tools, such as mobile interactive systems (Lai, et al., 2021) and freehand writing applications (Lai, et al., 2022), improved outcomes in virtual classrooms, while collaborative learning strategies (Herrera-Pavo, 2021) support knowledge sharing and peer interactions.

Many existing systems still lack effective ways to predict and adapt to learning styles. This study aims to address this gap by developing a Personalised and Collaborative Learning Experience (PCLE) framework that integrates learning styles with collaborative filtering and machine learning. Learning style frameworks are particularly relevant in health science education (Childs-Kean, et al., 2020), and structured frameworks like Information Technology Capability (ITC) (Lew & Krishnasamy, 2023) and Technological Pedagogical and Content Knowledge (TPACK) (Lai, et al., 2021) enhance engagement and performance. Integrating learning styles into the framework (Taheri, et al., 2021) enhances tailored learning, and advanced collaborative filtering techniques, such as Adaptive KNN and SVD (Rahman, 2023) significantly improve recommendation accuracy.

This study lies in the potential to contribute to Malaysia's post-COVID-19 educational landscape by integrating personalised learning and collaboration to support future-ready talent development. Literature review and machine learning applications (William Fernandes, et al., 2023) identify factors influencing student performance and engagement. The study by Moubayed, et al (2018) highlighted links between engagement patterns and academic outcomes. Building on this foundation, this study evaluates benchmark collaborative filtering

methods, including K-Nearest Neighbours (KNN), Singular Value Decomposition (SVD), and Neural Collaborative Filtering (NCF) to analyse recommendation performance in personalised learning environments.

Existing LMS often fail to integrate personalised learning styles with collaborative methods effectively (Jena, et al., 2023; Sanjabi & Ali Montazer, 2020), limiting support for diverse learning needs. Understanding Generation Z healthcare students' preferences (Shorey, et al., 2021), is crucial for adaptive education. Collaborative filtering improves recommendation accuracy (Joorabloo, et al., 2020), but structured methods to combine learning styles with collaboration remain limited. This study bridges these gaps by introducing a PCLE framework to address these challenges and enhance student engagement outcomes.

This study develops and evaluates a PCLE framework to enhance student engagement and performance in AI-driven environments. The specific objectives are: (1) To determine factors contributing to students' academic performance in AI-driven digital transformation. (2) To investigate effects of a learning style, academic records and intelligence agent assistance on personalised collaborative learning experience (PCLE). (3) To develop a PCLE framework for predicting and improving students' engagement and academic performance. (4) To evaluate student's engagement and academic performance with the proposed PCLE framework. This study is divided into five sections: introduction, literature review, methodology, results and discussion, and conclusion. The methodology in this study builds on prior work involving model evaluation and comparative analysis of machine learning techniques in education (Ling & Weiling, 2025), as demonstrated in a previously published study in IEEE Access.

2. Literature Review

2.1 Introduction to Learning Styles

Waladi, et al. (2023) highlighted various learning style models, including VARK, Honey and Mumford, Kolb's Experiential Learning, Gregorc Style Delineator, and Dunn and Dunn, in adaptive educational environments. AI technology has advanced e-learning by enabling adaptive learning based on individual styles, though this approach requires large datasets and real-time adaptation. This study aims to overcome these challenges by evaluating AI-driven methods within the Personalised and Collaborative Learning Experience (PCLE) framework to adapt and predict preferences.

The study by Mpwanya & Dockrat (2020) emphasised the importance of understanding students' learning styles for effective instruction. Most undergraduate logistics students displayed an accommodator style, preferring hands-on learning, though the study was limited by small sample size and single institution focus. The findings provide valuable insights into the relationship between learning styles and demographics, guiding tailored instructional methods. Similarly**,** Subagja & Rubini (2023) showed aligning materials with preferred learning styles enhances knowledge acquisition among science students, with 35% kinaesthetic, 30% visual, 21% auditory, and 14% reading or writing preferences. Despite being limited to one institution, these findings highlight style diversity. This study will also build on such findings by exploring different learning styles in the PCLE framework to ensure inclusivity and adaptability.

2.2 Kolb, Felder-Silverman, VARK and Other Learning Models

Key learning style models include Kolb, Felder-Silverman, VARK, Gregorc's Mind Styles, Riding's Cognitive Styles, and Myers-Briggs Type Indicator, providing insights to support adaptive education environments. This study applies KNN, SVD and NCF models for collaborative filtering-based course recommendations, evaluated using MAE, HR, and ARHR, creating data-driven learning experience. The study by Mwangi and Muchiri (2019) assessed physiotherapy students' learning preferences at Kenya Medical Training College using Honey and Mumford (1982) and Neil Fleming (1987) questionnaires. Results showed Reflector was most prevalent style, with Kinaesthetic also common. The VARK questionnaire effectively identifies learning preferences to enhance teaching, though the study was limited to one college, with a small sample size and not considering confounding factors. The findings provide insights into how learning preferences impact student performance in medical education. Furthermore, the study by Zine, et al. (2019) investigates the effectiveness of various learning style models in adaptive educational environments. The author evaluated Gregorc, Riding, Myers-Briggs, Felder-Silverman, and Kolb models in adaptive environments, finding Felder-Silverman model is the most suitable for adaptive e-learning due to the comprehensive approach to learning styles. However, the finding's applicability is limited to adaptive systems. Zine's study provides valuable insights for designing adaptive educational environments by emphasising popular learning styles like VARK and Kolb models. Building on these insights, this study uses VARK within the PCLE framework with KNN, SVD, and NCF to enhance personalised learning through data-driven adaptation, addressing gaps in traditional LMS approaches.

2.3 Integrating Learning Styles in e-Learning

With the rapid advancement in technology, the application of learning styles in e-learning has demonstrated significant value, particularly in personalising learning paths (Seghroucheni & Chekour, 2023). The Felder-Silverman model has proven effective but functions optimally only under specific technical conditions, limiting adaptability to mobile platforms. Similarly, Glazunova, et al (2020) adapted educational content based on learning styles, customising materials to individual preferences. Limitations include restricted testing of scalability and real-time adaptation. These studies highlight the potential of data-driven learning style identification to improve adaptive learning platforms and inform tailored educational strategies.

Many current personalised educational platforms often struggle to address diverse student abilities, learning paces, and preferences (William Fernandes, et al., 2023). To address this issue, the study by William employs supervised machine learning techniques to dynamically schedule assignments based on student characteristics, evaluating Logistic Regression (LR), K-Nearest Neighbours (KNN), Support Vector Machine (SVM), Decision Tree (DT), and Random Forest (RF). Random Forest achieved the highest effectiveness with 94% F1-score and accuracy rate, successfully classifying students into appropriate learning modes. Building on these findings, this study incorporates machine learning methods like KNN and SVD within the PCLE framework to dynamically adapt learning paths for diverse students.

2.4 Impact of Learning Styles on Academic Performance and Engagement

The study by Subramaniam, et al (2023) investigated Kolb's learning styles among 80 students and the effect on learning outcomes. Diverger was the most common learning style among participants, followed by Assimilator, Accommodator, and Converger. Divergers engage in concrete experience and reflective observation, often brainstorming before making decisions. Assimilators focus on theoretical understanding rather than practical application. Convergers excel in problem solving and applying theories to real-world tasks, while Accommodators learn best through hands-on activities and direct engagement. Despite the small sample, the findings provide useful insights for educators to design instructional methods that accommodate different learning preferences. In a related study, Kamal, et al (2021) found healthcare students preferred unimodal styles, emphasising the need for personalised strategies. Besides that, the study by Yean, et al (2024) reported Reflector as the most popular style among third-language learners, highlighting tailored strategies for multilingual education despite not assessing learning outcomes.

The study by Taheri, et al (2021) examined Kolb and VARK styles with emotional creativity among 250 dental students, finding Accommodator as dominant. The limitations include focus on one field and uncontrolled variables, yet the study illustrates interactions between learning styles, creativity, and performance. Furthermore, Rastovski & Tomić (2023) examined VARK's recognition across 40 studies but noted limited empirical testing across contexts, highlighting the importance of individual differences in material design. AI-based personalised e-learning systems demonstrate effectiveness in providing tailored learning experiences (Murtaza, et al., 2022). While limited diverse user personas restrict understanding of varied behaviours, the framework successfully delivers individualised learning solutions.

2.5 Collaborative Learning Styles

The study by Khalaf, et al (2022) examined the effectiveness of e-learning management systems, Moodle and Blackboard, highlighting tools for personalised and collaborative learning. Moodle offers greater cost-effectiveness and flexibility, supporting external APIs and older systems better than Blackboard. However, limitations include management challenges, technical issues, and financial constraints. Despite this, the findings emphasise e-learning systems' potential to enhance engagement and optimise learning technologies, particularly during crises like COVID-19. The integration of analytics in collaborative learning platforms (Lai, et al., 2024) can further improve engagement and outcomes. Another study by Alanya-Beltran (2024) introduced a personalised learning recommendation system using collaborative filtering and machine learning. User-based and item-based filtering identified similarity patterns, while machine learning models, such as decision trees, generated tailored recommendations based on preferences, historical behaviour, and performance. The autoencoder model outperformed other methods in predicting course ratings.

Additionally, Jena, et al (2023) presented an e-learning course recommender using KNN, SVD, and NCF on one lakh Coursera reviews from Kaggle. The results show that KNN outperforms other models by achieving higher hit rates (HR), average reciprocal hit ranking (ARHR), and lower mean absolute error (MAE), supporting informed course selection based on learner preferences. A LMS is a digital platform designed to manage, deliver, and track

educational content and learning activities (Saleh, et al., 2024), facilitating online learning through content creation, communication, assessment, and progress monitoring.

2.6 Personalisation of Learning Styles

Sanjabi & Ali Montazer (2020) explored personalisation of e-learning using Kolb's learning style model, finding that tailoring strategies improved academic outcomes and satisfaction. Further real-world testing and scalability analysis are needed. The study by Sihombing, et al (2020) aimed to enhance e-learning by personalising content with the Felder-Silverman Learning Style Model (FSLSM), digitising the Index of Learning Styles (ILS) questionnaire to customise learning, which improved engagement and performance. However, the finding's limitation was the small sample size, with only 30 students participating. Furthermore, Rekha's study (Rekha, et al., 2024) investigated AI-powered personalised learning, showing adaptive paths, gamification, and predictive analytics enhance engagement and performance. Rekha's study showed that personalised learning systems cannot perfectly fit every student, but AI shows potential to address individual learning needs effectively.

3. Methodology

3.1 Dataset

This study uses both publicly available datasets and a self-collected dataset to implement and evaluate the proposed Personalised and Collaborative Learning Experience (PCLE) framework in an AI-driven Learning Management System (LMS). Initially, two education-related datasets from Kaggle were explored. The first dataset contains 100k scraped course reviews from the Coursera website as of May 2017 (Jena, et al., 2023). The second dataset is about the 209k courses detailed information and comments from the Udemy Courses website in Oct 2022. Figure 1 shows the proposed PCLE framework, from data collection and preprocessing to the integration of VARK learning styles, collaborative filtering, model evaluation, and results analysis.

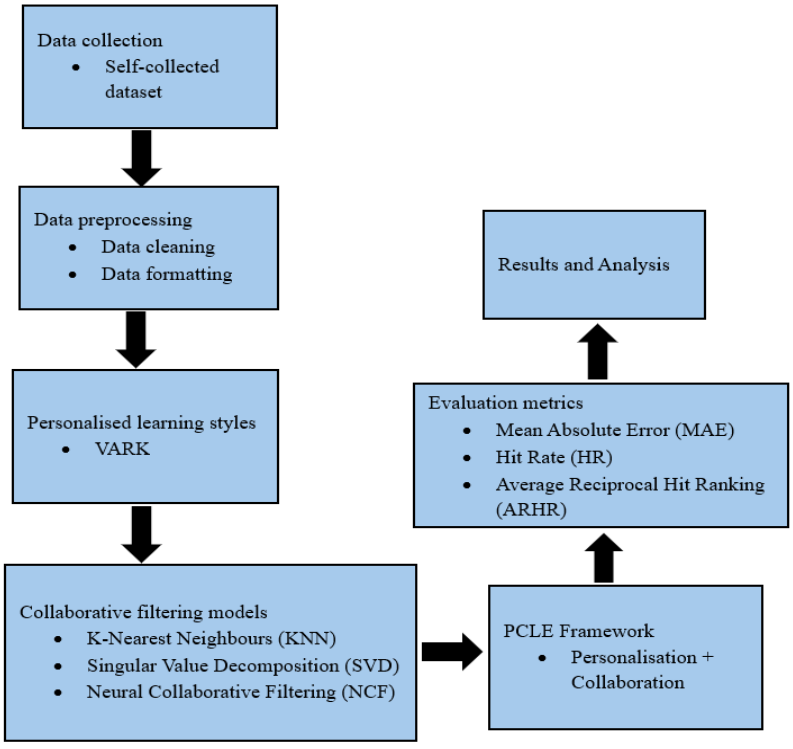

Figure 1: Proposed Framework

The first dataset (Adona, 2018) downloaded from Kaggle in the CSV file consists of 140,321 data and 4 columns. The second dataset (Hossain, 2022) that downloaded consists of 209,735 data and 25 columns. Figure 2 presents the features of dataset 1 and dataset 2. These two datasets provide benchmarks for evaluating baseline recommendation performance without personalised learning style attributes.

#	Dataset 1 Features	Description	Dataset 2 Features	Description
1	Id	The unique identifier for a review.	Comment Id	The unique identifier assigned to each comment row.
2	Course Id	The course tag found in the URL of the course on the Coursera website.	Course Id	The unique identifier or tag for each course.
3	Review	The actual text of the course review.	Rate	The numerical rating given by users for the course.
4	Label	The rating of the course review, categorised by score.	Date	The date associated with the comment.

Figure 2: Features in Datasets 1 and 2 (only the first 4 rows are shown to conserve space)

To address the limitation of existing datasets that lack personalised learning style attributes, a self-collected dataset was developed. This dataset includes participant responses from Multimedia University students and incorporates VARK learning style preferences. Figure 3 presents the features in self-collected dataset. The inclusion of this self-collected dataset enables a more accurate implementation of the PCLE framework by incorporating real learner preferences and personalised learning style data, which is an area often overlooked in existing datasets.

#	Features	Description
1	Response Number	A unique identifier assigned to each survey response.
2	Submitted Date and Time	The exact date and time when the response was submitted.
3	Course	The name of the course.
4	Full Name	The complete name of the respondent.
5	Username	The username or ID used by the participant in the system.
6	Complete	Indicates whether the survey was fully completed by the respondent.
7	Email Address	The participant's email address.
8	Question 1	Questions related to the preferred learning styles in the VARK model.
9	Question 2	Questions related to the preferred learning styles in the VARK model.
10	Question 3	Questions related to the preferred learning styles in the VARK model.
11	Question 4	Questions related to the preferred learning styles in the VARK model.
12	Question 5	Questions related to the preferred learning styles in the VARK model.
13	Personalised Learning Styles	Indicates the respondent's preferred learning style, categorised by models like VARK.
14	Module	The specific module of the course.
15	Rating	The overall rating given by the participant to the module.
16	Comment	Additional open-ended feedback provided by the participant.

Figure 3: Features in the Self-Collected Dataset

3.2 Data Preprocessing

After loading the dataset into Jupiter Notebook, the two CSV files were merged to combine relevant information. Duplicate entries were removed to maintain a clean and unique dataset. Next, missing values were checked, and rows containing "NaN" were dropped. Additionally, text preprocessing was performed on the "Review" column, including removing special characters, extra whitespace, and converting text to lowercase for consistency. For

the self-collected dataset, VARK questionnaire responses were encoded into categorical features and merged with course-rating data. The resulting sparse matrix was stored in Compressed Sparse Row (CSR) format for efficiency. Finally, all datasets were split into training and testing subsets.

3.3 Personalised Learning Styles

The VARK (Visual, Auditory, Reading/Writing, and Kinaesthetic) model was applied to assess learning preferences. Responses determined the dominant learning style for each participant, and these attributes were integrated into learner profiles. This model is commonly used in education to tailor content delivery to different learning styles, enhancing engagement and effectiveness. In the PCLE framework, this enabled personalisation by grouping learners with similar VARK profiles and combining this with course interaction patterns, allowing recommendations to reflect both personal preferences and collaborative filtering. By incorporating this model into the study, the aim is to create a more personalised learning experience based on the identified preferences.

3.4 K-Nearest Neighbours (KNN) Model

Next, this study implemented a K-Nearest Neighbours (KNN) algorithm to recommend courses based on user preferences (Jena, et al., 2023). The KNN model was chosen due to simplicity and effectiveness in collaborative filtering. Secondly, using the scikit-learn library, the KNN model was initialised with cosine similarity as the distance metric. After training on the sparse course-user interaction matrix, a recommendation function retrieved the most similar courses, with lower cosine distance indicating higher similarity. Finally, the recommendations reveal course similarity patterns within the dataset. For the self-collected dataset, similarity was calculated using both course interactions and VARK attributes, ensuring that recommendations reflected collaborative patterns enriched by personalised preferences.

3.5 Singular Value Decomposition (SVD) Model

Besides that, the Singular Value Decomposition (SVD) model was used to recommend courses based on user preferences (Jena, et al., 2023). SVD is a technique that breaks down the user-item interaction matrix into smaller parts, which helps identify hidden factors influencing user choices. This allows the model to predict missing ratings or interactions, which is useful for recommending courses that users may be interested in. For the benchmark datasets, this process was based on course ratings alone. For the self-collected dataset, VARK attributes were embedded into the interaction matrix, aligning predictions with learner preferences.

3.6 Neural Collaborative Filtering (NCF) Model

Neural Collaborative Filtering (NCF) is a deep learning-based approach to collaborative filtering that uses neural networks to model user-item interactions (Jena, et al., 2023). Unlike traditional methods like KNN or SVD, which rely on linear relationships, NCF learns complex, non-linear interactions between users and items. This approach is better suited for large and complex datasets. For the self-collected dataset, VARK features were added as additional embeddings, allowing the model to generate recommendations based on both rating behaviour and learning style profiles.

3.7 Train-Test Split and Model Evaluation

To evaluate the performance of the recommendation model, the dataset was split into training and testing subsets using a 60-40 ratio, 70-30 ratio and 80-20 ratio (Jena, et al., 2023). The training data was used to train the KNN model, SVD model and NCF model. On the other hand, the test set contains unseen user-course interactions that the model has not encountered before. The model is trained on the training data and evaluated using the test data. The purpose of using test data is to simulate how well the model would perform in a real-world scenario, where predictions would need to be made based on unseen interactions. This helps in assessing the accuracy and effectiveness of the model in recommending courses that match user preferences.

3.8 Performance Metrics Calculation

The performance of the model was analysed by calculating Mean Absolute Error (MAE), Hit Rate (HR), and Average Reciprocal Hit Ranking (ARHR) (Jena, et al., 2023). The “calculate_metrics” function compared the model’s recommendations with actual ratings in the test dataset. The Mean Absolute Error (MAE) assessed overall accuracy, where lower values indicate predictions closer to actual ratings. The Hit Rate (HR) measured how often relevant courses were recommended, with higher values indicating better performance. The Average Reciprocal Hit Ranking (ARHR) evaluated ranking quality, with higher values showing relevant courses appearing near the top of the recommendation list. The benchmark datasets reflected baseline collaborative filtering

performance, while the self-collected dataset highlighted the PCLE contribution by balancing prediction accuracy with learner-centred personalisation.

4. Results and Discussion

4.1 Performance Results of KNN, SVD, and NCF Models

The KNN model was evaluated using three training-test splits for Datasets 1 and 2, and the self-collected dataset. In Dataset 1, results improved as training size increased, with MAE decreasing, HR increasing, and ARHR stable for 70-30 and 80-20 splits, confirming the findings of Jena et al. (2023) and validating the reliability of the benchmark dataset in testing collaborative filtering methods. In Dataset 2, performance declined as the training size increased, highlighting the influence of dataset structure and sparsity on algorithm effectiveness. In the self-collected dataset, performance remained stable for smaller splits, while the largest split showed slightly reduced accuracy but improved ranking, indicating that incorporating personalised learning styles may reduce accuracy (MAE) while improving ranking quality (ARHR), aligning more closely with learner relevance.

The SVD model showed consistent performance across splits in Dataset 1, while Dataset 2 showed less accurate predictions but stable ranking quality. In the self-collected dataset, smaller splits maintained stable performance, while the largest split improved ranking despite some reduction in accuracy.

The NCF model performed steadily on Dataset 1 with Dataset 2 maintaining stable rankings despite decreased prediction accuracy. In the self-collected dataset, smaller splits were stable, and the largest split showed reduced prediction accuracy but enhanced ranking quality. Figure 4 summarises MAE, HR, and ARHR for all three models across datasets and splits.

Model	Ratio	Dataset	MAE	HR	ARHR
KNN	60-40	Dataset 1	0.0152	0.9000	0.1267
		Dataset 2	2.8332	0.8000	0.1783
		Self-collected dataset	0.7507	0.6667	0.4167
	70-30	Dataset 1	0.0131	0.9200	0.1500
		Dataset 2	2.6253	0.6000	0.2044
		Self-collected dataset	0.7507	0.6667	0.4167
	80-20	Dataset 1	0.0080	0.9600	0.1500
		Dataset 2	2.3101	0.4000	0.1067
		Self-collected dataset	0.7937	0.3333	0.5000
SVD	60-40	Dataset 1	0.0103	0.7000	0.1370
		Dataset 2	1.4842	0.7000	0.1370
		Self-collected dataset	0.7507	0.6667	0.6667
	70-30	Dataset 1	0.0100	0.7000	0.1370
		Dataset 2	1.4556	0.7000	0.1370
		Self-collected dataset	0.7507	0.6667	0.6667
	80-20	Dataset 1	0.0105	0.7000	0.1370
		Dataset 2	1.4511	0.7000	0.1370
		Self-collected dataset	0.7937	0.3333	1.0000
NCF	60-40	Dataset 1	0.0115	0.9000	0.1370
		Dataset 2	1.6667	0.9000	0.1370
		Self-collected dataset	0.7507	0.6667	0.4167
	70-30	Dataset 1	0.0121	0.9000	0.1370
		Dataset 2	1.6667	0.9000	0.1370
		Self-collected dataset	0.7507	0.6667	0.4167
	80-20	Dataset 1	0.0085	0.9000	0.1370
		Dataset 2	1.6667	0.9000	0.1370
		Self-collected dataset	0.7937	0.3333	0.5000

Figure 4: KNN, SVD and NCF Model Results for Three Ratios across Three Datasets

4.2 Comparative Analysis Of KNN, SVD, and NCF Models

A comparison of KNN, SVD, and NCF models on Dataset 1 and Dataset 2 revealed several key observations. KNN performed best on Dataset 1, showing the lowest MAE, highest HR, and stable ARHR, confirming earlier findings by Jena et al. (2023) that KNN performs well in collaborative filtering with well-structured review data. SVD also performed well in Dataset 1, but minimal variation across training-test splits suggested limited responsiveness to data size. Dataset 2 posed more challenges as SVD and NCF maintained stable HR and ARHR values, but with much higher MAE, while KNN's performance dropped sharply as data sparsity increased. These results underline how strongly dataset characteristics influence algorithm behaviour.

The self-collected dataset was evaluated separately because personalised learning style attributes were included, unlike in the other two datasets. This dataset represents the key contribution of the PCLE framework, as user preferences based on VARK were integrated into the recommendation process. Although the same

models were applied, the inclusion of learning styles represents a methodological difference, so results were not directly compared with Dataset 1 and 2. Predictive accuracy (MAE) was lower compared to Dataset 1, but ranking quality (ARHR) improved, showing that personalisation enhanced recommendation relevance for learners even when overall error rates were higher. Results from the self-collected dataset provide additional insight into how personalised features can enhance AI-driven recommendations. This reflects a different priority where, instead of maximising accuracy alone, the PCLE framework aims to support learner-centred outcomes through a balance of prediction and relevance. Unlike traditional approaches that focus on a single dataset, this study compares model performance across datasets with different characteristics, emphasising data structure's impact on recommendation effectiveness.

5. Conclusions

In summary, this study explored the development and evaluation of a Personalised and Collaborative Learning Experience (PCLE) framework in AI-driven learning environments. Findings highlight the importance of AI-driven collaborative learning strategies, particularly in the post-COVID-19 era. A comparative analysis of KNN, SVD, and NCF models showed KNN performed best for Dataset 1, while SVD and NCF showed stable predictive accuracy, indicating that dataset characteristics significantly influence recommendation effectiveness. A key limitation was the lack of publicly available datasets with learning style data, addressed by using a self-collected dataset incorporating personalised learning styles. This contribution extends evaluation beyond standard rating-based datasets and demonstrates how personalisation can improve relevance for learners, even with some reduction in accuracy. By combining personalisation with collaboration, the PCLE framework offers insights into how adaptive learning systems can better align recommendations with learner needs. Future work could involve larger, more diverse datasets, additional learner attributes, and advanced recommendation models to enhance adaptability and performance. The findings of this study contribute to research on adaptive learning, emphasising the importance of dataset structure and personalised features in optimising recommendation effectiveness.

Ethics Declaration: This manuscript is an original work, has not been submitted elsewhere, and all authors approve its submission.

AI Declaration: No generative Artificial Intelligence (AI) tools were used in the preparation of this manuscript.

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AI-Enhanced Stakeholder Engagement for Climate Adaptation: Evidence from Lithuania

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Abstract. Civil engineering faces the dual challenge of decarbonisation and resilience under increasing threat of climate change. While artificial intelligence (AI), machine learning, and digital twins are increasingly applied to optimise design, material reuse, and hazard modelling, most systems remain techno-centric and overlook the human dimensions of adaptation. This article addresses this gap by combining a nationally representative survey of Lithuanian residents (n = 1,013, 2023) with the design of an AI-enabled platform for civil engineering adaptation. The survey captured six domains (hazard experiences, adaptation behaviours, motivational drivers, preparedness levels, institutional linkages, and climate attitudes) providing a behavioural evidence base that reveals how climate concerns and motivations translate into action. The results highlight differentiated motivational pathways, moderate levels of preparedness, uneven institutional communication, and four distinct citizen profiles with specific adaptation probabilities. Building on these insights, the article proposes the Citizen-informed AI for Climate Adaptation (CiA-CA) framework, which systematically maps citizen evidence onto AI system design variables. The framework informs the development of the Lithuanian Construction Materials Reuse Optimization (LSEPO) platform, created under the Civil Engineering Research Centre (CIMC), by integrating hazard-prioritised digital twins, recommender systems with motivational weighting, clustering for personalisation, and preparedness-aware interfaces. Conceptually, CiA-CA advances the integration of behavioural adaptation evidence with socio-technical AI design. Empirically, it provides one of the first nationally representative datasets on climate adaptation behaviours in the Baltic region. Practically, it offers a blueprint for municipalities and industry partners in Lithuania to embed citizen evidence into AI-enabled platforms, with potential transferability to similar European contexts.

Keywords: Artificial intelligence, Climate adaptation, Civil engineering, Civil engineering adaptation, Stakeholder engagement, Behavioural evidence, Human-centred AI, Circular economy

1. Introduction

Climate change is redefining the conditions under which civil engineering systems are designed, built, and maintained. According to the Global Status Report for Buildings and Construction 2024/2025, the sector is responsible for approximately 32% of global final energy consumption and 34% of energy-related CO_2 emissions (UNEP & GlobalABC, 2025). Beyond operational energy, the rapid growth of demolition waste and embodied carbon from construction materials creates systemic pressures that demand new circular solutions (Kovacic et al., 2020; Wynn & Jones, 2022). In response, artificial intelligence (AI), machine learning, and digital twin technologies are increasingly deployed to optimize resource flows, predict hazards, and model resilient infrastructure futures (Rodrigo et al., 2024; Therias & Rafiee, 2023; Iranshahi et al., 2025). Initiatives such as the "D5 digital circular workflow" for material reuse (De Wolf et al., 2024), infrastructure digital twins spanning design through operations (Moshood et al., 2024), and policies incorporating material passports and circular construction material flows exemplify how AI and digital twins are being mobilized globally to optimize resource reuse and reduce waste across the construction lifecycle. While technically sophisticated, current AI tools often omit the human dimensions of adaptation. Several recent studies document these gaps: AI systems for climate evaluation frequently neglect local social-ecological variables and community values (Adaptation Fund, 2025); organizational readiness is shaped not just by capability, but by how individuals perceive limitations, risk, and trust (Übellacker, 2025); and psychological barriers such as transparency, fairness and perceived risk strongly mediate adoption even when technical performance is high (De Freitas et al., 2021; Ghosh et al., 2025).

This article addresses that gap by combining a nationally representative survey of Lithuanian residents (n = 1,013; 2023) with a design blueprint for AI-enabled adaptation support that will be operationalised in the Lithuanian Construction Materials Reuse Optimization (LSEPO) platform under the Civil Engineering Research Centre (CIMC). The survey systematically captured six domains (hazard experiences, adaptation actions, motivational drivers, preparedness levels, institutional linkages, and climate attitudes) providing a behavioural evidence base that explains how concerns and motivations translate (or fail to translate) into action. Crucially, these domains map to design variables (hazard priorities, motivational weights, preparedness-aware interfaces, and user profiles) that can be embedded in decision-support for municipal partners and industry stakeholders in Lithuania, with portability to similar Baltic and Northern-Central European contexts. Guided by research in adaptation psychology and technology adoption, we address four research questions: RQ1: How do citizens' experiences of climate hazards relate to their concerns and reported adaptation actions?; RQ2: Which

motivational and perceptual factors are most strongly associated with different types of adaptation behaviours?; RQ3: How do preparedness and institutional contact influence the translation of concern into action?; and RQ4: In what ways can these behavioural insights be operationalised as features and profiles for AI-enabled adaptation platforms?

The remainder of the article proceeds as follows. Section 2 reviews the literature on AI and digital twins in civil engineering, behavioural adaptation, sustainability-oriented recommender systems, and trustworthy/ participatory AI. Section 3 outlines the survey design and analytical approach. Section 4 reports results aligned with RQ1-RQ4. Section 5 situates the findings in the international literature and develops the CiA-CA framework into a concrete blueprint for LSEPO deployment. Section 6 concludes with contributions, limitations, and directions for longitudinal validation and live pilots with municipal and industry partners.

2. Literature Review

Recent scholarship has explored how AI and digital twin technologies can advance civil engineering by improving predictive modelling, optimising material flows, and supporting transitions to circular construction systems. Applications range from hazard simulation and resilience planning to life-cycle analysis and secondary material markets (Iranshahi, Zhang, & Xu, 2025; Therias & Rafiee, 2023; Wynn & Jones, 2022). These tools are noted for their ability to generate multiple alternatives, balance objectives (e.g., cost and carbon), and support decisions at scales beyond human capacity (Rodrigo, Omrany, Chang, & Zuo, 2024). However, most of this work has concentrated on technical optimisation, with comparatively limited attention to the behavioural and social conditions that shape adoption.

Behavioural research has consistently shown that citizens' responses to climate risks depend not only on technical feasibility but also on perceptions, motivations, and institutional trust. Theories such as the *Theory of Planned Behaviour* and the *Value-Belief-Norm framework* underline the role of attitudes, perceived control, and normative values in shaping adaptation choices (Ajzen, 2020; Stern, Dietz, Abel, Guagnano, & Kalof, 1999). Empirical studies confirm that risk perception and efficacy beliefs are key predictors of whether individuals act on climate concern (Van Valkengoed, Perlaviciute, & Steg, 2024). Psychological distance and climate anxiety further influence outcomes: climate change is often seen to affect "others" or future generations, while anxiety can either mobilise or inhibit action depending on efficacy and preparedness (Clayton, 2020; Kühner, Schäfer, & Wamsler, 2025). Longitudinal studies also highlight the mediating role of institutional trust and perceived preparedness in the concern-action link (Wong-Parodi & Rubin, 2024). Together, this evidence shows that adaptation behaviour is contingent on socio-cognitive factors. Yet these insights are rarely operationalised into data structures that could inform AI-enabled civil engineering platforms, leaving a gap between behavioural evidence and system design.

In parallel, recommender systems research demonstrates the value of personalisation in promoting sustainable choices. Personalised decision support has been shown to increase the acceptance of pro-environmental actions compared to generic campaigns, particularly when recommendations align with user motivations and values (Debnath, Chattopadhyay, & Ray, 2025; Sander, 2025). Multi-objective optimisation approaches allow such systems to balance criteria such as adoption probability, carbon reduction, financial savings, and equity (Satinet, De Wolf, & Reisch, 2025). However, most implementations stop short of linking behavioural survey data to computational pipelines. While conceptual calls for personalised sustainability tools are common, few blueprints exist for translating motivational profiles or preparedness gaps into feature vectors and objective functions in civil engineering contexts. In addition, trust and participation are also central to the AI adoption in public-facing systems. Scholars and policymakers emphasise that for AI to gain legitimacy it must be transparent, explainable, and accountable (Albahri et al., 2024; Agbabiaka, Haque, & Afolabi, 2025). OECD guidance similarly stresses citizen engagement and governance mechanisms that ensure fairness and accountability (OECD, 2025). Research in human-centred AI shows that uptake depends not only on accuracy but also on alignment with user values and well-being (Sebestyén, 2025; Shin & Lee, 2025). Yet much of this literature remains normative, offering principles without empirically grounded variables that platforms can use to adapt interfaces and recommendations.

Finally, existing participatory AI frameworks face well-documented limitations. Many remain confined to small-scale pilots or experimental case studies, raising questions about scalability when applied across national or international contexts (Bryson & Theodorou, 2019; Jasanoff, 2020). Others encounter inclusivity gaps, since engagement processes often attract digitally literate or already motivated participants, while more vulnerable or less-connected populations (those typically most at risk from climate impacts) are underrepresented (Birhane et al., 2022). Furthermore, these frameworks often emphasise aspirational principles such as transparency,

fairness, and accountability, but provide limited methodological guidance on how behavioural variables such as motivations, preparedness, or trust can be systematically translated into system design logics (Shneiderman, 2020; Rahwan, 2018). This results in a persistent gap between what participatory AI advocates in theory and what can be operationalised in practice.

Together, these strands of literature underscore the need for socio-technical approaches to civil engineering adaptation, which this study develops through empirical survey evidence and AI design.

3. Methods

3.1 Study Design, Sample and Data Collection

This study was designed to address four research questions (RQ1-RQ4) on how citizens' hazard experiences, motivations, preparedness, and institutional contact relate to adaptation behaviors and how these insights can inform AI-enabled civil engineering design. To generate the necessary evidence, a nationally representative survey of Lithuanian residents (n = 1,013) was conducted in October-November 2023. The questionnaire, originally developed by Brink and Wamsler (2019), was adapted to the Lithuanian context using a back-translation procedure to ensure conceptual equivalence. The analysis focuses on six domains that provide direct inputs for AI-supported adaptation: (i) Hazard experiences: self-reported exposure to storms, floods, heatwaves, cold spells, mould, or coastal flooding (measured as Yes/No); (ii) Adaptation actions: grouped into four categories: *technical* (e.g., installing flood barriers, retrofitting windows/roofs), *social/organisational* (e.g., helping neighbours, joining community preparedness initiatives), *institutional* (e.g., contacting municipalities, participating in public meetings), and *ecosystem-based* (e.g., tree planting, garden adaptation).

Each reported adaptation action was recorded in binary form, distinguishing between those who had undertaken the measure (coded as 1) and those who had not (coded as 0). From these items, indices were constructed for each domain (technical, social, institutional, ecosystem-based) by calculating the proportion of actions undertaken within that category. In addition to actions, several attitudinal and contextual measures were included. Motivational drivers were captured across four dimensions: economic ("I act because it saves money"), ecological ("to protect nature"), social ("to help the community"), and ethical ("because it is the right thing to do"). All were measured using five-point Likert scales ranging from low to high importance. Preparedness was assessed through a single item asking respondents to rate their ability to cope with climate hazards, also on a five-point scale (1 = not at all prepared, 5 = very prepared). Institutional contact was measured by whether respondents reported having received information on climate risks from municipalities or other public bodies (Yes/No). Finally, climate attitudes were measured using two indices: general concern about climate change and climate-related anxiety, both rated on five-point scales. To account for heterogeneity in the population, the survey also collected socio-demographic variables including age, gender, education, income, and place of residence. These variables provided the basis for examining group-level differences in adaptation behaviour and for informing AI-driven segmentation and personalisation.

The survey used a multistage stratified random sampling method, ensuring representation by geography (urban/rural), gender, age, education, and occupation. Data were collected through face-to-face interviews across 31 cities and 43 villages. The sample was balanced by gender (54% women, 46% men) and broadly reflected national population structures in age, income, and education. All fieldwork was conducted by *Baltijos tyrimai*, following ESOMAR guidelines and EU standards for survey research. Participation was voluntary, informed consent was obtained, and all responses were anonymized and securely stored.

3.2 Analytical Approach

Survey data were analysed using Python (pandas, numpy, scipy.stats). Analyses were organised around the four research questions. For RQ1, descriptive statistics were used to summarise the proportion of respondents reporting exposure to storms, heatwaves, flooding, and other hazards, and regression models tested whether hazard experience was associated with higher concern and a greater likelihood of adaptation actions. For RQ2, adaptation behaviours were examined by calculating the frequencies of technical, social, institutional, and ecosystem-based measures, and regression models estimated how different motivational dimensions (economic, social, ecological, ethical/other) predicted these behaviours. For RQ3, preparedness was analysed as an intermediate variable linking motivations to actions, and municipal information was examined as a potential moderator of the concern-action relationship. These associations were tested using mean comparisons, ANOVA, and regression models with interaction terms. For RQ4, population heterogeneity was explored through clustering analysis. A four-class solution was selected based on fit statistics and interpretability, and predicted

probabilities of each adaptation action were calculated for each class to identify distinct citizen profiles relevant for AI personalisation.

Instrument reliability was confirmed with Cronbach's alpha (overall α = 0.92; subscales 0.76-0.80). Missing data were minimal (<2% per item) and addressed using multiple imputation by chained equations, with listwise deletion applied as a robustness check. Survey weights were applied to correct for small deviations from national population distributions. These procedures ensured that the analyses rested on a validated and representative evidence base suitable for translating behavioural patterns into AI design features.

4. Results

The results are presented in line with the four research questions (RQ1-RQ4), moving from hazard exposure, through motivational drivers and mechanisms, to population profiles that inform AI personalisation.

RQ1. Hazard exposure and adaptation responses*. A significant minority of Lithuanian households has already been affected by climate hazards. The most frequently reported experiences were storms and strong winds (11.4%) and temperature extremes (8.3%), with smaller proportions reporting flooding (4.6%) or humidity-related mould (3.7%), and coastal flooding virtually absent (0.1%). Table 1 summarises these findings. Respondents who had experienced any hazard reported slightly higher climate concern (average score 3.23 vs. 3.14 on a five-point scale) and far higher adaptation activity (average of 34% vs. 12% of actions taken). The difference in behaviour was statistically large (Δ = 0.225; t ≈ 14.8), confirming that direct experience is a strong driver of action.*

Table 1: Hazard exposure among Lithuanian households

Hazard type	Respondents (%)
Storms/wind/hail	11.4
Heatwaves/cold spells	8.3
Heavy rain/flooding	4.6
Mould/humidity	3.7
Coastal flooding	0.1

RQ2. Motivations associated with different adaptation behaviours. *Four categories of motivation were analysed: economic, social, ecological, and ethical/other. All scored relatively high (mean values between 3.5 and 4.0 on a five-point scale), but they were associated with behaviour in different ways. Regression models showed that economic motives were the strongest predictors of technical measures (e.g., retrofitting, protective investments). By contrast, social and ethical motives were most strongly linked to community-oriented and ecosystem-based actions (e.g., helping neighbours, planting trees). Ecological concern correlated positively with overall action levels but lost significance once other motivations were included, suggesting its effect is mediated by more immediate drivers.*

Table 2: Motivations predicting adaptation behaviour

Motivation type	Effect on action (β)	Significance
Economic	0.027	p < .01
Social	0.040	p < .01
Ecological	0.012	n.s.
Ethical/Other	0.022	*p < .05*

These relationships are visualised in Figure 1, which plots respondents' mean motivation scores against the number of adaptation actions undertaken. The scatter shows that while most individuals report high motivation (≈4/5), the majority cluster at low to moderate action counts (0-4 actions). The positive trendline indicates that greater motivation is indeed associated with more actions, but the spread of points highlights a persistent

"concern–action gap." This gap is particularly visible among respondents with high motivation but very few reported actions.

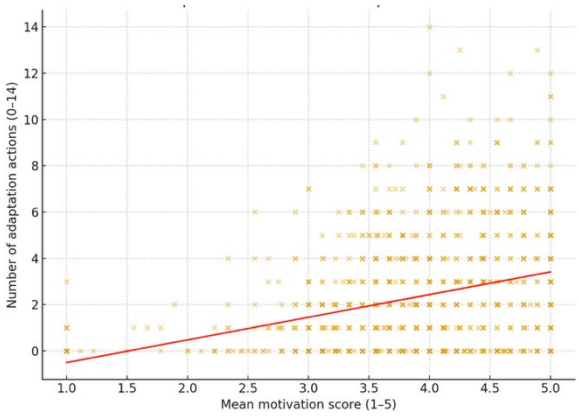

Figure 1: Motivation vs Adaptation Actions

Taken together, Table 2 and Figure 1 demonstrate that different adaptation actions are fuelled by different motives, and that motivation alone does not guarantee action. For AI-enabled platforms, this underscores the need for tailored recommendations: technical actions should be framed in terms of affordability and economic incentives, while community and ecosystem measures can be promoted through appeals to ethical responsibility and social solidarity.

RQ3. Preparedness and institutional contact. *On average, citizens rated themselves only moderately prepared for climate risks (mean = 2.9 on a five-point scale). Preparedness was positively correlated with all motivational drivers (r ≈ 0.44-0.50), indicating that individuals with stronger economic, social, or ecological values also tended to feel more capable of responding. The results are consistent with a mediation pattern in which stronger motivational drivers are associated with higher perceived preparedness, which in turn predicts greater adaptation behaviour. Municipal information provided only a limited additional mechanism: respondents who reported receiving communication from municipalities were somewhat more likely to act, but the interaction between concern and municipal contact was small and statistically uncertain. These findings suggest that institutional information on its own is insufficient to generate behaviour change unless it is coupled with motivational and efficacy supports.*

RQ4. Adaptation profiles for AI personalisation. *To capture heterogeneity in the Lithuanian population, a clustering analysis was applied to motivational indices, concern, anxiety, preparedness, and institutional variables. A four-profile solution provided the clearest structure (Figure 2). The largest group, Baseline pragmatists (48%), were characterised by mid-level motivations and only average readiness. Their uptake of adaptation actions was modest, with relatively low shares across all categories (10% technical, 18% social, 8% institutional, 16% ecosystem). A smaller but broadly engaged group, High-motivation all-in adopters (31%), scored very high across all motives and reported strong readiness. They showed consistent action across categories, particularly in social (31%) and ecosystem measures (23%). Two minority profiles stood out. The Community & nature oriented (8%) group combined high ecological and social motives with high readiness but low municipal communication. They displayed the highest uptake of community and ecosystem measures (41% and 40%, respectively), alongside above-average technical (24%) and institutional (23%) actions. By contrast, the Low engagement group (13%) had the lowest motivations, concern, and readiness, translating into minimal action across all categories (4-9%).*

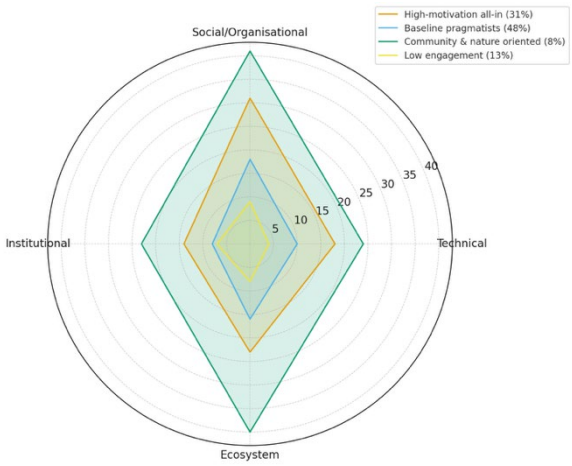

Figure 2: Motivations predicting adaptation behaviour

These profiles illustrate actionable levers for AI design: for example, emphasising cost savings for pragmatists, ecological/community benefits for the nature-oriented, and confidence-building tools for the low-engagement group. They provide a direct pathway from behavioural evidence to personalisation parameters for the conceptual framework discussed in Section 5.2.

5. Discussion

5.1 Results in Context

The Lithuanian findings broadly align with international research on climate adaptation while also offering contextual nuances that sharpen their relevance for AI-enabled civil engineering. Hazard experience emerged as a strong driver of both concern and action, consistent with global evidence that lived experience intensifies perceived risk and motivates protective behaviour (Wong-Parodi & Rubin, 2024; Van Valkengoed et al., 2024). What the Lithuanian data add is specificity: storms and heatwaves were identified as the most influential triggers. This points to clear priorities for digital twin scenarios in mid-latitude contexts, where system design should emphasise, hazards already recognised as pressing by citizens.

The analysis of motivations similarly extends behavioural theory. Prior work highlights the importance of efficacy beliefs and value orientations (Ajzen, 2020; Stern et al., 1999) but often collapses these into a single "pro-environmental" dimension. Our results show instead that different motivations map onto different action types: economic concerns underpin technical measures, while social and ethical values drive community and ecosystem-based responses. This differentiation supports global findings that motivations matter (Clayton, 2020) while providing operational clarity for recommender systems, which can assign motivational weights to actions rather than assuming a universal driver. Preparedness reinforced these patterns by acting as an intermediate factor: stronger motivational orientations were associated with higher self-reported readiness, which in turn predicted greater behavioural uptake. This echoes international work linking efficacy and readiness to adaptation (Kühner et al., 2025), but the Lithuanian case also underscores limits to institutional influence. Municipal communication was only weakly associated with increased action, diverging from studies that stress trust in institutions as a primary driver (Albahri et al., 2024). The implication is that information campaigns alone are insufficient; without reinforcing motivation or building efficacy, institutional contact does little to convert concern into practice.

Finally, the clustering analysis confirmed international evidence on heterogeneity in sustainability adoption (Shin & Lee, 2025) while advancing it in two ways. First, it quantified the behavioural implications of different profiles across technical, social, institutional, and ecosystem domains. Second, it highlighted distinctive combinations (e.g., community- and nature-oriented citizens) were highly active in ecosystem measures despite limited municipal communication, while low-engagement citizens remained resistant across all domains. These findings suggest both opportunities and challenges: bottom-up ecological action can thrive even in the absence of institutional support, but low-readiness groups require new strategies if they are to be mobilised.

5.2 From Evidence to Conceptual Framework

A central contribution of this study is to show how empirical evidence on citizens' adaptation behaviours can directly inform the design of AI-enabled platforms. Prior research has noted that decision support must align not

only with technical optimisation but also with user values, capacities, and institutional contexts (Baxter & Sommerville, 2011; Sander, 2025). By linking survey results to system design, this study demonstrates how behavioural data can serve as inputs rather than background context. Four design implications follow. First, hazard experience matters: citizens affected by storms or heatwaves were more active, suggesting digital twins should prioritise these hazards to increase salience and legitimacy (Therias & Rafiee, 2023). Second, motivations are diverse: economic motives drive technical measures, while social and ethical concerns support community and ecosystem actions, meaning recommender systems should weight recommendations according to user profiles (Ajzen, 2020; Sander, 2025). Third, preparedness shapes uptake: higher self-assessed readiness mediates between motivation and action. Interfaces should therefore adapt to user readiness, offering simple, confidence-building options to low-readiness users and more complex portfolios to high-readiness ones (Kühner, Schäfer, & Wamsler, 2025; Albahri et al., 2024). Finally, population heterogeneity enables personalisation: clustering revealed four citizen profiles with distinct probabilities of action, providing a natural basis for profile-based segmentation in human-centred AI (Shin & Lee, 2025).

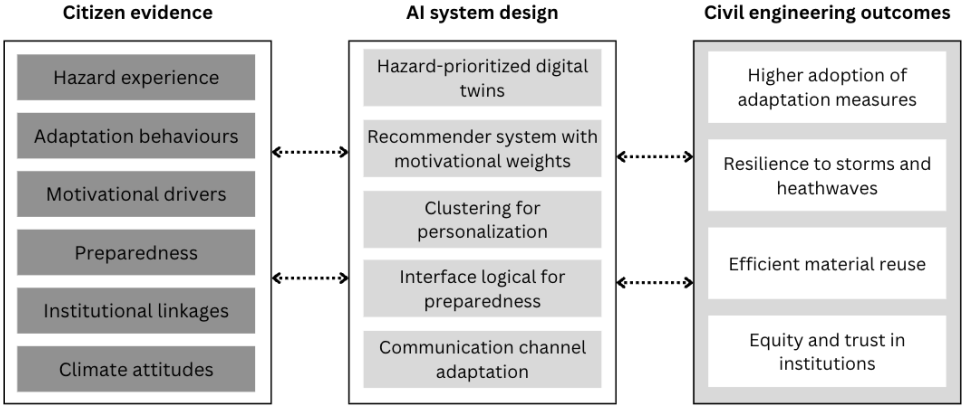

Figure 3: Citizen-informed AI for Climate Adaptation framework

Synthesising these insights, we propose a socio-technical design blueprint. At its centre is a recommender system that evaluates candidate measures against four objectives: adoption probability, expected CO_2 reduction, financial savings, and equity. The weight given to each objective is adjusted by citizen profile, ensuring that the system reflects the motivational and readiness patterns observed in the population. The pipeline unfolds in five stages: (i) profiling users into clusters, (ii) setting profile-specific priorities, (iii) generating candidate measures across technical, social, institutional, and ecosystem domains, (iv) scoring measures against weighted objectives, and (v) presenting tailored recommendations with transparent explanations. These design principles are brought together in the Citizen-informed AI for Climate Adaptation (CiA-CA) framework (Figure 1). The framework connects three layers: (i) Citizen evidence (hazard experiences, adaptation behaviours, motivations, preparedness, institutional linkages, and climate attitudes); (ii) AI system design (hazard-prioritised digital twins, recommender systems with motivational weighting, clustering for personalisation, and interfaces adapted to preparedness and communication channels); and (iii) Civil engineering outcomes (higher uptake of adaptation measures, greater resilience to storms and heatwaves, more efficient material reuse, and stronger equity and trust). By grounding system logic in behavioural evidence, the CiA-CA framework advances civil engineering adaptation as a socio-technical process. It responds to international calls for human-centred AI in sustainability (Debnath, Chattopadhyay, & Ray, 2025) and provides both a conceptual advance and a practical blueprint for platforms that are technically robust, socially resonant, and trusted by the citizens they aim to serve.

5.3 Integration Path: LSEPO Deployment

The CiA-CA framework will be implemented in the platform as a staged but continuous socio-technical integration. At the data layer, survey-based constructs (hazard exposure, motivational profiles, perceived preparedness, and institutional contact) are compacted into a LSEPO user model that can be elicited through a short onboarding module and, with consent, softly updated from in-platform interactions. On the modelling side, the digital-twin library will prioritise storms and heatwaves, reflecting the empirical salience of these hazards in Lithuania; scenario cards will render before/after material-reuse and household-adaptation outcomes parameterised by municipal and regional data where available. The recommender then operationalises the framework's behavioural logic by ranking technical, social, institutional, and ecosystem measures against four

objectives (adoption likelihood, CO_2 reduction, cost savings, and equity) with profile-dependent weighting derived from the survey. Interfaces will be preparedness-aware: users who report lower readiness first encounter low-threshold, confidence-building steps and interactive simulations, whereas users with higher readiness are offered richer portfolios and bundled measures. To support legitimacy and governance, each recommendation is paired with a concise "why this?" explanation anchored in motivational fit and expected benefits; privacy, consent, and data minimisation are enforced, and model cards document data sources, assumptions, and equity checks. Technically, integration proceeds through an alpha phase in the CIMC lab (back-testing and expert review), followed by a beta with one or two municipalities (A/B testing of profile-aware explanations and preparedness-tailored flows), culminating in a pilot scale-up that incorporates market signals for secondary materials and municipal incentives. Although tuned for Lithuania, the same pipeline can be ported to Baltic and Northern-Central European contexts with minor recalibration of hazard priors and motivational weights, thereby providing a practical route from population-level evidence to operational decision support. At the same time, it should be noted that the underlying evidence base comes from self-reported survey data and a cross-sectional design. This may limit generalisability beyond Lithuania, as hazard recall, motivational reporting, and adaptation behaviours can vary across countries and over time. Accordingly, transfer to other contexts requires recalibration with locally validated data and, ideally, longitudinal evidence to capture how motivations and preparedness evolve.

6. Conclusions

This study demonstrates how nationally representative behavioural evidence can be mobilised to design AI-enabled adaptation support in civil engineering. Using a Lithuanian survey (n = 1,013), we showed that lived hazard experience (especially storms and heatwaves) correlates with higher concern and substantially greater action uptake; that motivations are differentiated, with economic drivers linked to technical measures while social and ethical values underpin community and ecosystem actions; that perceived preparedness functions as an intermediate factor between motivation and behaviour; and that citizens cluster into distinct profiles with characteristic action probabilities. Taken together, these results move beyond descriptive analysis to provide design variables (hazard priorities, motivational weights, preparedness-informed interface rules, and user profiles) that can be directly operationalised in decision-support systems. Building on these insights, we proposed the CiA-CA framework. The framework connects behavioural adaptation research with socio-technical AI design; empirically, it introduces one of the first nationally representative datasets on adaptation in the Baltic region; and practically, it provides a blueprint for translating population-level evidence into implementable AI features for municipal and engineering platforms in Lithuania and beyond. Importantly, this framework is not abstract. It will be integrated into the LSEPO platform. This integration ensures that the behavioural insights gathered here will inform real-world digital twins, recommender logics, and municipal communication strategies. In this way, CiA-CA contributes not only to academic debate but also to the operationalisation of national and regional adaptation infrastructures.

Several limitations qualify these contributions. The data are self-reported and cross-sectional, which constrains causal inference and may over- or under-estimate real behaviours. Some constructs, such as preparedness, were measured parsimoniously, and institutional communication effects may depend on message quality and governance capacity not fully captured here. The framework itself remains design-oriented and requires prospective validation in live systems. Future work should therefore: (1) test CiA-CA in prototype deployments within LSEPO, evaluating offline accuracy and online outcomes such as adoption uplift, preparedness gains, and trust; (2) conduct longitudinal follow-ups to recalibrate motivational and preparedness weights as hazard experiences evolve; (3) expand explanation and governance layers, including profile-aware explanations, model cards, and equity auditing; and (4) assess transferability to other European contexts where hazard profiles and motivational structures may differ. By advancing adaptation support as a socio-technical endeavour (where optimisation is explicitly aligned with motivations, readiness, and institutional realities) this work outlines a path toward AI platforms that are technically robust, socially legitimate, and practically deployable. In doing so, it positions Lithuania, through CIMC and LSEPO, as a regional testbed for citizen-informed, AI-enabled climate adaptation that can inform broader European transitions.

Acknowledgements

This research received funding from the European Union's Horizon Europe research and innovation programme (Grant No. 101094021) and Center of Excellence Project "Civil Engineering Research Center" (Grant No. S-A-UEI-23-5).

Ethics and AI declaration: This research was conducted in accordance with institutional and national guidelines for research involving human participants. Ethical clearance for the survey of Lithuanian residents was obtained from Ethical monitoring board at Citizen Science Hub at VILNIUS TECH No. CSH-2023-02. All participants provided informed consent prior to the interviews, and their responses were anonymised and stored in line with GDPR requirements. No vulnerable groups were specifically targeted in the study.

During the preparation of this manuscript, AI tools were used to support tasks such as drafting and refining sections of text, improving clarity and flow, checking consistency of terminology, and suggesting alternative formulations. All statistical analyses, interpretation of results, and conceptual contributions (including the design of the CiA-CA framework) were carried out by the authors. The authors reviewed and take full responsibility for the content of the final manuscript.

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Explaining Consumer Preferences for AI- and Human-Authored Books: An Explanatory Experimental Study

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Abstract: Books—both fiction and nonfiction—are among the first consumer goods that artificial intelligence (AI) can fully generate at a quality indistinguishable from that created by humans. While prior research in domains such as art and music documents a preference bias against AI-created works, the transferability of these findings to typical consumption contexts—and whether such biases persist amid rapid AI diffusion—remains unclear. This study examines the effect of authorship disclosure on consumer preferences for AI- versus human-authored books, while also exploring psychological and economic mechanisms that may explain these differences. It further investigates heterogeneity of this effect by factors such as familiarity with AI to anticipate future states of AI adoption. For empirical evaluation of the effects, we conducted an online experiment that systematically manipulated authorship of books from multiple literary genres, using a representative sample of approximately 1,500 U.S. adults. Results showed a consistent preference bias against AI-generated books across genres. Among the potential explanatory mechanisms, perceived author effort, emotional attachment, and perceived proximity to the author emerged as the most influential. Heterogeneity analysis among early adopters and AI welcomers revealed that these effects are weakened but remained persistent. The findings indicate that consumers' reluctance towards AI-created books arises not only from assessments of product utility but also from psychological factors. Although technological advances may alleviate consumer quality concerns, persistent social and emotional attachments are likely to result in separate market segments for AI- versus human-created works.

Keywords: AI-generated content, Consumer preferences, Adoption, Psychological barriers

1. Introduction

The rapid rise of generative artificial intelligence (AI) is transforming many industries by enabling the faster, cheaper and more scalable production of digital and physical products. One sector already undergoing this transformation is publishing. Its core product can be digitally created and offered, so the book market serves as an early blueprint for the upcoming transformations in other consumer markets. With minimal production costs and rapid content generation, AI-written books have the potential to flood the market—raising important practical and theoretical questions.

From a practical perspective on the supply side, publishers and sellers face the problem of decreasing production prices and the expansion of offerings by self-publishing services. They have introduced countermeasures like their own guidelines requiring authors to disclose their degree of AI use. Authors try to defend their intellectual rights and differentiating positions in the market. The Authors Guild in the United States have recently launched the 'Human Authored' label, which should '*provide authors a way to distinguish their work in an increasingly AI-saturated market*' (Authors Guild, 2025). On the demand side, book buyers feel uncertain and desire more transparency about the origin of the content they read (Marsden, 2023), as research shows that, in many cases, they can no longer distinguish between AI- and human-written texts (Gunser et al., 2021; Hakam et al., 2024). Transparency about authorship also seems to be a main hope for policymakers who are about to introduce obligatory labelling for AI-generated content, as planned by the EU AI Act for 2026 (European Union, 2024). Whether these hopes and efforts about transparency will just slow down the ongoing market disruption or lead to emergence of new segments or separation in the market, however, depends primarily on consumers' reaction to this transparency.

These practical demands raise several questions in academic research. Are consumers' valuations and attitudes towards AI-written versus human-written books inherently different? Will consumer behaviour change with the disclosure of authorship? Which attitudes and perceptions can explain the potential differences in preference and behaviour? Will these differences remain transient until AI and AI-authored books are widespread in the market and there is greater consumer familiarity with them?

To approach these questions, we conducted an experimental study exploring consumer reactions to AI- versus human-written books, along with a variety of underlying explanations and moderating mechanisms collected from related literature. The aim of this exploratory study is to provide broad empirical evidence on the questions raised, focusing more on implications rather than specific theories.

2. Research Background

Rapid development in the capabilities of AI have catalysed research investigating humans' perceptions and valuations of works created by artificial agents (Epstein et al., 2020). Especially considering that in many areas AI outputs have reached a level of quality indistinguishable from that created by humans (Köbis and Mossink, 2021), the question arises whether the same work would induce different attitudes and preferences if it were made by AI versus a human. Some recent research investigating such a question has focused mainly on the evaluation of art and creativity (Demmer et al., 2023; Millet et al., 2023). In this context the findings predominantly indicate a devaluation of AI-created works, often called *bias against AI* (Horton Jr et al., 2023; Tubadji et al., 2021) or the *word-of-machine effect* (Longoni and Cian, 2022).

Only a small amount of research has focused on such effects in the context of consumer goods, resulting in mixed findings. Thus, Granulo, Fuchs and Puntoni (2021) report reduced purchase intentions and preferences for AI-designed posters, eyeglasses or tattoos, whereas Zhang, Bai and Ma (2022) find a higher willingness-to-pay for AI-designed than for human-designed T-shirts or mugs.

In our study on books as a consumer good, which can be generated by AI without a significant human contribution, we aim to investigate the differences not only in preferences but also in perceptions and attitudes. Thus, we focus on consumer preferences as central outcome variables in the form of *reading consideration* and the monetary valuations of books captured by *expected prices* and *willingness-to-pay* (WTP). Additionally, aligned with the findings reported for artwork, we also investigate whether there are perceptional differences between AI- versus human-written books with regard to *utilitarian and hedonic value* (Longoni and Cian, 2022), *creativity* (Millet et al., 2023), *uniqueness* (Granulo et al., 2021), *expected quality* (Bellaiche et al., 2023), *proximity to the author* (Tubadji et al., 2021), *perceived effort* (Horton Jr et al., 2023) or *emotional attachment* (Demmer et al., 2023). We selected these constructs as they have been reported as potential explanation mechanisms for the preference differences.

Hence, we first address the following two research questions (RQ):

RQ1: Do consumers have different perceptions and preferences for AI- versus human-created books?

RQ2: To what extent can the identified perceptional differences explain the differences in preferences?

An evident problem relating to the research findings about attitudes towards AI technology lies in its rapid proliferation and the corresponding transformations in society and markets that make these findings quickly outdated (Daly et al., 2025). For this reason, we explore the heterogeneity in findings from RQ1 and RQ2 regarding the factors that allow approximative mid-term predictions of how persistent these findings are. For this purpose, we identified such factors as *attitudes towards AI*, *AI literacy*, *consumer innovativeness* and *experience with AI books*. The key idea relies on the concept of the classical innovation diffusion models (Bass, 1969) that describe consumers in different stages of ongoing transformation. Hence, refining the findings of RQ1 and RQ2 for '*welcomers*' or '*early adopters*' of AI technologies, we strive to interpolate the future state, i.e., the persistence of these findings:

RQ3: To what extent do the identified differences in perception and preference differ for consumers who are early adopters and welcomers of AI technologies?

Figure 1 presents the postulated research questions in the research model, which we investigated in an experimental study manipulating the disclosure of authorship.

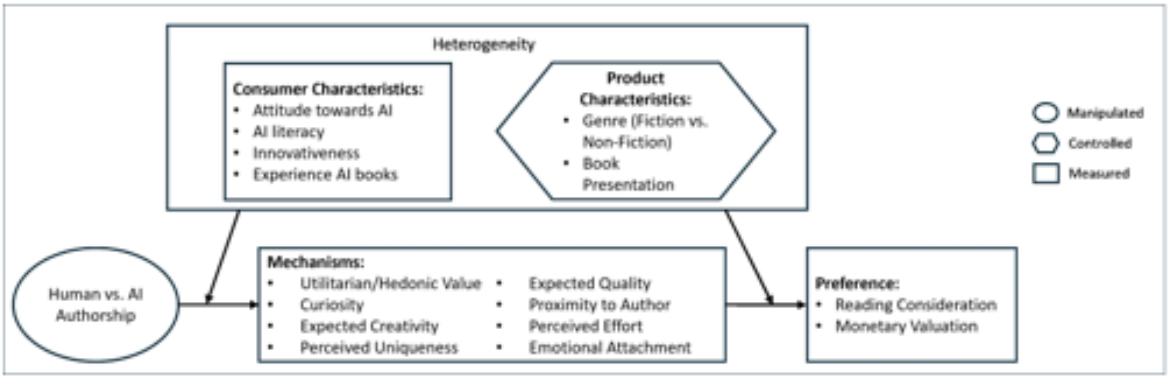

Figure 1: Research model

3. Method

3.1 Experimental Setup

To investigate the proposed research questions, we conducted an online survey-based experiment following a between-subjects design. After an introduction and screening for book-purchasing behaviour in general, the experiment began by surveying subjects with standard demographic questions. To increase personal relevance and involvement, participants then had to choose their most preferred book category from a pre-defined selection of 10 genres. The selection consisted of five fiction genres (romance; crime & thriller; fantasy & science fiction; mystery & horror; historical fiction) and five nonfiction genres (biographies, memoirs & historical nonfiction; self-help & personal development; health, fitness & wellness; cookbooks; business, investing & personal finance). We then presented participants with mock websites of a book from the selected category mimicking typical presentations in online bookstores.

Each stimulus consisted of a display of the cover and a short teaser text, along with key facts like title, author, publication date, number of pages and book size (Figure 2). To avoid interference with existing books, all materials other than author names were generated from scratch by a GenAI tool. Two fictive author names were thoroughly selected, and it was verified that there are no (well-known) authors with these names on major selling platforms. The experimental manipulation consisted of varying the author's name both on the cover and in the description for each book, whereas no further explicit instructions about authorship were given to the participants to avoid priming. Thus, half the participants were randomly selected and presented with a book supposedly written and published by a human author. To keep the presentation realistic, another half were shown a book written by AI but solely published by a human.

After the presentation of the book, the participants were immediately surveyed on the outcome variables and the potential mediators. Finally, a set of potential moderating and control variables was surveyed.

3.2 Data Collection

The used stimuli and measurement scales were first pretested at the beginning of February 2025 with a sample of 400 U.S. consumers, who were collected representatively of the adult U.S. population (18+) in terms of age and gender via the research panel provider Prolific. After minor adjustments of the stimuli to improve the recognisability of authorship, the main study was conducted in mid-February 2025. Aligning to RQ1 to determine the required sample size, we assumed an (average) effect size of d = 0.20, alpha = 0.05 and power = 0.95 for the main study, resulting in n = 650 for each (between-subjects) group (Zhang and Yuan, 2018). Anticipating from the pretest that not all respondents would correctly recognise the intended manipulation of authorship, we collected a sample of n = 1500 representative of the adult U.S. population in terms of gender, age and ethnicity that was evenly randomised between both experimental groups. The respondents completed the experiment in about 9–33 minutes and received fixed participation compensation of 2.50 GBP. After screening out non-buyers of books (n = 95) as well as respondents failing to answer correctly an attention-check question (n = 72) or one manipulation check question (n = 232), the final dataset consisted of n = 1101 total.

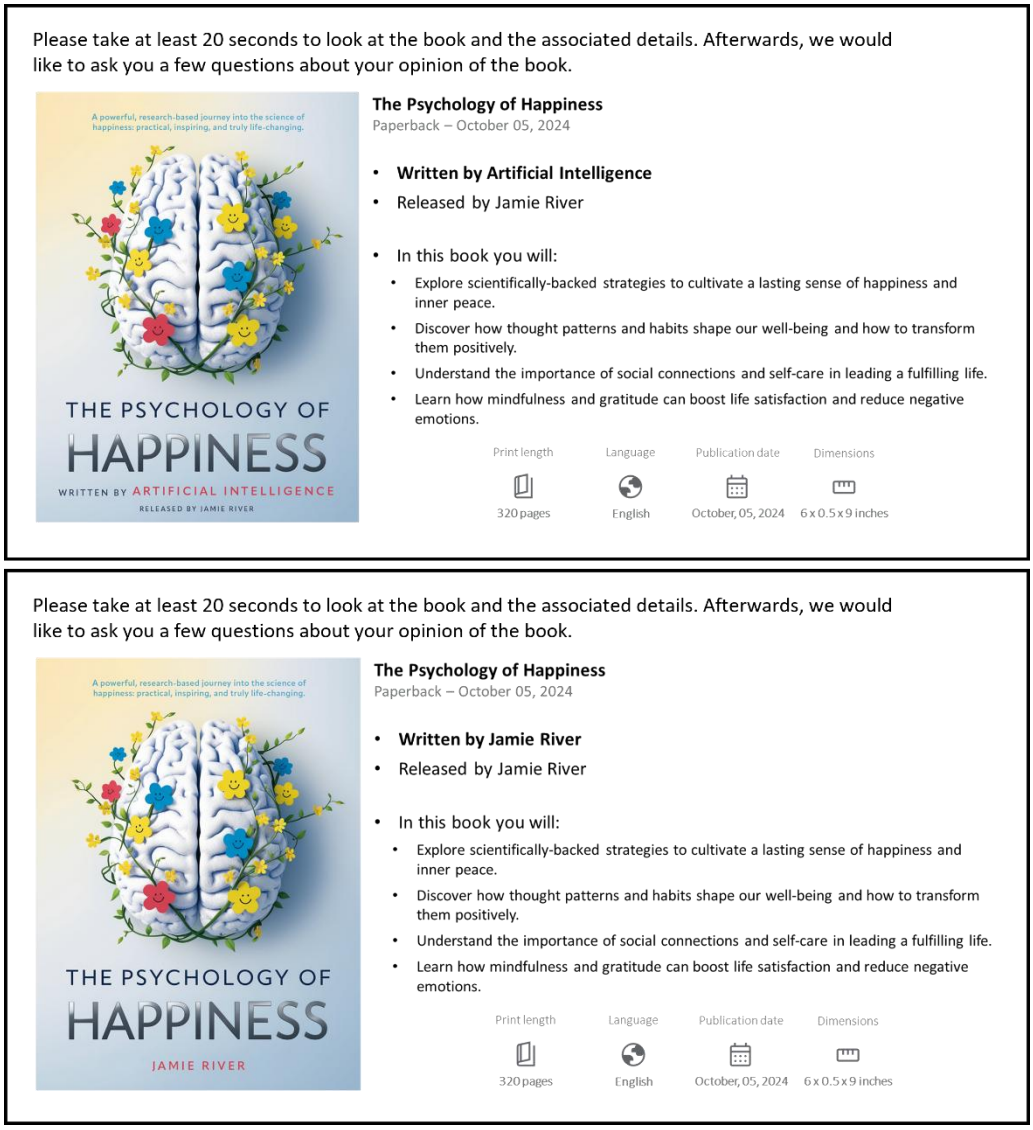

Figure 2: Experimental Stimuli with AI versus Human Authorship

The described data cleaning resulted in slightly unbalanced experimental groups, with n = 536 versus n = 565 first evaluating an AI-written versus human-written book, respectively. The subsequent statistical tests with the collected pre-treatment variables on demographics and purchasing behaviour revealed no significant differences (at 5% significance level) between the two groups, with a breakdown as shown in Table 1. In addition, the distribution of manipulation within each genre exhibited no significant differences between the experimental groups, so we found no evidence that the randomisation of the manipulation would not hold in the final dataset.

Table 1: Background characteristics of experimental groups

Experimental group	AI book	Human book	*p-value*
Sample size	*536*	*565*	
Gender (portion female)	*0.50*	*0.52*	*0.184*[2]
Age	*47.5*	*46.4*	*0.242*[1]
Education (7-point scale)	*3.42*	*3.36*	*0.648*[1]
Financial Status (7-point scale)	*3.27*	*3.26*	*0.729*[1]
Purchase frequency (5-point scale)	*2.50*	*2.46*	*0.432*[1]
Reading frequency (7-point scale)	*2.07*	*2.12*	*0.447*[1]

Experimental group	AI book	Human book	*p-value*
Experience AI-Books (portion yes)	*0.12*	*0.10*	*0.204*[2]

Note: [1]Chi-squared test, [2]Welch t-test

3.3 Measures

In the accompanying survey, we applied different scales and single-item measures to capture the relevant dependent variables (DV), as well as the potential mediators and moderators of the effect of manipulation. For each book, we collected three dependent variables as single-item measures: reading consideration (DV1) on a 7-point Likert-scale ranging from 1 = *'Not at all interested'* to 7 = '*Absolutely interested*', expected price (DV2) and willingness-to-pay (DV3) requesting a numeric input in USD.

For most potential mediators and moderators, we adapted different measurement scales from literature using 7-point Likert-scale items ranging from 'strongly disagree' to 'strongly agree'. Based on the pretest, the original scales for the potential mediators were reduced to 2 or 3 items to reduce respondent fatigue. Thus, for mediators we used our own 3-item scales for *hedonic value* based on work of (Lee and de Villiers, 2025), *utilitarian value* (Merga and Mat Roni, 2018), *curiosity* (Yang et al., 2020), *perceived uniqueness* (Franke and Schreier, 2008), *expected quality* (Magni et al., 2024), *emotional attachment* (Thomson et al., 2005) and 2-item scales for *creativity* (Magni et al., 2024) and *proximity to the author* (Wu et al., 2020), as well as a single item for *perceived effort* (Bellaiche et al., 2023) ranging from 1 = '*No effort*' to 7 = '*The highest level of effort*'.

For the potential moderators collected at the end of the survey, we used the original scales from literature whenever it was meaningful regarding the context of the experiment, and the scale was confirmed as unidimensional in our pretest. Accordingly, we collected a 6-item scale for *positive attitudes towards AI* (Schepman and Rodway, 2020) and a 6-item scale for *consumer innovativeness* (Roehrich, 2004). For *AI literacy*, we collected a 9-item scale for *familiarity with AI* (Wang et al., 2023) and two of our own 2-item scales for frequency of (passive and active) *AI usage* and for *self-assessment of AI expertise*.

Table 2: Reliability and Validity of mediating constructs

Mediators	Min Factor Loading	Cronbach's Alpha	Composite Reliability	Average Variance Explained	Max Shared Variance
Hedonic Value	*0.75*	*0.86*	*0.87*	*0.69*	*0.76*
Utilitarian Value	*0.85*	*0.90*	*0.90*	*0.75*	*0.69*
Curiosity	*0.90*	*0.95*	*0.96*	*0.88*	*0.71*
Expected Creativity	*0.85*	*0.83*	*0.84*	*0.73*	*0.76*
Perceived Uniqueness	*0.90*	*0.95*	*0.95*	*0.85*	*0.63*
Expected Quality	*0.86*	*0.94*	*0.94*	*0.84*	*0.71*
Proximity to Author	*0.93*	*0.93*	*0.94*	*0.89*	*0.54*
Emotional Attachment	*0.87*	*0.95*	*0.95*	*0.87*	*0.69*

Table 3: Reliability and Validity of moderating constructs

Moderators	Min Factor Loading	Cronbach's Alpha	Composite Reliability	Average Variance Explained	Max Shared Variance
Attitude towards AI	*0.56*	*0.86*	*0.87*	*0.53*	*0.43*
Usage of AI	*0.78*	*0.76*	*0.76*	*0.61*	*0.46*
Familiarity with AI	*0.46*	*0.63*	*0.75*	*0.46*	*0.51*
Expertise about AI	*0.91*	*0.90*	*0.90*	*0.82*	*0.51*
Consumer innovativeness	*0.73*	*0.92*	*0.92*	*0.66*	*0.31*

The collected constructs underwent a comprehensive evaluation of their reliability and validity (Tables 2 and 3). The results show that the measured scales fulfil the required criteria (Fornell and Larcker, 1981; Hair et al., 2018). Solely deviating from our pretest, the mediator constructs for hedonic value and creativity failed to fulfil the discriminant validity criterion. Nevertheless, we used both constructs in the statistical analysis of the results, as they did not enter any test or model simultaneously. Verifying the discriminant validity of the collected dependent variables measured on single-item scales, their intercorrelations ranged from 0.27 between DV1 and DV2 up to 0.74 between DV2 and DV3.

3.4 Statistical Analysis

To address our RQ1 about perceptual or preference-related differences between AI- versus human-written books, we used standard two-sided *t*-tests and reported the corresponding mean differences, effect sizes (Cohen, 2013) and *p* values adjusted for family-wise error rates (Holm, 1979) for all DVs and all potential mediators. We verified the effects in a series of two-way ANOVAs in which, in addition to the manipulation of authorship, we also included the book presentations (i.e., cover and description) as a second factor for control. This allowed us also to control for the category (i.e., fiction versus nonfiction) and the genre selected by a respondent, as well as for the potential confounding effects of the (visual and textual) stimuli on the experimental manipulation of authorship.

To explore the potential explanation mechanisms for the found differences, we draw on causal mediation analysis (Imai et al., 2010; VanderWeele, 2015), applying the R-mediation software package (Tingley et al., 2014) as intended by our RQ2.

We use this approach to estimate a grid of independent single-mediator models for comparing explanatory strength of the evaluated mediators for each dependent variable. Thus, we calculated 27 mediation models: i.e., for each of nine potential mediators and each of three DVs. In these linear models, we also included the book presentations for control.

To address our RQ3 about the heterogeneity of the total and mediated effects with regard to the selected moderating factors, we applied a simple stratification approach. Thus, for each potential moderator on a continuous scale, we defined an upper quartile stratum (n = 275) of respondents with the most *positive attitudes towards AI*, the highest *familiarity with AI*, the highest *consumer innovativeness*, the highest *frequency of AI usage* or the highest *self-assessment of AI expertise*, respectively. The last potential moderator reflecting the subjects' *experience with AI books* was measured on a binary scale (yes/no), so we selected the stratum with such experience (n = 121) for analysis. We reran all previous mediation analyses run for RQ2 on the data for each moderator-specific quartile stratum and compared the estimates of the total and mediated effects from each stratum with the corresponding estimates from the total sample.

4. Results

4.1 Results for RQ1

The experimental manipulation of authorship had a statistically significant effect (at 5% significance level) on all dependent variables in favour of human authorship. The effect sizes are 0.55 for reading consideration (DV1), 0.27 for expected price (DV2) and 0.37 for WTP (DV3). Table 4 also shows statistically significant differences in the investigated potential mediators, revealing more favourable perceptions for human-written books.

We verified the reported results with a series of corresponding two-way ANOVAs controlling for book presentations. For all investigated DVs and mediators, the ANOVA results show significant main effects (at 5% significance level by Holm-adjusted *p* values) for both factors, but no significant interactions. As both factors are nearly orthogonal ($p = 0.997$ for $\chi^2(19) = 4.49$ test statistic) and there were no significant interactions, the reported sizes of the main effects for manipulation of authorship (Table 4) remains nearly unchanged after controlling for book presentations. The main effects for the latter factor indicate that nonfiction books exhibit slightly higher reading consideration (DV1) and higher monetary valuations (DV2 & DV3). However, the effect of manipulation is nearly stable in all genres, indicating comparable bias against AI for fiction and nonfiction books. The detailed results are not shown here for reasons of brevity but are available upon request.

In summary, our results for RQ1 confirm perceptual or preference-related differences between human- versus AI-written books—i.e., bias against AI—as reported in the literature from other domains.

Table 4: Preferences and Perceptions of AI- versus Human-books

	Mean AI book	Mean Human book	P value (Holm-adjusted)	Effect size with 95% Confidence Interval
DV1 – Reading Consideration	*2.84*	*3.78*	*<0.001*	*0.55 [0.42, 0.67]*
DV2 – Expected Price	*16.56*	*19.51*	*<0.001*	*0.27 [0.15, 0.39]*
DV3 – Willingness to Pay	*14.13*	*19.76*	*<0.001*	*0.37 [0.25, 0.49]*
Mediators				
Hedonic Value	*4.18*	*5.17*	*<0.001*	*0.68 [0.56, 0.80]*
Utilitarian Value	*4.11*	*4.76*	*<0.001*	*0.42 [0.30, 0.54]*
Curiosity	*4.55*	*5.22*	*<0.001*	*0.41 [0.29, 0.53]*
Expected Creativity	*3.74*	*4.72*	*<0.001*	*0.64 [0.52, 0.76]*
Perceived Uniqueness	*3.24*	*3.83*	*<0.001*	*0.37 [0.25, 0.49]*
Expected Quality	*4.03*	*5.19*	*<0.001*	*0.77 [0.64, 0.89]*
Proximity to Author	*2.12*	*3.45*	*<0.001*	*0.96 [0.84, 1.09]*
Emotional Attachment	*3.57*	*4.81*	*<0.001*	*0.82 [0.70, 0.94]*
Perceived Effort	*3.30*	*5.29*	*<0.001*	*1.73 [1.60, 1.87]*

4.2 Results for RQ2

The results of mediation analysis decomposing the (total) effects from the RQ1 into direct and indirect effects reveal that the explanatory strength of the investigated mediator variables is notably heterogeneous but largely consistent over all dependent variables (Table 5). For DV1, DV2 and DV3, the results suggest that the variables for *expected quality*, *proximity to the author*, *emotional attachment* and *perceived effort* can largely or fully explain the observed differences between AI- versus human-written books, as their indirect effects are statistically significant and render the corresponding direct effects to be comparatively low in magnitude, insignificant or even of the opposite sign to the corresponding total effect.

Table 5: Mediation analysis

	DV1		DV2		DV3	
Mediator	Indirect Effect (P value)	**Direct Effect (P value)**	**Indirect Effect (P value)**	**Direct Effect (P value)**	**Indirect Effect (P value)**	**Direct Effect (P value)**
Hedonic Value	*0.80 (<0.001)*	*0.13 (1.000)*	*1.56 (<0.001)*	*1.38 (1.000)*	*4.15 (<0.001)*	*1.37 (1.000)*
Utilitarian Value	*0.46 (<0.001)*	*0.46 (<0.001)*	*1.10 (<0.001)*	*1.84 (0.713)*	*2.79 (<0.001)*	*2.71 (0.039)*
Curiosity	*0.46 (<0.001)*	*0.46 (<0.001)*	*0.76 (<0.001)*	*2.18 (0.400)*	*2.40 (<0.001)*	*3.10 (<0.001)*
Expected Creativity	*0.65 (<0.001)*	*0.27 (0.072)*	*1.63 (<0.001)*	*1.29 (1.000)*	*3.93 (<0.001)*	*1.56 (1.000)*
Perceived Uniqueness	*0.37 (<0.001)*	*0.55 (<0.001)*	*1.12 (<0.001)*	*1.80 (0.713)*	*2.49 (<0.001)*	*3.02 (<0.001)*
Expected Quality	*0.88 (<0.001)*	*0.04 (1.000)*	*2.15 (<0.001)*	*0.79 (1.000)*	*5.25 (<0.001)*	*0.27 (1.000)*
Proximity to Author	*0.85 (<0.001)*	*0.07 (1.000)*	*2.48 (<0.001)*	*0.43 (1.000)*	*5.67 (<0.001)*	*-0.20 (1.000)*
Emotional Attachment	*0.96 (<0.001)*	*-0.03 (1.000)*	*2.09 (<0.001)*	*0.84 (1.000)*	*5.27 (<0.001)*	*0.22 (1.000)*
Perceived Effort	*1.35 (<0.001)*	*-0.43 (0.039)*	*5.17 (<0.001)*	*-2.22 (0.882)*	*9.64 (<0.001)*	*-4.15 (0.026)*

Across all the investigated DVs, the strongest mediation was observed for *perceived effort* variable. Its indirect effects even exceeded the corresponding total effects, indicating that the differences in this mediator induced by the manipulation of authorship are capable of causing differences in the DVs larger than the manipulation itself. This finding also suggests the existence of mechanisms alternative to perceived effort (e.g., creation costs) counteracting its effects. The variables for *perceived uniqueness*, *curiosity* and *utilitarian value* exhibited the weakest but still substantial mediation effects.

In summary, our results for RQ2 identified several core, possibly interrelated, explanation mechanisms for the effect of the disclosure of authorship.

4.3 Results for RQ3

Rerunning mediation analysis for the sub-samples of the data defined by the selected moderators revealed their considerable role in the reported effects. Thus, restricting the data to the upper quartile with the most positive *attitude towards AI* shrinks the total effect (i.e., in the total sample, but after controlling for book presentation) for reading consideration (DV1) from 0.92 to 0.34, for expected price (DV2) from 2.93 to 1.18 and for WTP (DV3) from 5.50 to 1.79. For the upper quartile of respondents with the highest frequency of *AI usage*, this shrinkage is moderate, i.e., up to 0.60, 0.92 and 4.03 for DV1, DV2 and DV3, respectively. Furthermore, no considerable differences to total effects in the total sample were observed for the upper quartiles defined by *familiarity with AI* and *expertise about AI*, indicating minor role of AI literacy. For the respondents from the upper quartile with the highest *consumer innovativeness*, no such shrinkage is observed for reading consideration (DV1), but moderate effect shrinkages were observed for expected price (DV2) up to 2.53, and up to 3.85 for WTP (DV3). Finally, for the respondents who already had experience with AI-written books (n = 121), we observed moderate shrinkages in total effects for reading consideration (DV1) from 0.92 to 0.66 and WTP (DV3) from 5.50 to 4.55, but a considerable change in the total effects for expected price (DV2) from 2.93 to -0.34. This effect of -0.34 is not statistically significantly different from zero, indicating no significant difference in expected prices for AI- versus human-written books in this sub-sample, thus possibly reflecting better awareness of current market prices by these respondents.

To verify whether the explanation mechanisms identified in the RQ2 analysis remain effective for respondents who are early adopters or supporters of AI innovations, we restricted our investigation to those mediators that exhibited high explanatory strength in the total sample. Hence, we reran the mediation analysis on these subsamples with mediator variables for *expected quality*, *proximity to author*, *emotional attachment* and *perceived effort*. The results show that these variables provide almost full mediation for the described effects on all three DVs, indicating the effectiveness of these mechanisms for these subgroups as well. The detailed results are not shown here for reasons of brevity but are available upon request.

In summary, we see that the effects of authorship disclosure are weaker but not vanishing for the respondents who are early adopters or welcomers of AI innovations.

5. Discussion

Returning to the research questions posed, we can conclude that consumers show a similar bias against AI in books as they do in works of art (RQ1). We observed this finding in both preferences and perceptions of books. This aversion is comparable across the examined genres, which suggests that the book category, i.e., fiction versus nonfiction, does not play a significant role in this finding. By means of causal mediation analysis, we find empirical evidence for several (possibly interrelated) explanation mechanisms for this bias (RQ2). Some of these mechanisms, like *emotional attachment* and *proximity to the author*, have their origins in the emotional or psychological realm, while others, like *expected quality* or *perceived effort*, have a more rational or economic background. Furthermore, the results exploring the heterogeneity show that the identified aversion against AI also exists for early adopters and welcomers of AI innovations, albeit to a lesser extent, but the corresponding explanatory mechanisms remain effective (RQ3).

In practice, these findings suggest that with disclosure of authorship a devaluation of AI books can be expected. With the further spread of AI in markets and society, this devaluation will probably diminish but not disappear in the medium term. Thus, the quality concerns will probably lessen in the near future by advancements in AI technology. However, psychological factors influencing the valuation of AI, such as proximity to the author or emotional attachment, are likely to remain effective. In conjunction with the expectation that AI books will increasingly replace human works due to low production costs, the results nevertheless suggest that a market segment for human authors will continue to exist.

While our study provides some empirical evidence for the investigated academic and practical questions, several limitations and suggestions for future research must be acknowledged. In view of plenty of the estimated mediation models, we didn't discuss the assumptions needed for identification of the mediation effects, as it mostly needs some domain knowledge-based justification and sensitivity analysis (Imai et al., 2010) for each model. Furthermore, our experiment put respondents in a hypothetical scenario, and therefore results may be subject to hypothetical bias (Murphy et al., 2005). Therefore, it would be necessary to verify the results under more ecologically valid conditions.

Ethics Declarations: Ethical approval was not sought for the present study because it was conducted in accordance with institutional guidelines that do not require ethical approval for this type of research.

AI Declarations: The authors declare that they have not used generative artificial intelligence in the writing of this manuscript and creation of images, graphics, tables or their corresponding captions. Generative artificial intelligence (Leonardo.AI) was used to create the stimuli used for the survey as declared in the manuscript.

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Mapping the Research Landscape of Transparent AI in University Assessment: A Bibliometric Investigation

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Abstract: This study presents a systematic bibliometric investigation of AI transparency research in university assessment contexts. Following GLOBAL recommendations (Ng et al., 2024), we examined 72 peer-reviewed publications from Scopus (2019-2025) using performance metrics and science mapping techniques. Findings reveal exponential growth from single publications in 2019 to 26 documents in 2024 ($R^2 = 0.7666$, $p = 0.0098$). The domain generated 655 citations achieving h-index of 13. China leads in output (8 documents) while Sweden demonstrates highest citation efficiency (25.50 citations per document). Science mapping identifies four primary clusters: technical transparency methodologies, educational analytics frameworks, machine learning applications, and performance prediction systems. Co-citation analysis establishes Adadi and Berrada's XAI survey (2018) as the foundational framework (11 citations, 24 total link strength). Temporal evolution shows progression from basic concepts toward practical implementations, reflecting regulatory compliance following GDPR and EU AI Act. International collaboration reveals South-South partnerships and high-impact contributions from countries with strong data protection frameworks. These patterns provide evidence for an emerging interdisciplinary domain addressing AI accountability in higher education, offering insights for researchers, practitioners, and policymakers.

Keywords: Artificial intelligence Transparency, Higher education assessment, Bibliometric analysis, Explainable AI, Educational technology, Regulatory compliance

1. Introduction

The integration of artificial intelligence systems within university assessment practices has experienced significant changes following the implementation of comprehensive data protection regulations requiring explicit algorithmic transparency in automated decision-making processes (Voigt & Von dem Bussche, 2017). This regulatory evolution began with the General Data Protection Regulation (GDPR), which established substantial requirements for meaningful information about automated processes through Article 22, considerably altering how educational institutions must approach AI-driven assessment systems (Edwards & Veale, 2017).

The regulatory landscape has developed further with the European Union's Artificial Intelligence Act (2024), which specifically classifies educational AI systems as "high-risk" applications requiring comprehensive transparency measures, human oversight, and detailed risk management protocols (European Commission, 2024). While these regulatory frameworks establish transparency requirements for automated decision-making in education, legal analysis suggests persistent gaps in guidance for hybrid assessment systems that integrate human oversight with algorithmic processes (Boccuzzi et al., 2025). These regulatory developments have created substantial demands for transparent, interpretable, and accountable AI systems within higher education contexts, requiring fundamental reconsideration of traditional machine learning approaches to educational assessment.

Traditional machine learning models employed in educational contexts typically operate as opaque computational systems where decision-making logic, feature importance, and prediction rationale remain hidden from educational stakeholders including students, instructors, and administrators (Rudin, 2019). This algorithmic opacity creates substantial challenges for universities where transparency, fairness, accountability, and pedagogical effectiveness constitute important institutional requirements and regulatory obligations.

Explainable Artificial Intelligence (XAI) has developed as a significant technological response to these "black box" limitations, enabling human-understandable insights into algorithmic decision-making processes while maintaining predictive performance standards (Gunning et al., 2019). XAI encompasses diverse methodological approaches including post-hoc explanation techniques, inherently interpretable models, and human-centered design principles that address transparency requirements in high-stakes decision-making contexts.

1.1 Literature Review and Knowledge Gaps

Despite growing research activity at the intersection of AI transparency and educational assessment, comprehensive systematic reviews have consistently identified significant gaps in current knowledge frameworks and methodological approaches. Altukhi and Pradhan (2024) conducted extensive analysis revealing the absence of standardised XAI definitions across educational contexts, leading to conceptual fragmentation and implementation inconsistencies that may hinder both theoretical development and practical deployment.

Bond, Zawacki-Richter and Nichols (2024) performed meta-systematic review of artificial intelligence applications in higher education, identifying apparent methodological inconsistencies in AI education research alongside insufficient attention to ethical implications and transparency requirements. Their analysis revealed patterns where technical performance metrics often superseded considerations of algorithmic accountability and stakeholder understanding.

Türkmen (2025) noted through comprehensive literature review that while XAI algorithms are increasingly recognized as potentially valuable in educational research contexts, there remains insufficient systematic analysis of how these transparency systems are being developed, validated, and implemented specifically within higher education assessment environments. This gap is particularly concerning given the high-stakes nature of educational decisions and their long-term impact on student outcomes.

Zawacki-Richter and colleagues (2019) provided foundational systematic review of AI applications in higher education, noting limited attention to ethical considerations and transparency requirements across the broader educational AI research landscape. Their work established baseline understanding while highlighting apparent needs for systematic investigation of emerging transparency-focused research domains.

1.2 Research Objectives and Framework

This investigation employs the Population-Concept-Context (PCC) framework (Peters et al., 2015) to attempt comprehensive coverage. Population encompasses researchers, practitioners, and developers working on AI transparency in higher education. Concept includes explainable AI methodologies applied to educational evaluation. Context addresses university assessment environments requiring regulatory compliance and institutional accountability.

This study addresses five research questions: (RQ1) What are temporal patterns of publication growth and associated factors? (RQ2) Who are the most productive authors, institutions, and countries, and what collaboration patterns exist? (RQ3) What are primary publication venues and highly cited contributions? (RQ4) What are main research themes and their evolution? (RQ5) What foundational works appear to underpin current research?

2. Methods

2.1 Methodological Design and Theoretical Framework

This investigation employs bibliometric analysis following GLOBAL recommendations (Ng et al., 2024) and BIBLIO requirements (Montazeri et al., 2023). The methodology integrates performance analysis examining productivity metrics and citation impact with science mapping techniques visualizing knowledge structures and collaborative networks. Scopus database was selected for its substantial coverage of peer-reviewed literature and robust indexing systems (Mongeon & Paul-Hus, 2016). The study acknowledges constraints inherent in analyzing emerging interdisciplinary domains, including small corpus size and temporal concentration that may reflect field development stage.

2.2 Search Strategy Development and Implementation

The search strategy captured literature at the intersection of explainable AI, higher education, and assessment practices using Boolean logic with three components connected by AND operators. The XAI component included “explainable AI”, “interpretable AI”, “AI transparency”, “algorithmic accountability”, “responsible AI”, and specific methods like “Shapley Additive Expla*”. The education component encompassed “higher education”, “university”, “college”, “tertiary education”. The assessment component covered “assessment”, “evaluation”, “academic performance”, “learning analytics”, “automated scoring”, “student dropout”. The search excluded medical domains and limited results to peer-reviewed English publications. Conducted on July 5, 2025, it yielded 141 documents comprising articles (54.6%), conference papers (39.0%), book chapters (4.3%), reviews (0.7%), and books (1.4%).

2.3 Data Collection and Screening Process

Systematic screening using Rayyan (Ouzzani et al., 2016) applied inclusion criteria requiring peer-reviewed publications addressing XAI in higher education assessment. Exclusion criteria eliminated non-peer-reviewed materials, K-12 studies, and research lacking explicit transparency focus. After screening, 72 studies met inclusion criteria from the initial 141 documents. Data processing employed Publish or Perish v8.0 and Excel for bibliometric indicators, VOSviewer v1.6.20 for network analysis (van Eck & Waltman, 2010), and statistical validation including linear regression and correlation analysis.

2.4 Methodological Constraints

This investigation acknowledges methodological constraints that require consideration. The small corpus size (72 documents) and substantial temporal concentration (81.9% in 2023-2025) reflect the nascent stage of AI transparency research in educational contexts, which may limit pattern generalizability and could indicate coincidental rather than systematic relationships. Additionally, the specialized search strategy may systematically exclude relevant research employing alternative terminological frameworks, while exclusive Scopus reliance may underrepresent studies in discipline-specific databases or publications with limited international indexing. These characteristics necessitate cautious interpretation of identified trends and require validation through expanded datasets and longer observation periods.

3. Results

3.1 Research Productivity and Growth Patterns

Temporal analysis of publication distribution reveals notable growth patterns that may suggest systematic research attention following regulatory and technological developments within the AI transparency domain. The field emerged with limited contributions including single publications in 2019 and 2020, representing foundational exploratory work addressing algorithmic transparency requirements within higher education contexts and establishing preliminary conceptual frameworks for GDPR Article 22 compliance in educational AI applications.

The period spanning 2021-2022 witnessed moderate expansion with 6 and 5 documents respectively, coinciding with increased institutional awareness of data protection regulations and growing recognition of transparency requirements for educational AI systems. This developmental phase appears to have marked transition from theoretical exploration toward methodological development as researchers began addressing practical implementation challenges for explainable assessment systems within university environments.

Considerable growth occurred during 2023-2024, with publications increasing from 16 to 26 documents, representing over 300% growth and indicating accelerated research attention to this specialized intersection. This expansion may reflect convergence of multiple factors including maturation of XAI methodological approaches, increased availability of educational datasets suitable for transparent analysis, growing institutional demand for accountable automated assessment systems, and heightened awareness of regulatory compliance requirements.

Linear regression analysis provides statistical validation for observed growth trends, achieving $F(1,5) = 16.42$ with $p = 0.0098$ and $R^2 = 0.7666$, indicating that approximately 77% of variance in publication numbers can be explained by temporal progression. This statistical significance suggests the possibility of systematic rather than random growth patterns, though the limited temporal baseline requires cautious interpretation of trend extrapolation given the early stage nature of this research domain.

The dataset spanning six citation years (2019-2025) demonstrates building scholarly influence with 655 total citations distributed across 72 papers, yielding average citation rate of 109.17 citations per year. This citation accumulation may reflect growing academic engagement, while the finding that 61.1% of papers have received at least one citation suggests broad research community recognition. Seven papers achieving 10 or more citations indicate the possible emergence of a core set of influential contributions establishing theoretical and methodological foundations for the field.

3.2 Geographic Distribution and International Collaboration

International engagement analysis reveals substantial global reach with research contributions spanning 43 countries across six continents, indicating widespread international interest in AI transparency applications for educational contexts. This geographic diversity suggests that concerns about educational AI transparency

transcend specific national regulatory contexts and appear to reflect common challenges in implementing accountable automated assessment systems.

Research concentration patterns show moderate distribution with the top 5 contributing countries (China: 8 documents, Italy: 7 documents, Australia: 7 documents, Germany: 7 documents, Bangladesh: 6 documents) accounting for 33.0% of total publications, while the remaining 67.0% is distributed among 38 additional nations. This balanced distribution suggests relatively distributed global participation rather than extreme concentration in dominant research centers.

Continental analysis reveals different regional engagement characteristics with Europe emerging as the leading contributor, providing 43.8% of total publications (49 documents from 19 countries). This European prominence may reflect strong regulatory frameworks and institutional responses following GDPR implementation, possibly creating research incentives for developing compliant educational AI systems requiring transparency and accountability measures.

Asia demonstrates substantial momentum as the second-largest regional contributor with 29.5% of publications (33 documents from 9 countries), suggesting growing recognition of AI transparency requirements within rapidly expanding higher education sectors across Asian nations. This engagement pattern may reflect both regulatory influences from international frameworks and domestic policy development addressing educational AI governance.

Citation analysis reveals interesting patterns diverging from simple productivity rankings. Sweden emerges as a strong performer in citation metrics, achieving 25.50 citations per document despite contributing only 4 documents, demonstrating quality-focused research strategies that achieve substantial international influence. Italy and Australia demonstrate consistent performance combining substantial output (7 documents each) with strong citation performance (11.14 and 11.00 citations per document respectively), suggesting both nations function as key regional hubs that appear to successfully integrate productive research output with scholarly impact.

International collaboration network analysis reveals varied partnership structures, particularly among developing economy institutions. Malaysia and Saudi Arabia both demonstrate high collaborative intensity (total link strength of 4.00), though Saudi Arabia shows higher citation performance (10.80 citations per document) compared to Malaysia (5.83 citations per document), indicating different collaborative strategies and research focus areas.

3.3 Key Contributors and Scholarly Networks

Author collaboration analysis using fractional counting methodology reveals different productivity and impact patterns within the research community. Individual researcher analysis identifies Dragan Gasevic as a highly productive contributor with 5 documents and 61 citations, achieving 12.20 citations per document alongside substantial collaborative integration (total link strength of 5.00). This positioning suggests sustained research leadership spanning multiple collaborative projects and theoretical framework development within the domain.

A group of four authors comprising Muhammad Afzaal, Uno Fors, Jalal Nouri, and Aayesha Zia demonstrates strong coordination with identical metrics of 3 documents and 101 citations each, achieving high citation performance of 33.67 citations per document. Their consistent collaborative integration (total link strength of 3.00 each) suggests these researchers function as a closely integrated research unit, possibly co-authoring the same influential publications focused on explainable AI applications for educational feedback and student self-regulation systems.

Gabriella Casalino represents productive European engagement contributing 3 documents with 51 citations, achieving 17.00 citations per document and strong collaborative integration (total link strength of 3.00). This performance suggests sustained contribution to methodological frameworks bridging computer science and educational applications within the AI transparency domain.

Institutional analysis reveals distributed engagement patterns with 121 institutions contributing to the research landscape. Productivity concentration analysis shows balanced distribution, with top 5 contributing institutions (Monash University: 5 documents, King Abdulaziz University: 3 documents, Stockholm University: 3 documents, Universiti Teknologi Malaysia: 3 documents, University of Bari Aldo Moro: 3 documents) accounting for only 11.6% of total publications. This low institutional concentration suggests widespread

scholarly engagement rather than dominance by specialized research centers, indicating that AI transparency research addresses challenges that appear to resonate across diverse institutional contexts globally.

3.4 Publication Venues and Scholarly Impact

Publication venue analysis demonstrates the interdisciplinary character of AI transparency research spanning computer science, educational technology, policy studies, and applied ethics domains. This diversity may reflect the complex nature of implementing transparent AI systems within educational contexts, requiring integration of technical expertise, pedagogical understanding, and regulatory compliance knowledge.

Conference proceedings dominate the publication landscape with "ACM International Conference Proceeding Series" leading with 6 publications, followed by "CEUR Workshop Proceedings" with 4 publications. This conference prevalence may reflect the rapidly evolving nature of the research domain, where conference presentations enable faster knowledge dissemination compared to traditional journal publication cycles, potentially facilitating timely sharing of methodological innovations and practical implementation experiences.

Journal venue diversity includes "IEEE Access" with 3 publications and "International Journal of Artificial Intelligence in Education" with 2 publications, representing established channels for methodologically rigorous research addressing technical innovations and educational applications respectively. The presence of diverse publication venues across multiple disciplines suggests integration of AI transparency research within established scholarly communication networks.

Citation impact analysis identifies influential foundational contributions establishing theoretical frameworks and practical methodologies for the emerging field. Susnjak, Ramaswami and Mathrani (2022) achieved substantial impact with 103 citations (34.33 cites per year) for their work on learning analytics dashboards providing actionable insights to learners, developing integrated theoretical and practical frameworks for transparent learning analytics interfaces focused on actionable feedback mechanisms supporting student self-regulation.

Afzaal and colleagues (2021) generated considerable influence with 77 citations (19.25 cites per year) for their research on explainable AI applications for data-driven feedback and intelligent action recommendations supporting student self-regulation. Their work established approaches to XAI-driven educational feedback systems with explicit focus on student agency and transparent algorithmic recommendations.

Technical methodology contributions include Baranyi, Nagy and Molontay (2020) achieving 61 citations (12.20 cites per year) for developing methodological frameworks for transparent student retention prediction using interpretable deep learning approaches. Their work addresses important institutional needs for understanding and explaining automated early warning systems while maintaining predictive accuracy requirements.

3.5 Thematic Structure and Intellectual Evolution

Comprehensive keyword co-occurrence analysis reveals the conceptual architecture underlying AI transparency research in higher education through systematic examination of author-assigned terminology and thematic relationships (Figure 1). Following extensive thesaurus development that standardized 220 author keywords into 147 core concepts to address terminology fragmentation, VOSviewer's clustering algorithm identified 22 thematic clusters based on co-occurrence patterns and link strength relationships.

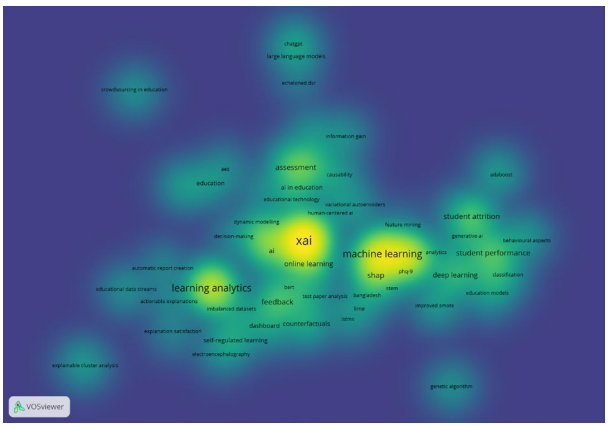

Figure 1: Co-occurrence analysis of author keywords. Density visualization

Statistical validation demonstrates thematic organization achieving structural properties with silhouette coefficient of 0.68, indicating cluster formation and thematic boundaries. To enhance interpretability and identify broader research themes, the 22 clusters were systematically aggregated into four primary macro-clusters based on conceptual similarity, temporal evolution patterns, and theoretical coherence.

“AI Ethics and Educational Technology” aggregates clusters focusing on responsible implementation and human-centered approaches, combining research on responsible AI frameworks, emerging generative technologies including large language models and ChatGPT applications, and core XAI theoretical foundations with human-centred computing principles. This macro-cluster encompasses research addressing ethical implications of transparent AI systems, stakeholder engagement in algorithmic decision-making, and value-aligned design principles for educational contexts requiring accountability and fairness considerations.

“Deep Learning and Predictive Analytics” consolidates technically-oriented clusters focusing on advanced methodological approaches, integrating predictive analysis methodologies with SHAP interpretability techniques, machine learning foundations addressing student performance prediction, student attrition modeling with optimization approaches, and algorithmic implementations including fuzzy clustering and prototype-based methods. This macro-cluster represents the technical infrastructure supporting transparent educational AI applications, addressing challenges of maintaining predictive performance while providing explanations for high-stakes educational decisions.

“Learning Analytics and Feedback Systems” synthesizes application-focused clusters addressing practical implementation within educational environments, combining learning analytics infrastructure with feedback mechanisms and counterfactual explanations, higher education contextual applications including degree completion studies, online learning environments with adaptive student modeling, and real-time educational data stream processing. This macro-cluster emphasizes actionable insights and student-centered design principles, bridging technical capabilities with educational practice requirements through transparent interfaces and decision support systems.

“Assessment and Educational Evaluation” encompasses evaluation-oriented clusters addressing formal measurement and monitoring systems, integrating assessment methodologies with behavioral analysis, student wellbeing monitoring through interpretable deep learning approaches, international large-scale assessment frameworks, quality assurance mechanisms, actionable explanation generation, user trust evaluation, and evaluation methodologies for interpretable systems. This macro-cluster focuses on transparency requirements for high-stakes assessment decisions, fairness considerations in automated evaluation, and institutional accountability frameworks requiring algorithmic explanation capabilities.

Temporal evolution analysis reveals four developmental phases characterizing the field’s intellectual progression (Figure 2). Foundation establishment (2021-2022) introduced core XAI concepts and basic learning analytics frameworks, establishing theoretical groundwork for educational applications. Methodological expansion (2023) integrated advanced interpretability techniques and developed specialized applications addressing specific educational contexts and stakeholder needs. Application maturation (2024) focused on predictive analytics combined with feedback systems, demonstrating integration of technical advancement with practical educational requirements.

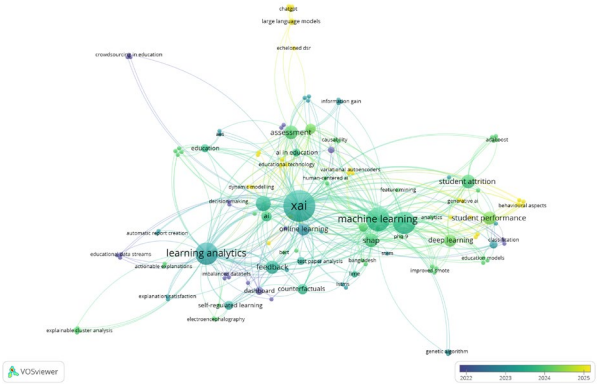

Figure 2: Co-occurrence analysis of author keywords. Overlay visualization

3.6 Intellectual Foundations and Theoretical Frameworks

Co-citation analysis provides systematic identification of intellectual foundations supporting current research development within the AI transparency domain. Statistical validation reveals that 30% of reference pairs exhibit strong co-citation relationships ($r > 0.5$), which may exceed typical bibliometric baselines and suggests theoretical integration across previously distinct knowledge domains including foundational XAI theory, educational AI applications, and technical implementation methodologies.

Adadi and Berrada's (2018) survey of explainable artificial intelligence emerges as a frequently cited theoretical reference with 11 citations and 24 total link strength, providing conceptual foundations that appear to be consistently applied across educational contexts. Their systematic framework for understanding XAI methodologies, explanation types, and evaluation approaches functions as a theoretical anchor for educational applications requiring algorithmic transparency.

Additional foundational works include Alamri and Alharbi (2021) with 5 citations and 11 total link strength, providing systematic review of explainable student performance prediction models that bridge general XAI theory with educational applications. Baranyi and colleagues (2020) contribute technical foundations with 4 citations and 57 total link strength, establishing methodological approaches for interpretable deep learning in educational contexts.

Educational psychology foundations include Hattie and Timperley (2007) with 3 citations and 17 total link strength, providing theoretical frameworks for effective feedback systems that inform transparent AI applications in educational contexts. Technical methodology references include Ribeiro, Singh and Guestrin (2016) for LIME methodology (3 citations, 39 total link strength), Chen and Guestrin (2016) for XGBoost approaches (3 citations, 15 total link strength), and Molnar (2020) for interpretable machine learning frameworks (4 citations, 23 total link strength).

4. Discussion

4.1 Theoretical Contributions and Domain Development

This systematic bibliometric investigation provides evidence for the emergence of an interdisciplinary research domain that appear to address AI transparency within higher education assessment contexts. The identification of four thematically organized clusters (silhouette coefficient of 0.68) suggests theoretical coherence within this specialized intersection, though expanded datasets and longitudinal validation remain necessary for examining domain stability and conceptual boundaries.

The documented progression from foundational XAI concepts toward education-specific applications may indicate development beyond technical application toward theoretical frameworks that appear to address educational contexts. This evolution suggests possible synthesis of technical transparency requirements with pedagogical effectiveness principles, regulatory compliance demands, and institutional accountability frameworks, potentially offering models for other high-stakes application domains requiring AI explainability.

Co-citation analysis revealing 30% of reference pairs exhibiting strong relationships ($r > 0.5$) suggests intellectual integration across previously separate domains including computer science, educational psychology, regulatory compliance, and applied ethics. This interdisciplinary synthesis may indicate theoretical development emerging from domain intersection rather than application of existing frameworks to educational contexts.

4.2 Practical Implications for Implementation

For educational practitioners and institutional administrators, the concentration of highly cited works addressing transparent learning analytics interfaces, explainable feedback systems, and interpretable prediction models may provide evidence-based guidance for implementation strategies. The prevalence of conference proceedings over traditional journals suggests active knowledge translation between research and practice communities, indicating that research findings may be rapidly incorporating practical implementation experiences and stakeholder feedback.

The identification of collaborative models, particularly coordinated multi-institutional initiatives among developing economy institutions, may offer viable frameworks for international knowledge sharing and capacity building in AI transparency implementation. These partnership patterns could provide practical approaches for institutions seeking to develop XAI capabilities while addressing local regulatory requirements and pedagogical contexts.

Geographic concentration of high-impact research in countries with strong data protection frameworks suggests possible relationships between regulatory environments promoting AI transparency and research excellence. While causal relationships require systematic investigation, these patterns indicate that regulatory frameworks mandating algorithmic accountability may facilitate rather than hinder research innovation and practical implementation.

4.3 Policy and Regulatory Implications

For policymakers developing AI governance frameworks, the documented research community responsiveness to regulatory developments following GDPR implementation suggests that targeted transparency requirements may stimulate relevant academic investigation and practical innovation. The growth pattern (R^2 = 0.7666) following major regulatory milestones suggests that research communities may adapt rapidly to address policy-driven transparency demands.

The emergence of specialized research addressing educational AI transparency indicates that sector-specific regulations may be necessary and effective in driving research attention and implementation standards. The observed relationship between countries with robust data protection frameworks and research excellence warrants systematic investigation for policy design implications.

4.4 Theoretical Synthesis and Framework Development

The co-citation analysis reveals how XAI theory, educational assessment literature, and regulatory frameworks appear to be converging into a distinctive theoretical synthesis. Rather than simple application of existing XAI methodologies to educational contexts, the evidence suggests development of what might be characterized as "Educational Algorithmic Accountability" frameworks. These emerging approaches appear to integrate technical transparency requirements with pedagogical effectiveness principles, institutional accountability demands, and regulatory compliance standards.

This theoretical convergence may represent a significant departure from traditional educational technology adoption patterns, where technical solutions are often retrofitted to educational contexts. The identified macro-clusters suggest instead that educational requirements are fundamentally shaping XAI development, potentially contributing novel approaches to the broader AI transparency field.

4.5 Future Directions

Future research should prioritize developing evaluation frameworks for XAI effectiveness in educational contexts, expanding investigation from performance prediction toward engagement analytics, and systematically investigating relationships between regulatory environments and research excellence. Longitudinal studies tracking domain evolution and empirical validation of identified collaborative models will be essential for determining whether observed patterns represent field characteristics or transitional phenomena.

4.6 Conclusions

This bibliometric investigation of 72 peer-reviewed publications spanning 2019-2025 provides systematic empirical evidence for the emergence of an interdisciplinary research domain that appears to address AI transparency and accountability within higher education assessment contexts. The analysis reveals growth trajectories with publication output expanding from limited contributions in 2019 to 26 documents in 2024, demonstrating statistically significant trends (R^2 = 0.7666) that may suggest systematic rather than random research attention development.

The domain has generated scholarly impact with 655 total citations achieving h-index of 13 and g-index of 24, indicating academic engagement despite the field's recent emergence. Geographic distribution analysis reveals international collaboration patterns including South-South partnerships among developing economy institutions alongside strong citation performance in countries with established data protection frameworks, suggesting possible relationships between regulatory environments and research excellence.

Science mapping through systematic keyword analysis identified four thematically organized clusters with structural properties, providing evidence for theoretical coherence within this specialized intersection of technical transparency requirements and educational applications. Co-citation analysis suggested intellectual integration across computer science, educational psychology, and regulatory compliance domains, indicating possible development of frameworks rather than application of existing approaches.

For academic researchers, this systematic mapping identifies collaboration opportunities and research gaps while highlighting needs for standardized terminological frameworks and expanded methodological approaches. For educational practitioners and administrators, the concentration of influential works may provide evidence-based guidance for implementation strategies while identified collaborative models may offer frameworks for international knowledge sharing. For policymakers, the observed research community responsiveness to regulatory developments suggests that targeted transparency requirements may stimulate relevant academic investigation and innovation.

These findings should be interpreted as systematic evidence for an emerging research domain requiring validation through expanded datasets, longer observation periods, and complementary analytical approaches as the field continues developing. Future research should prioritize developing evaluation frameworks, expanding investigation toward engagement analytics, and systematically investigating relationships between regulatory environments and research excellence to support continued domain maturation.

Ethics declaration: This study involved analysis of publicly available bibliometric data retrieved from Scopus database and did not require institutional ethics approval. All analyzed publications were already published and accessible through standard academic databases.

AI declaration: AI tools were used minimally for manuscript formatting and reference style verification. All research design, data analysis, interpretation of results, and scientific conclusions were developed entirely by the authors without AI assistance.

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Sensory Characterization of Mezcal Using Free Choice Profiling and Machine Learning Tools

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Abstract: This study characterized the sensory profiles of four regional mezcals by integrating free-choice profiling with machine learning. A total of 1,148 consumers across four Mexican cities described the samples using their own vocabulary and rated attribute intensities. Machine learning analysis revealed significant correlations between sensory descriptors and demographic variables—such as age, gender, and origin—identifying detailed consumer preference patterns. The findings enable producers to customize products for specific market segments, enhancing their commercial strategies. By supporting traditional producers, this research also promotes sustainable economic growth in rural communities, aligning with the objectives of SDG 8.

Keywords: Consumer description, Agave spirits, Intelligent systems, Sensory evaluation

1. Introduction

The sensory characteristics of a product are decisive for both its quality and its identity, particularly when it comes to traditional beverages (García-Barrón et al. 2021). These characteristics are the result of the production process, raw materials, handling, and storage, among others (Lücke et al. 2019). On the other hand, there are non-sensory factors that influence the perception of these characteristics, such as familiarity with the product, consumer sensitivity, and the sociocultural environment (Köster, 2009). The type and number of words used to describe the odor, aroma, mouthfeel, texture, and appearance reflect different factors such as the culture to which consumers belong (Chen and Antonelli, 2020).

There are different methodologies available for carrying out the sensory characterization of a product. Among these tools is the Free Choice Profile (FCP) (Williams and Langron, 1984; Varea and Ares, 2014). The FCP is based on the idea that consumers can describe the sensory characteristics of a product using their own vocabulary (Varela and Ares, 2014). Through FCP, it is possible to understand how consumers describe and differentiate food and beverages, as intensity data is obtained, providing quantitative information and allowing different aspects related to the product to be quantified, in addition to gathering information on cognitive perception directly from consumers (Tarrega and Tarancón, 2014).

However, one of the main drawbacks of the FCP is the complexity of analyzing and interpreting sensory vocabulary, differences in how participants use the scale, which increases interindividual differences among participants and, therefore, the difficulty of analyzing them (Varela and Ares, 2014). In this regard, machine learning (ML) tools have begun to be used to analyze the sensory characteristics of different alcoholic beverages, such as wine. These tools are well-suited for extracting useful information from noisy, uncertain, and nonlinear dynamic sensory data (Wang et al., 2022).

On the other hand, mezcal is a traditional alcoholic beverage made from the fermentation and distillation of agave juices, which has great cultural and economic importance (García-Barrón et al., 2017). Its production and consumption have increased significantly, particularly since it obtained the Denomination of Origin, where sensory characteristics play a significant role (Lazo et al. 2025). In this regard, several studies have been conducted on the sensory characterization of mezcal using trained judges (Garcia-Barrón et al. 2012; Mosqueda-

Balderas et al. 2018; Lazo et al. 2025; Vazquez-Lecona et al., 2025). However, while these studies are important for ensuring product quality and identity, there is little information on consumer perception and level of liking (García-Barrón, 2023).In this regard, the objective of this study was to analyze the description of sensory attributes obtained through the free-choice profile and processed with ML tools. Additionally, the descriptive data were correlated with the level of liking.

2. Methodology

This study employed a quantitative research design. The methodological framework was structured into three main phases: (1) data acquisition and preprocessing, (2) classification, and (3) prediction using machine learning techniques. This approach integrates established sensory science protocols with advanced computational tools to extract meaningful insights from complex consumer data.

2.1 Data Acquisition and Preprocessing

Sensory data were collected using the Free Choice Profiling (FCP) protocol, selected for its ability to capture authentic consumer vocabulary without the constraints of a predefined lexicon. A total of 1,748 consumers, all regular mezcal drinkers, were recruited for the panel. Each participant evaluated four distinct mezcal samples. For each sample, consumers generated their own descriptors and rated the perceived intensity of each attribute on a 9-point scale. This process yielded a raw data matrix in which rows corresponded to consumers and columns to an extensive, idiosyncratic set of sensory descriptors.

Given the high dimensionality and variability of FCP data, preprocessing was essential to ensure analytical robustness. Data cleaning involved identifying and addressing missing values, duplicates, outliers, irrelevant features, and inconsistent formats. These procedures are critical in machine learning applications, as they reduce noise, optimize feature representation, and mitigate the risks of model overfitting or underfitting.

The raw dataset was initially examined through descriptive statistics and exploratory visualizations to assess its structure and detect anomalies. Rows or columns with substantial missing values were considered for elimination, provided their removal did not compromise dataset representativeness. The goal of this stage was to transform the raw data into a structured and reliable dataset suitable for downstream analysis.

Subsequently, all odor, flavor, and sensation descriptors were standardized and grouped into predefined semantic categories using a keyword dictionary. Non-matching descriptors were classified as “other,” and a record was maintained for further analysis. Finally, mezcal samples were differentiated by brand, enabling consumer behavior to be analyzed within a product-specific sensory framework.

As part of the data preprocessing, the descriptors underwent a standardization process. Three researchers conducted an independent analysis of the descriptors to ensure consistency in their classification. Subsequently, through consensus, the descriptors used in the final analysis were defined. Those with a frequency of less than 2% or that could not be classified appropriately were eliminated.

2.2 Classification

The second stage involved the classification of sensory descriptors into relevant categories in order to simplify analysis and reduce dimensionality. After preprocessing, descriptors were clustered into odor, flavor, and sensation groups, each representing a higher-level construct of consumer perception. This classification step provided a structured input for subsequent machine learning models.

To evaluate classification performance, supervised machine learning algorithms were implemented. Among these, Support Vector Machines (SVM), Decision Trees (DT), and k-Nearest Neighbors (k-NN) were applied, as they are well-suited to handling nonlinear relationships and high-dimensional datasets. Cross-validation (k-fold, with $k = 10$) was employed to assess model generalizability and to prevent overfitting.

Model performance was evaluated using accuracy, precision, recall, and F1-score, ensuring a balanced assessment of classification effectiveness across descriptor categories. The outcomes of this step provided a clearer understanding of how consumers differentiate sensory attributes across mezcal brands.

2.3 Prediction

The third phase focused on predicting consumer satisfaction levels, operationalized as the target variable “level of liking.” Using the cleaned and categorized dataset, machine learning regression models were trained to identify the most influential sensory attributes and to forecast consumer preferences.

Multiple algorithms were tested, including:

Support Vector Regression (SVR): chosen for its robustness in handling nonlinear relationships.

Random Forest Regression (RFR): effective in capturing complex variable interactions and reducing variance.

Multiple Linear Regression (MLR): included as a baseline model for comparison.

The predictive models were trained on 70% of the dataset and validated on the remaining 30%, using stratified sampling to preserve representativeness across brands and consumer profiles. Model performance was assessed using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R^2 (coefficient of determination).

The predictive framework allowed us not only to identify the sensory attributes most strongly associated with consumer liking but also to generate practical insights into how producers can optimize sensory profiles to meet consumer expectations.

2.4 Evaluation Metrics

For regression tasks, evaluation focused on the magnitude of prediction errors. Two primary indicators were applied:

Mean Absolute Error (MAE): the average of the absolute differences between predicted and actual values.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

Mean Squared Error (MSE): the average of squared differences between predicted and actual values, penalizing larger errors more heavily.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

These metrics provided a robust assessment of predictive accuracy and enabled comparative evaluation across alternative regression models.

3. Results and Discussion

The final dataset comprised responses from 1,148 participants. A detailed overview of the key demographic characteristics of the sample is presented below.

The sample was predominantly male, with men representing nearly two-thirds of respondents (65.85%), compared to women (34.15%) (Fig. 1).

In terms of age distribution, participants were primarily young adults, with almost 80% falling between 18 and 34 years of age. Specifically, 38.33% were between 18–24 years, 40.42% between 25–34 years, 11.50% between 35–44 years, 5.92% between 45–54 years, and only 3.83% were aged 55 years or older (Fig. 2).

Regarding educational attainment, the largest group of respondents held a Bachelor's degree (37.63%), followed by those with a high school diploma (33.10%). Participants with a Master's degree represented 14.63%, those with a technical degree 9.06%, and those with middle school education 3.14%. A small proportion held a doctoral degree (2.44%).

Participants were distributed across four principal urban centers. The largest proportion resided in Oaxaca (33.80%), followed by Durango (24.04%), Mexico City (CDMX) (21.25%), and the Guadalajara Metropolitan Area (ZMG) (20.91%) (Fig. 3).

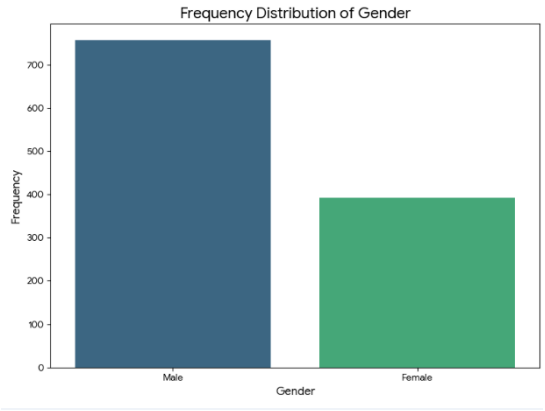

Figure 1: Distribution by Gender

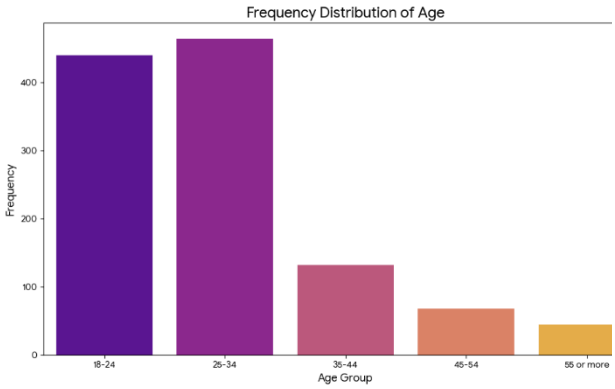

Figure 2: Distribution by Age group

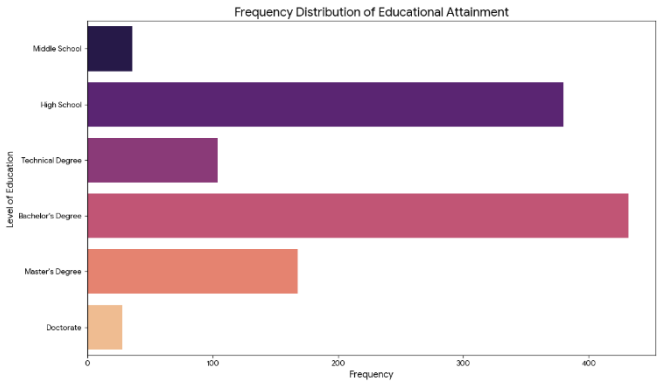

Figure 3: Distribution by Educational level

This study presents the sensory analysis of four mezcal brands. The analysis began with the estimation of Spearman's rank correlation coefficients to explore the associations between sensory descriptors and consumer preferences. These correlations revealed consistent relationships between specific aromas and overall consumer taste, providing a statistical basis for subsequent predictive modeling. Correlations between the variables age, gender, and origin were also measured with respect to the level of linking feature. The correlations show that the feature most strongly correlated with the target variable is origin, and the gender variable has a negative correlation with the target variable (Table 1).

Building on these findings, the study addressed the machine learning classification task by systematically comparing the performance of three widely used algorithms: Random Forest (RF), Support Vector Machine (SVM), and Logistic Regression (LR) (Table 2). Each model was trained to classify consumer responses based on sensory descriptors, allowing for an objective assessment of their predictive capacity.

The results demonstrated that SVM consistently achieved superior performance, reflecting its robustness in handling high-dimensional and nonlinear data structures typical of Free Choice Profiling datasets. Random Forest also performed well, benefiting from its ensemble structure and ability to capture complex attribute interactions, though with slightly lower accuracy compared to SVM. In contrast, Logistic Regression, while offering interpretability and simplicity, exhibited the weakest predictive power, underscoring the limitations of linear models for this type of heterogeneous sensory data.

Overall, these results highlight the potential of advanced machine learning approaches to complement traditional sensory analysis by uncovering latent patterns and improving classification accuracy. By demonstrating that nonlinear models outperform classical linear approaches, this work provides a methodological basis for applying machine learning in the study of traditional beverages, where consumer perceptions are highly variable and multidimensional.

Table 1: Spearman´s correlations for target variable (Level of linking)

Feature 1	Feature 2	Spearman´s Correlation
Agave odor	level of linking	0.148
Wood odor	level of linking	0.11
Vegetable odor	level of linking	0.098
Fruity flavor	level of linking	0.075
Gender	level of linking	-0.117
Origin	level of linking	**0.055**
Age	level of linking	0.029

The target variable "level of liking" was selected, as it directly reflects consumer preference. To evaluate predictive performance, three experiments were conducted, each employing a different algorithm: Support Vector Machine (SVM), Random Forest (RF), and Linear Regression (LR). The results of the classification task show that SVM achieved the best performance, yielding the lowest Mean Squared Error (MSE) value, and thus demonstrating superior predictive accuracy compared to the other models.

Table 2: Models Evaluation by means MSE

Model	MSE
SVM	4.238
Random Forest	4.576
Linear Regression	6.480

The developed classification model proved to be highly effective in predicting the consumer's level of liking. This variable was assessed using the 9-point hedonic scale, a well-established instrument for quantifying degrees of pleasure or displeasure in sensory and consumer research. The scale provides a standardized framework that allows for sensitive and reliable measurement of consumer preferences, with verbal anchors ranging from "dislike extremely" to "like extremely" (Table 3).

Analysis of the response distribution revealed that the majority of participants reported ratings clustered around the mid-to-high range of the scale, indicating a generally positive perception of the evaluated mezcal samples. Lower scores were less frequent, suggesting that negative evaluations were comparatively rare within the sample. This pattern reinforces the predictive capacity of the model, as it successfully identified the sensory attributes most strongly associated with higher hedonic scores.

Table 3: Hedonic standardized scale (9 points)

Hedonic Scale	Level of linking
9	Like Extremely
8	Like Very Much
7	Like Moderately
6	Like Slightly
5	Neither Like nor Dislike
4	Dislike Slightly
3	Dislike Moderately
2	Dislike Very Much
1	Dislike Extremely

Further analysis revealed that the maximum value of the target variable was predicted under a multivariate condition, rather than through the independent effect of single predictors. Specifically, the highest levels of liking were observed when an optimal configuration of the most influential variables was present simultaneously. This complex interaction highlights the model's ability to capture nuanced patterns in consumer data and to define the precise conditions under which consumer engagement is maximized.

Based on the best-performing model (SVM), a prediction was generated to visualize the values that key variables must take in order to achieve the corresponding level of liking. To emphasize the influence of the variables most strongly correlated with the target outcome, the mean values for Agave, Wood, and Vegetable odors, along with Fruity flavor, are presented in Table 4.

Table 4: Average values for the variables most correlated with level of linking.

Level of linking	Agave odor	Wood odor	Vegetable odor	Fruity Flavor
9	2.210	2.259	2.445	0.703
8	2.015	0.616	1.779	0.664
7	1.591	0.943	1.174	0.584
6	2.561	0.000	0.752	0.684
5	1.448	0.154	1.288	0.546
4	1.982	1.247	1.609	0.518
3	0.000	0.325	0.857	0.000
2	0.722	0.000	1.667	0.000
1	0.000	0.171	0.000	0.000

4. Conclusions

The results of this study provide compelling evidence that odors exert a stronger influence than flavors or sensations in shaping consumer preferences for mezcal. Spearman's correlation analysis revealed that agave and wood aromas are the most positively associated with consumer satisfaction, followed by vegetable odor, whereas fruity flavor showed the weakest correlation. This pattern underscores the central role of olfactory cues in consumer perception of mezcal, highlighting those preferences are not driven by single attributes in isolation but rather by the optimal interaction of key sensory variables.

The use of the Free Choice Profile (FCP) method was critical in capturing consumers' spontaneous vocabulary, thus providing an authentic view of the consumption experience. However, the inherent variability and subjectivity of FCP data required the integration of machine learning (ML) techniques to extract meaningful insights. Among the models evaluated, Support Vector Machines (SVM) demonstrated the highest predictive accuracy, confirming their suitability for handling nonlinear and high-dimensional sensory data. This highlights the potential of ML tools to complement traditional sensory analysis by revealing latent trends and multivariate interactions that are otherwise difficult to capture.

From an applied perspective, these findings carry practical implications for producers. By emphasizing sensory attributes most strongly linked to consumer liking—particularly agave and wood aromas—mezcal producers can strategically tailor their products to meet market preferences and differentiate themselves in a competitive landscape. Such approaches not only improve product positioning but also strengthen commercial strategies targeted at specific consumer segments. Importantly, this research also supports sustainable economic development in rural communities, aligning with the objectives of Sustainable Development Goal 8 (Decent Work and Economic Growth) by providing traditional producers with actionable insights for enhancing product value.

Finally, this work contributes a novel methodological framework by integrating classical sensory analysis protocols with advanced ML techniques. This hybrid approach offers a replicable model for investigating other traditional beverages and foods, enabling researchers and producers to systematically explore consumer perception while leveraging data-driven tools for innovation and sustainability.

Ethics statement: Ethical review and approval were not required for this study in accordance with the local legislation and institutional requirements.

AI statement: The authors certify that no generative artificial intelligence (AI) tools, such as large language models or image generators, were used at any stage of manuscript preparation.

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The Ethics and Security Risks of AI Note-Takers in the Workplace

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Abstract: The rapid adoption of Generative Artificial Intelligence (AI) has led to its deep integration into daily work environments, with AI note-takers emerging as a popular tool for transcribing and summarizing meetings using advanced Natural Language Processing (NLP). While these systems enhance workplace efficiency by providing real-time transcripts and concise summaries, they also introduce significant cybersecurity and ethical risks. Chief among these are questions of data ownership, third-party data sharing, and compliance with consent laws. In jurisdictions with two-party or all-party consent requirements, the deployment of AI note-takers raises legal challenges when participants are not fully informed or have not consented to being recorded. Moreover, consent mechanisms across AI platforms are inconsistent and often buried in complex disclosures, leading to uninformed use and potential violations of privacy. These risks are compounded by the opaque data practices of many AI companies, which may retain or monetize recorded conversations. This paper conducts a comprehensive analysis of privacy policies from leading AI note-taker providers, legislative frameworks across U.S. states, academic literature, and recent investigative reports. We identify key policy gaps and technical oversights that could compromise user trust, organizational data security, and regulatory compliance. Case studies are presented to illustrate both the productivity gains and the harms—such as unauthorized data exposure—that result from AI note-taker misuse. We conclude by offering targeted recommendations for policymakers, developers, and organizational decision-makers to mitigate ethical and security risks. These include harmonizing consent practices, enhancing user transparency, and enforcing stricter data governance standards. Our findings aim to promote responsible innovation and ensure that the deployment of AI note-takers is aligned with ethical principles and privacy rights in modern workplaces.

Keywords: Note-Takers, End user license agreement, Artificial intelligence (AI), Cybersecurity, Security risks

1. Paper Overview

1.1 Conceptual Framework

This paper takes the view that artificial intelligence (AI) is both a powerful tool for maximizing productivity and a potential risk to user privacy, especially when used in AI-powered notetaking tools. The focus is on the specific risks these tools introduce during virtual meetings, where sensitive conversations are often recorded and stored automatically.

A study by Majeed and Hwang (2023) helps frame this concern. They explain how synthetic data, which is information generated by AI to mimic real data, can act as adversarial background knowledge. Even though this synthetic data is not directly taken from users, it can be similar enough to real data that attackers might detect patterns, rebuild anonymized datasets, or even identify individuals. This creates serious privacy risks when proper protections are not in place.

We apply that same idea to AI note-taking tools used in video-calling platforms such as Zoom or Microsoft Teams. These tools often record and transcribe meetings without people fully realizing what is being stored or how it might be used later. That lack of clarity raises concerns about consent, data ownership, and how long this information is kept. Because of this, our paper also considers important ethical ideas such as informed consent, transparency, and privacy by design when evaluating how these tools are used.

1.2 Novelty and Innovation

This paper explores a part of AI privacy that has not received much attention. It focuses on the cybersecurity and ethical risks of AI-powered note-taking tools. While there has been an increase in research about AI and the ethics that surround it, very few studies directly examine the risks of data breaches or the ethics of storing personal data through transcription systems. Most existing research discusses areas such as surveillance and anonymization, but it rarely looks at the unique risks of utilizing AI note-taking tools. These tools record conversations passively, process them in real time, and store them long term. This project is one of the first to study this specific use of AI.

This work is different because it connects technical analysis with real-world insights, including Gartner's 2025 forecast, which predicts that 40 percent of AI-related data breaches by 2027 will come from the misuse of generative AI. This highlights how urgent and critical these concerns are becoming. The paper also uses the findings of Majeed and Hwang, who describe how synthetic data can be used in ways that threaten privacy. In addition, it includes an ethical analysis that focuses on informed consent, transparency, and accountability.

The purpose of this paper is to help users, developers, and organizations understand the hidden risks that come with using AI tools in everyday work settings. By addressing technical problems and ethical challenges, this paper encourages the development of safer AI systems and legal regulations that protect user privacy.

2. Problem Background

2.1 Review of Prior Events

According to ChatGPT in early June of 2025, the five top AI note-takers are Notion AI, Otter.ai, Fireflies.ai, Granola, and Google's NotebookLM. In late June of 2025, the Notetaking AIs mentioned by ChatGPT have changed to Otter.ai, Fireflies.ai, Fathom, Sembly AI, and Supernormal reflecting the constant shifting landscape of the AI market. Highlighting how fast the Generative AI landscape is developing and thereby compounding the larger issue of governmental legal systems' inability to advance at the same pace in order to maintain regulations.

On June 11th 2025, Disney and Universal filed a lawsuit against the AI firm Midjourney over the use of their copyrighted characters for training Midjourney's AI intelligence. Claiming that Midjourney is plagiarising their work through its online AI service, with a key point of Disney's argument being Midjourney has received financial gain from creating images of Disney and Universal's copyrighted works. In contrast, Midjourney is citing that their AI is simply a tool and how users utilize the system is up to them citing the United States' fair use policy as their defense. The outcome of this litigation could reshape how Image Generative AI is used throughout the United States as issues over AI plagiarism of artwork have been around since the inception of Image Generative AI. This litigation comes figuratively late in the game, as Midjourney's Image Generative AI program has celebrated its three year anniversary on July 12, 2025. OpenAI's DALL-E Image Generative AI program is even older, having been released back in 2021 to much fanfare.

Court cases regarding whether or not AI Generated work can be copyrighted first began appearing in August of 2023, two years after AI Image Generators first hit the open market. In Thaler vs Perlmutter, the court determined that "only human beings qualify as authors under U.S. copyright law, meaning that an AI-generated work like the one submitted by Thaler is not eligible for copyright protection." (*Thaler v. Perlmutter*, 2023). The gap between the rise of Image Generating AI and when legal cases started to appear highlights the slowness of the legal system in catching up to ethical issues related to AI. At the moment, there are no standard practices for the operation of such AI note-taking systems, and in certain cases such as in legal or medical settings, issues may arise regarding patients and attorney-client privilege and the Protected Health Information (PHI) of patients respectively. In a legal setting, it can also become difficult to conclude who has data ownership over the audio recordings once the meeting has come to an end.

2.2 Limitations in Existing Approaches

The previous litigation surrounding Generative AI can be used as a case study for AI Notetaking software, especially with the recent acquisition of Scale AI by Meta. However, we will first start with tech company privacy policies as it is no secret that various companies such as Google, Microsoft, and Facebook, now Meta, track user activities and sell that data to third party companies for targeted advertising. A particular climax of this issue came in 2018 with Mark Zuckerberg's senate hearing. This hearing took place after the Cambridge Analytica data breach where Cambridge Analytica harvested the data of millions of facebook user profiles to then build a software program to influence and predict decisions at the ballot box. Questions were raised regarding how much data Meta captures from their users, what that data is used for, and how transparent the whole process is to users. The end result of the hearing led to no major legislation or regulation changes outside of increased federal scrutiny of tech companies and Facebook having to pay 5 billion dollars in fines for misleading users about just how much (or how little) privacy they have over their data. Especially considering the AI note-taking companies utilize the same type of privacy policies as other tech companies.

Upon review of the privacy policies of the first set of AI Note-takers, many of the issues that led to the aforementioned 2018 hearing still persist. For example, the AI note-taking company Fireflies.ai collects device and usage data alongside any information provided over the use of their tools. They are then free "to provide

you with further information and offers from us or third parties that we believe you may find useful or interesting, such as newsletters, marketing or promotional materials." (Fireflies.ai, 2025) This allows Fireflies to sell user data to advertisers similar to what social media platforms such as Facebook and Instagram do. Otter.ai has a similar privacy policy where they provide their advertising partners with your data for targeted ads and analytics providers storing the personal data as long as necessary to fulfill the purposes of their privacy policy.

NotebookLM, a creation of Google, follows Google's privacy policy which allows for the collection of "the content you create, upload, or receive from others when using our services. This includes things like email you write and receive, photos and videos you save, docs and spreadsheets you create, and comments you make on YouTube videos." (Google, 2025) Providing that data to Google's affiliates and personalizing ads to a user. Meeting summaries and notes collected by NotebookLM would fall under this category. All of these privacy policies run into the questionable ethics of collecting so much information on the users of one's system and the cybersecurity risks of utilizing AI note-takers. What happens when an adversary taps into the AI note-taker company's cloud and makes off with last week's meeting notes? Or the information is improperly handled as in the case of Cambridge Analytica? Under current rules and regulations, these companies are only required to alert users of data breaches but housing all that user information does result in a large amount of cybersecurity risk on the part of the user. This issue has been thrust into the limelight recently with the class action lawsuit filed against Otter.ai on August 15th of 2025. The plaintiff, Justin Brewer, alleges the note-taker "deceptively and surreptitiously" recorded private conversations to train the tech company's transcription service. Furthermore, there have been complaints by users that the AI joins meetings automatically when the service is linked to workplace calendars. Immediately recording those meetings without user consent which is a clear privacy and compliance violation. Clearly showing that ethics are not properly being taken into account by AI note-taking companies.

Ethical issues and legal grey areas arise as AI note-takers become more mainstream as well. Some states have all-party or two-party consent states, which require the consent of each individual before it can be recorded. As shown in the recently filed Otter.ai legal case. With the standard practice of notifying users that an AI note-taker is being utilized in a meeting and not being universal to alert, there may be issues that increase if there are disputes across state lines or even internationally. Employees, partners, and clients may be unaware they are being recorded by AI tools, eroding trust if disclosed after the fact. With an already rocky territory, things can get even trickier when taking into account the user information associated with AI note-taking users and the direct correlation to what adversaries would target and seek.

3. System Design / Theoretical Framework

3.1 Architecture / Model Description

In our theoretical model of properly implemented AI note-taker ethics practices, the AI note-taker acquires conceptual space alongside existing virtual-meeting software, tuning in to the live audio stream. Feeding it into a generative AI summarization and transcription process. The system would insert a standardized "AI present" message into the meeting UI before any words are recorded or processed—similar to how mute/unmute icons are inserted—so all attendees clearly know that an automated listener has joined. After recognizing the alert, the sound passes through a black-box model (like a cloud-based Transformer) that converts speech to text, condensed into action-item summaries. Most importantly, we layer on top a consent-gating module: unless all participants explicitly give their consent via an in-UI prompt, their microphone is effectively muted to the AI pipeline. Conceptually, consent records and transcript snippets would be authored to an encrypted audit log, keeping a permanent chain of who agreed and when, independent of any tangible backend yet.

3.2 Key Design Decisions

Since this is a proposal for proper AI note-taker ethics rather than a deployed system, our design choices favor clarity and ethical "bake-in" over engineering detail. We've chosen an in-UI banner and modal dialog style of consent rather than email or post-meeting checkbox, to offer real-time awareness. We put the "AI present" notification at the top of the participant list, making it as noticeable as any human participant, and tie the microphone unmuting to consent acceptance—so you can't speak until you've acknowledged the AI. In doing so as a black box treatment of the generative engine, we circumvent model-specific implementation and focus instead on data flows and user interactions. Finally, our audit-log concept logs timestamped consent events and every summary generation call so that any retrospective audit can trace back exactly who gave consent to be recorded and what sections of conversation the AI processed.

3.3 Proposed Tools, Techniques, and Data

In place of code writing or system building, our methodology relies on:

- (1) Review of literature and policy—examining API documentation, privacy notices, and consent-law laws
- (2) UX/flow prototyping—authoring screen mockups to demonstrate how consent dialogs and notifications would appear
- (3) Scenario modeling—creating prototype meeting transcripts (single-language and multilingual) to experiment with how and when consent gates and notifications would trigger
- (4) Expert consultation—gathering feedback from privacy officers and meeting-platform engineers on feasibility and user experience.

3.4 Experimental or Analytical Approach

To validate the suggested framework, we perform comparative policy analysis, comparing existing AI-note policies with our consent-gated design and identifying where there are deficiencies. We also perform scenario walkthroughs, simulating mock meetings in which consent is withheld, given partially, or withdrawn afterward to analyze how the system would behave. Utilizing first NotebookLM then Fathom.ai, we tested these capabilities during our team tag up meetings to see how the AI system complied with US consent laws and determine what level of cybersecurity risk the note-taker represented if misused. Together, these analyses will indicate both the practical virtues of our proposal as well as the tension underlying seamless user experience versus demanding ethical compliance.

4. Results and Analysis

4.1 Evaluation Criteria

The evaluation of AI note-taking tools was based on privacy impact assessment principles and focused on three main areas. These include the risk of unauthorized data access or sharing, the extent to which users were properly informed and gave consent, and how the system would respond if an attacker tried to exploit it using AI-generated synthetic data as background knowledge.

While we assess the cybersecurity, ethical, and legal risks and issues that surround AI notetaking, we must consider the following to accurately decipher this largely uncertain topic area:

First, the harmonization and standardization of consent practices and user information policies is a key part to ensure informed consent from users regarding the handling of their sensitive information. It should also be reviewed if a state is a two-party or all-party consent state, and if so, how that would impact privacy policies moving forward.

Second, enhancing user transparency, and enforcing stricter data governance standards is another component that drives many of the ethical issues we found. For someone to use a software that inherently has many cybersecurity risks that may impact users directly, it is important that they know what they are putting themselves at risk for. In this we must also consider one's vulnerabilities to adversarial attacks.

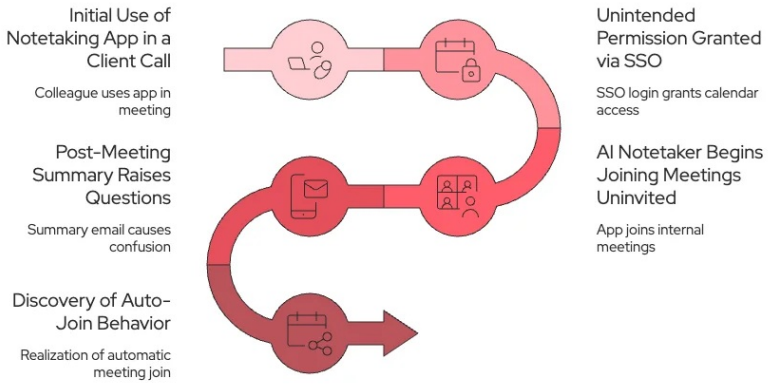
4.2 Observations and Outcomes

Recent studies have shown that AI Note-taking tools are vulnerable to attacks where adversaries exploit system behavior to extract sensitive information without triggering alerts. Majeed and Hwang (2023) demonstrated that synthetic data generated by AI can be used as background knowledge to analyze patterns in real or anonymized data and infer potentially private information. When applied to AI Note-taking tools, this raises significant concerns. Stored or generated transcripts from sensitive professional meetings could be exposed to privacy breaches, especially when shared across systems or used to train future AI models.

Gartner’s 2025 prediction states that more than 40 percent of AI-related data breaches by 2027 will result from the improper use of generative AI. This forecast closely matches the risks described by Majeed and Hwang. One major contributing factor is the lack of transparency in how AI note-taking tools are integrated into virtual platforms. Tools such as Microsoft Copilot, Otter.ai, and Fireflies capture and process meeting data automatically. They may transfer that information across international regions and store it in third-party systems, often without the user's full awareness or explicit consent.

These findings show that synthetic data risks combined with unregulated use of AI note-taking tools can create serious cybersecurity threats in both personal and professional environments. This not only weakens the principles of informed consent and data transparency but also leads to long-term vulnerabilities in settings that involve confidential or sensitive information.

Our policy mapping revealed that none of the leading AI note-taker platforms fully enforce real-time, all-party consent: most rely on pre-meeting checkboxes or buried disclaimers. For example, our team utilized Fathom.ai and Google's NotebookLM in three of our weekly Zoom meetings. Both AI note takers provide incredible functionality, with Fathom.ai being able to join ongoing meetings directly and then record them in real time. Emailing participants a summary of the key points from the meeting or a full transcript of the meeting. With the ability to join meetings directly, no consent from meeting attendants are needed. This issue is shown in the flowchart in Figure 1 by Socradar. In contrast, NotebookLM takes a prerecorded transcript of the meeting then can output a summary of the meeting or create a flow chart of key takeaways from there. In NotebookLM's case, no consent from meeting attendees was needed outside of Zoom's own recording consent popup. Together, these findings validate our framework's emphasis on seamless consent prompts and carefully tuned alerts, while underscoring the need to balance security safeguards with user experience.



In conclusion, the results support the need for ethical guidelines, greater transparency, and stronger security protocols for AI note-taking tools. These steps are necessary to prevent future data breaches caused by improper use or lack of oversight.

5. Discussion

5.1 Interpretation of Results

The results of our research conclude that there are significant challenges when it comes to addressing privacy concerns with AI Note-taking. Cybersecurity risks are heightened since sensitive user data is attached to users of the note taking software. There are also issues due to the speed and intensity of the growth of AI in general. This means there are many unknowns that have yet to be addressed, leaving an abundance of room for adversaries to step in and attack user data.

There are limited laws on privacy policies as well. Laws for consent vary from state to state and in most cases, this is a developing topic. As leading AI software companies such as Fireflies.ai and Google sell user information and data to advertisers, it is often something that users are unaware of. Ethical AI designs must be produced proactively to ensure that users are given transparent information for what they are partaking in and the consequences that may follow. While companies are actively using ambiguous language in their policies, it is important to note that it is not an excuse for poor ethical responses. Just as it is unclear whether people must know if there is an AI Note-taker present in their meeting, however, it is also unclear if a company should be held responsible to ensure their users are educated on their policies to ensure informed consent.

5.2 Limitations and Lessons Learned

The ambiguity of legal terminology in privacy policies reviewed as well as the lack of a universal set of consent laws,makes it difficult to assign any one party accountability for the cybersecurity risks and user's education while using software such as AI Note-taking. Many privacy policies tend to have vague and unclear information

regarding the kinds of information that will be collected, sold, used for AI model training, or for other uses. The internal handling of data is something that is kept fairly quiet which makes it challenging to analyze the true impact AI Note-taking has on the individual and broader security of those who may interact with such software. Generative AI, and by extension AI Note-takers, are essentially a black box with AI companies not wanting people to know exactly what goes on underneath the hood.

Despite how grey some areas of this topic may be, it is crystal clear that there are key elements to ensuring peak cybersecurity standards and critical information protection. Software systems such as AI Note-taking must remain transparent with users about the kinds of information that is shared and sold in terms the common person could understand so that sensitive information is less likely to be leaked to an adversary. It is essential that ethics are considered as AI Note-taking takes off in usage so that privacy, security, and consent are considered while developing these programs. Current laws are not developed enough to cover the topic at hand in depth so new standards and user guidelines must be added to this technology.

6. Conclusion and Future Work

6.1 Key Takeaways

Exploring how the adoption of Generative Artificial Intelligence has become more common in the daily life of individuals and companies, we were able to see that AI notetaking has been utilized and adopted too quickly due to its ability to efficiently summarize meetings and streamline information distribution in the workplace.

As shown by Google, Fireflies.ai, and Otter.ai's privacy policies, tech companies can obtain a vast amount of information that can then be stored for an indeterminate amount of time. With many of these companies not properly scrubbing the PII of the users before the information is sent off to either the US Government or third party actors that work with these AI companies. The lack of clear and concise user consent mechanisms is also problematic. Resulting in the possibility that many of these AI note-takers could be in breach of state level privacy laws within the US and the AI Consent Act if the data obtained by these AI is used to train the AI note-takers without the user's consent. One key risk that is shown in the Otter.ai legal case is that many AI notetakers capture every word spoken in a meeting—including sensitive or confidential information—and in some cases automatically share transcripts with all participants.

Studies have also shown that AI note-taking tools are vulnerable to attacks and exploits by adversaries. Making their relative cybersecurity questionable at best, woefully lacking at worst. While there are many benefits to using this tool, it does not seem to outweigh the risks associated with it. Data and user privacy, ethical concerns, and consent issues all play a valid and important role when determining the acceptance of AI note-takers despite its clear impact on cybersecurity risks and personal privacy problems.

As it is known that human error plays a major role in cybersecurity risks manifesting into something of substantial impact, it is vital that users are educated on the data that may be given up as a response to using a software. The ethics of making sure users are informed directly correspond to the cybersecurity risks and steps that can be taken to ensure strong security.

6.2 Potential Extensions and Impact

Future work would evolve our consent framework into a universal standard for AI Note-taker integration across all virtual-meeting platforms, ensuring each participant's preferences are honored in real time. For example, dynamic per-user consent prompts could appear before someone speaks and transcript segments with low model confidence could be automatically flagged as "Needs Review". This would guide moderators to verify content thereby maintaining both accuracy and trust between the users and AI note-takers. This would be done in conjunction with establishing clear guidelines for when and how these tools may be used, with explicit restrictions for sensitive or confidential discussions.

Modifications to the Cybersecurity Information Sharing Act (CISA) that inhibit the amount of Personally Identifiable Information (PII) not directly related to a cybersecurity threat that can be collected by tech companies alongside requiring tech companies to undergo rigorous scrubbing of user data before that data is sent to the US government. In addition to requiring any approved vendor to provide transparency on how data is stored, retained, and whether it is ever used for AI training.

Ethics Declaration: No ethical clearance was needed for this research.

AI Declaration: ChatGPT was used to determine what were the top AI Note-takers in June of 2025. Fathom.ai was used to record and provide notes from team meetings. NotebookLM was used to create meeting notes from team meeting recordings.

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Artificial Intelligence as a Tool in Cognitive Warfare on Digital Platforms

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Abstract: Cognitive warfare uses selective framing, AI and ICT to manipulate cognition, exploit vulnerabilities, and influence beliefs and decisions. AI supports both offensive and defensive cognitive warfare, feeding into kinetic warfare through psychological tactics. Cognitive warfare is immersive and long-term, often unnoticed, even via trusted actors. As AI and ICT evolve, unpredictable uses will emerge, raising ethical, legal, and moral challenges that demand multidisciplinary research. Future warfare will involve complex trade-offs, while democracies must prevent adversaries from weaponizing these tools—by using them strategically themselves.

Keywords: AI, Cognitive Warfare, Vulnerabilities, Internet, Digital platforms

1. Introduction

Cognitive warfare makes use of cognitive vulnerabilities, credibility, and authority. Artificial intelligence (AI) and various information and communication technologies (ICT) are used during this process. Cognitive warfare has strengthened its place in the strategic, operational and tactical levels of warfare. By targeting cognitive elements such as attitudes, beliefs, and understandings as well as the causal relations these create, cognitive warfare aims to shape the attitudes, beliefs, values, and heritage as well as behaviour of people and compel them to the adversary's aims. Moreover, it aims to compromise, disrupt, or destroy information systems, networks, and infrastructure. It also includes a wide range of activities, including espionage, sabotage, and propaganda, conducted by state and non-state actors who act as proxies. People rely heavily on digital platforms (social media, the Internet, and gaming) as spaces for facts and fiction as well as belonging to in-groups where they find truths, causes, safety, and reasons to live. These platforms, content, and actors producing the content are believed and consumed selectively based on individuals' values, beliefs, cognitive vulnerabilities, and biases. Digital platforms are used effectively as battlefields in cognitive warfare besides kinetic warfare. Next to the traditional five operational domains—land, air, maritime, space, and cyber—the human mind can be considered a new domain of operations in warfare (Neculcea & Răpan, 2022).

RQ1: The research question is, can AI be used as a tool in cognitive warfare?1

During and in between warfare, AI and various other ICT tools are used to create content, people, profiles, images, narratives, and realities. These are also used to create, collect and analyse data in intelligence analysis and, for example, in drone warfare. The tools have limitless potential in warfare. They do not bleed or demand physical geographical locations to operate. AI-driven and algorithm-aided viral actors (influencers) and content such as deepfakes, memes, fake news, ads, mis- and disinformation offer innovative possibilities but also pose significant risks to authenticity, privacy, and national security (Babaei et al., 2025; Maik & Afridi, 2024; Samoilenko & Suvurova, 2023; Meriläinen, 2025; Collier, 2025). AI and various ICT tools can be used successfully in cognitive warfare on digital platforms across the globe in information operations. Information operations succeed on digital platforms since people are prone to regard their critical media literacy as strong, simultaneously showcasing a lack of it. People believe they cannot be targets of information operations during cognitive warfare (Meriläinen, 2024; 2025). Meanwhile, various countries struggle to hold various technology giants, from Meta and Discord to TikTok, accountable as platforms in cognitive warfare. Politicians simply pay lip service to the platforms as places for warfare due to a lack of political will or know-how about how these platforms operate as places for war. Thus, we need to look at how, if at all, cognitive warfare can benefit from AI and ICT to guide the research going forward.

2. Related Works

2.1 Cognitive Warfare

Cognitive warfare influences how a target population believes, thinks, and acts (Backes & Swab, 2019; Meriläinen, 2025). It is a strategic, non-physical form of conflict that modifies perceptions and thought processes by weaponizing the content people consume and trust (Putter, 2025). However, it can escalate into physical violence and contribute to kinetic warfare. Non-kinetic methods, such as cognitive warfare, can lead to kinetic warfare—and vice versa (Saressalo, 2025), which is why the author discusses lethal and non-lethal

warfare. Cognitive warfare involves manipulating individuals', groups', or whole populations' cognition to gain an advantage over adversaries, transforming human cognition into a critical realm of warfare. It is the art of using cognitive attributes and technology to change the cognition of human targets, who are often unaware of any such attempt, as are those entrusted with countering, minimising, or managing its results (Claverie & Du Cluzel, 2022). Both defensive and offensive counterintelligence operations are used in tandem with cognitive warfare strategies and tactics (Putter, 2025). However, Gergelewicz (2024) argues that there is a low level of understanding of information threats during the ongoing cognitive warfare. Thus, there is a lack of holistic, practical solutions in the field of building social resilience against disinformation used in cognitive warfare in the form of information operations. Information operations are a tool in cognitive warfare as cognitive warfare often takes the shape of information operations. Information operations use any attributes, vulnerabilities, values and beliefs as well as information to affect an adversary's cognition and accomplish strategic goals. Giles (2016) and Meriläinen (2025) note that, for example, digitally enabled information operations as part of cognitive warfare are not random.

Careful planning and intelligence gathering from OSINT and SOCMINT are done prior to information operations (Giles, 2016; Putter & Henrico, 2022). From military doctrines and cross-sectional influencing, information operations benefit from social and political agendas, memes, online activism, dis- and misinformation, hashtags, historical narratives, humour, AI-generated fake accounts, imagery, narratives, algorithms, and bots (Meriläinen 2024; Eleferenko 2023; Weedon et al., 2017; Mozur et al., 2021). Please see more on information operations on digital platforms and cognitive warfare (Starbird et al., 2019; Turan, 2018; Thomas, 1998; Cox, 2006; Darczewska, 2014; JCS, 2012; Chochowski, 2022; Knapp, 2024). Information operations operate within the realm of politics and society, utilising psychological tactics to achieve strategic objectives (Putter, 2025) with AI and various ICT tools. Previously, Backes & Swab (2019) argued that cognitive warfare will remain a constant threat to Western political systems. By targeting cognitive elements such as vulnerabilities, values, attitudes, beliefs, and understandings, cognitive warfare aims to shape the behaviour of adversaries and compel them to accede to one's aims.

2.2 Cognitive Vulnerabilities

Cognitive warfare takes advantage of vulnerabilities to reach the goal of military operations. Cognitive vulnerabilities and biases are faulty beliefs or structures that are hypothesised to set the stage for later psychological problems when they arise (Riskind & Black, 2005). Vulnerabilities are not static but change as time and related issues, actors and events, and the causal relationships they form change. They are subjected to selective framing and priming. They can be defined differently even in research (Parley, 2011). Previous passive cognitive vulnerability can be activated if a person encounters stressful events, such as social rejection (Abramson et al., 2002). Different sets of cognitive vulnerabilities are all aligned with the inability and unwillingness to decode new information, leading to false and inadequate understanding of current situations and new information (Trent, 2005). This serves as the exact point of entry for information operations as part of cognitive warfare.

Ryan and Deci (2017) discuss self-determination by highlighting the need for people to be able to make their own choices, decide on their lives, and experience their value in society and in their community. If, for example, due to vulnerabilities, these are prevented or impossible to fulfil, people can be targeted by cognitive warfare. This gives them reasons why their self-determination is taken away, and they are subsequently targeted by AI- and ICT-driven cognitive warfare online. During this warfare, an emphasis is made on who is to blame and how to get the determination back. Cognitive vulnerability can make people believe false information, nefarious actors, and realities. Vulnerable people can be influenced and manipulated and cannot make informed decisions (Van Dongen et al., 2011; Block & Gordon, 2019). Cognitive vulnerabilities may be as simple as being tired or otherwise having a "bad day", which directly impacts a person's ability to be alert. When a person is in a vulnerable state, they can be targeted by various cognitive attacks. Thus, detecting the vulnerabilities of individuals is a useful tool in cognitive warfare. When a person is cognitively vulnerable, they are likely to attach themselves to credible situations, truths, information, and sources of these that align with their values and beliefs in accordance with confirmation biases. Informational and psychological influence is an important tool for conducting information and psychological wars (Habro et al., 2022).

2.3 Cognitive Authorities and Credibility

Cognitive authority refers to the source or content of knowledge that credibly shapes thinking. It involves recognizing information as trustworthy and worthy of belief, emphasizing its quality, usefulness, currency, and accuracy (Wilson, 1983; Rieh, 2002). For cognitive warfare to succeed, the actor, their communication, and the

platforms they communicate, must appear credible to the receiver, exploiting cognitive vulnerabilities as tools (Meriläinen, 2025). Drawing on Aristotle, the influencer's ethos, pathos, and logos—along with the platform and message—must align with the audience's pre-existing values and beliefs. Furthermore, selective framing (Meriläinen, 2014) must present narratives as facts or embed emotional hooks to reinforce persuasive power. There must also be a connection to cognitive attributes, credibility and authority. Umeogu (2012) defines credibility as the sender's belief in the receivers' minds, emphasizing the significance of charisma. Credible actors function as authority and distributors of messages, thus holding immense power. Traditionally, credible leaders have been connected to certain traits or behaviours (Ivancevich et al., 2013). Kamau and Oginde (2022) listed attributes related to a credible, authentic leader, from honesty to values. For example, related to cognitive warfare, Kalpokas (2017) argues that so-called sofa warriors are active information spreaders or part of DDoS attacks, working in the background by making the information atmosphere favourable for the main information operation. Meanwhile, Meriläinen (2024; 2025) notes that influencers are credible actors in information operations and work as proxies between adversary states and young people, drawing people into the influence of states like Russia and China, while not doubting the purpose and aims of the influencers or even recognising the usage of AI and ICT.

2.4 Cognitive Warfare and Artificial Intelligence

While cognitive warfare is nothing new, it benefits from AI, neuroscience, and digital platforms to influence human cognition (Fenstermacher et al., 2023). The shaping of cognition relates to earlier notions of biases and selective framing by legacy media and the pictures in the heads people live in (Lippmann, 1922). Nowadays framing is done to a lesser degree by legacy media. Now it is done with the help of AI and ICT on various digital platforms by actors known and unknown. AI is used by states in a variety of ways to improve, automate, or intensify cognitive warfare strategies and modern military operations.

AI is used in cognitive warfare for:

- strategic (cyber) deception and espionage,
- social engineering of people, their values, beliefs, habits and members of their ingroups,
- in the creation of credible and legitimate actors, from influencers to sofa warriors,
- in the creation of viral online content from memes to satire,
- in the creation of deep fakes,
- (social) bots,
- mis- and disinformation, hashtags,
- algorithms, ads,
- censorship,
- mental and physical intimidation and control,
- bullying, harassment and violence.

AI also has a massive role in intelligence gathering and analysis, which is furthermore used in both cognitive and kinetic warfare. The strategic use of AI, espionage, various types on content and online communication methods, algorithms, ads, influencers, mis-disinformation and by attaching them to human emotions, this numerous threats to personal safety, corporate and national security. (Rosli, 2025; Maik & Afridi, 2024; Samoilenko & Suvurova, 2023; Meriläinen 2025; Collier, 2025; Kalpokas, 2017) The aim is to undermine shared values, by undermining trust in institutions and authority (Albert et al., 2023). AI is an effective tool for adversary states for generating fake content to use in information warfare (Lande & Danyk, 2025) as part of cognitive warfare. The new(er) content utilizes cognitive vulnerabilities and people's needs to find information and truths that help them make informed decisions and to make sense of their surroundings in the world riddled with uncertainties. AI+ICT driven cognitive warfare offers vast opportunities to manipulate and control people, to sow distrust towards democratic institutions from schools to national defense and even legitimize kinetic wars.

Indeed, the rapid development of AI and ICT has created new possibilities for malicious use as part of warfare (Samoilenko & Suvorova, 2023). These tools facilitate massive, rapid, disruptive, and subversive campaigns designed to have serious cognitive and emotional impacts on international audiences and present multiple threats to organisational safety and national security (Pashentsev, 2021). AI breaks down national borders, creating a limitless workforce and operating at superhuman speed. While moral objections exist, the alternative is allowing enemies to manipulate people's minds using advanced AI technologies. Thus, AI must be

utilised in warfare in offensive and defensive warfare. (van Diggelen et al., 2025) Indeed, there is a growing interest in harnessing AI and related tools to serve national defense and warfare (Rani et al., 2025).

Some argue that NATO does not have a ready-to-use concrete doctrine on cognitive warfare, while Russia has one (Miron & Thornton, 2024). NATO must catch up with Russia. The Russian military employs AI and deepfakes as part of their cyberpsychological and cybertechnical operations to create strategic, potentially war-winning effects, aiming to undermine state adversaries and weaken them through influence operations long-term, while NATO has no clearly defined policies to counterattack these operations (Miron & Thornton 2024). However, Bykov (2025) argues that NATO's cognitive security strategies and informational environment analysis can counter Russia's cognitive warfare and following cyber-attacks, requiring state, civil society, private sector, and international partnerships for coordinated efforts within NATO. Russia is just one example of how a state effectively uses cognitive warfare and AI to gain a strategic advantage in conflicts. Various countries use propaganda and psychological operations to divide the enemy's population, while the increased use of social media makes people vulnerable (Afridi, 2025). Examples can be found globally from China, Taiwan, and the USA (Hung & Hung, 2022; Mozur et al., 2021; Reinhold & Reuter, 2022.)

Young people showcase a lack of critical media literacy online and are especially indifferent towards the power of AI, ICT, advertising, algorithms, bots, deepfakes etc. (Meriläinen, 2024; 2025). This makes them potential targets of cognitive warfare in the form of information operations. People may not think to doubt digital platforms, influencers, AI, algorithms, bots, ICT and digital advertisements. They are something that people cannot or do not care to doubt or think twice about (Meriläinen 2025). At the same time, AI and algorithms can be viewed as tools for control and coercion, leading to the consumption of mis- and disinformation on various digital platforms. Numerous problems are associated with AI. Previous studies have shown that AI has built-in misogyny, discrimination and racism and allows doxxing, discrimination and sexism (Burak 2021; Soh & Connolly 2021; Waelen & Wieczorek 2022). The same tools can be used to disseminate war-related information and to monitor and document human rights violations during wartimes (Nemkova et al., 2023), while others claim that AI and machine learning bear no accountability for anyone and allow bullying, harassment and violence (Razmetaeva, Barabash & Lukianov, 2022; Langford, 2020). All of these can be utilised in cognitive warfare to create AI-assisted us-versus-them realities. However, we get back to the question: can and should we use AI to defend ourselves? Yes. While moral objections exist, the alternative is allowing enemies to manipulate society's minds using advanced AI technologies. Thus, AI must be utilised in warfare in offensive and defensive warfare. (van Diggelen et al., 2025)

3. Discussion and Conclusions

Relating to Lippman's seminal research (1922), people live in mental constructs. These were previously influenced and shaped by the legacy media selectively by selective framing (Meriläinen 2014). Nowadays, this phenomenon illustrated by Lippman is holding strong within cognitive warfare. The influencing occurs via digital platforms by actors not even known to people consuming the content. Cognitive warfare exploits people's need to belong, various cognitive vulnerabilities, basic needs, societal silos and political movements. The rapid development of AI and subsequent ICT tools has created new possibilities for the adversary actors to use AI in malicious ways as part of information and psychological warfare (Albert et al., 2023). AI, ICT, and cognitive vulnerabilities and biases are heavily used as tools in cognitive warfare. This critical realm of warfare is designed by adversary states to modify the perceptions of reality by nefarious means, benefiting from AI and various ICT tools. Cognitive warfare utilises various content (data, information, and knowledge) to manipulate cognition and create uncertainty, often to exploit vulnerable populations or achieve strategic gains, to influence target audiences' values, beliefs, behaviours and decisions (Putter, 2025; Bykov, 2025). Moreover, AI technologies are used to gain knowledge and further control over people in cognitive wars against their own or foreign nationals (Hung & Hung, 2022). AI enhances kinetic warfare through intelligence gathering, audience manipulation, and technologies such as drone operations (Johnson, 2020; Giles, 2016; Putter & Henrico, 2022). Moreover, cognitive warfare can escalate into kinetic warfare, revealing their intrinsic interdependence at the core of modern conflict.

Adversary states do their research to find divisions and cognitive strengths and vulnerabilities in the target societies. To exploit these divisions and vulnerabilities, AI and ICT is employed as a tool in cognitive warfare, both locally and globally. Geological restrictions and proximity are removed in cognitive warfare because AI-assisted attacks can take place and be coordinated anywhere globally (Veljković, 2024). AI serves as a tool in both defensive and offensive cognitive warfare operations on strategic, operational and tactical levels. As cognitive warfare occurs in virtual spaces and uses AI and ICT to inflict damage on opponents, potentially the

consequences of the war are not immediately apparent. This type of warfare takes time. AI-aided cognitive warfare operates within the realms of cyber, politics, and society, utilising psychological tactics to achieve strategic objectives (Putter, 2025). In this process, AI is a significant tool together with bots, deepfakes, memes, narratives, realities, and credible actors such as newer agenda setters, e.g., influencers. The influencer economy combined with various AI and ICT tools has transformed legacy media and previous gatekeepers as truth-tellers, influencing various aspects of life, including entertainment, consumerism, news, and even national security as well as warfare (Meriläinen, 2025). AI serves as a cross-national tool in cognitive warfare against states globally. With the use of AI, ICT and digital platforms, kinetic warfare seems to have an excellent partner in cognitive warfare online. Victims may not even be aware, or care, that they are under immersive, long-term attacks from multiple platforms, even via actors they trust. With its capacity to absorb, analyse and create vast volumes of data, comprehend human behaviour, and swiftly and efficiently manipulate information and create trustworthy actors and realities, AI serves a central and advancing role in cognitive warfare.

As AI develops and is used more profoundly, there will probably be new and unpredictable uses for it in cognitive warfare, which raises important ethical, legal, moral and not yet foreseeable questions regarding the future of cognitive and kinetic warfare. Rani et al. (2025) and van Diggelen et al. (2025) argue that many decisions in this realm involve complex moral trade-offs that require careful analysis and more research. AI cannot fully replicate human judgement. Thus, we should not follow AI-driven recommendations blindly amidst warfare. Because of AI, do we need to prove that we are real humans? Are we the adversaries or the defenders? Is our war offensive or defensive? These are questions that we must address in future research regarding AI and warfare.

AI creates a limitless workforce and operates at superhuman speed, yet ethical and moral objections exist. If we decline to use AI and ICT tools in warfare, the alternative is to allow enemies to manipulate people and their minds using advanced these technologies. Thus, AI must be utilised in our warfare. (Rani et al., 2025; van Diggelen et al., 2025) Informational and psychological influence is an important tool for conducting informational psychological wars and operations and is seriously detrimental to social consciousness. (Habro et al., 2022) We need more multidisciplinary research to address the ethical, defensive and human perspectives in warfare. In future research we should focus on how and why people are targeted by warfare on digital platforms. How is AI and ICT used in each case example, and how influencers are utilised in warfare? More focus must be placed on framing, confirmation biases and cognitive elements such as cognitive vulnerabilities, credibility, and authorities and how these are and can be utilised in warfare with the help of AI and ICT.

Acknowledgement

I wish to thank the reviewer of this paper.

Ethics declaration: No ethical clearance was required.

AI declaration: No AI tools were used in creation of this paper.

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Patterns of Adoption and Learning: Students' Relationships with Generative AIs

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Abstract: Generative AIs have become part of increasingly intimate relationships between humans and technologies, and have created both serious concerns and heightened pedagogical interest in higher education. However, though interest in generative Ais and their contribution to education is spreading, little is still known about how they are used by students in their everyday lives and how this affects education. In this paper we investigate how GAIs such as ChatGPT enter students' lives and become part of their learning. The paper draws on observations and interviews with students in a Master Program where students partnered with ChatGPT to investigate concepts and philosophical aspects of technology. The aim of the study was to understand how ChatGPT could support students' collaborative group work as part of problem-based learning practices. As our study involved investigations of students' everyday uses of generative AIs as well as their learning we were able to make connections between students' learning strategies and their emerging experiences with GAI technologies. In the paper we investigate these relationships focusing on how GAIs are enrolled and participate in students' lives and in collaborative learning contexts where uses and understandings of GAI technologies are negotiated in group sessions. Our data suggest that some students enter education with extensive experiences with generative AIs and others commence their engagement after meeting these technologies through education. What characterizes these patterns of adoption - and what are their effects on learning? Theoretically, we draw on sociomaterial approaches to understand GAIs as material agents in students' lives and in education building on the concepts of *patterns of relations* and *distributed agency*. These concepts emphasize the collaborative relationship of humans and GAI technologies, underlining both the specifics of GAIs as 'human-like' agents and the blurring of agencies and authorship involved in e.g. AI-generated writing.

Keywords: GAIs in higher education, Students' perspectives, Sociomateriality

1. Introduction

In this paper we investigate ways in which Generative AIs (GAIs) become part of and act as material agents in students' everyday lives, emergent work practices and academic activities. Our research contributes with empirical knowledge to studies in the high-paced development and dissemination of GAIs currently affecting higher education. This is a development that has initially created serious concerns for academia, however, the discourse of concern is increasingly paired with empirical research in the learning potentials of GAI. Drawing on interview data from a Master Program in *ICT Learning and Organizational Change* our research therefore contributes to this emergent field of research by investigating the specifics of how GAIs enter, form and affect higher education in the context of relationships between students and GAIs. In addition to this we argue that GAIs should be made controversial, ie critically addressed in terms of their stability and unity in and outside of education.

In the paper we ask *What characterizes students' relationships with GAIs - and what are their effects on learning*? In investigating this question we attach specific significance to how GAIs are involved in both students' private lives, work and education, providing a complex qualitative perspective on practices of use.

2. Data and Methodology

Our paper builds on data from a course in *Concepts and philosophical aspects of technology* (5 ECTS) at a Danish university in Copenhagen. The course was part of a Master Program (MSc) in *ICT, learning and Organizational Change* that builds on problem-based learning practices (Savin-Baden 2014). Problem-based learning is a broad concept that in our case is defined by a focus on problem-solving and collaborative group work (Ryberg et al 2018). For the course students were asked to work with ChatGPT in different ways during group work in class in order to reflect on eg ethical perspectives and uses of GAI in education, understanding concepts of technology relevant for the course, and assessing frameworks for responsible innovation (see Figure 1). Students were in each case asked to reflect on feedback given by ChatGPT to specific prompts formulated either by the teacher or through their own prompting strategies, and to upload reflections to Moodle. Prior to teaching, the students were asked to create a profile at https://chatgpt.com/ and recommended to check university regulations for using GAI. Groups were organized at the outset, each comprising 3-4 students and totaling 56 students. Group work was followed up by mandatory written work focusing on further uses of ChatGPT for exploring learning

and technology adoption. 4 students did not give consent, which meant that 52 students participated in the research.

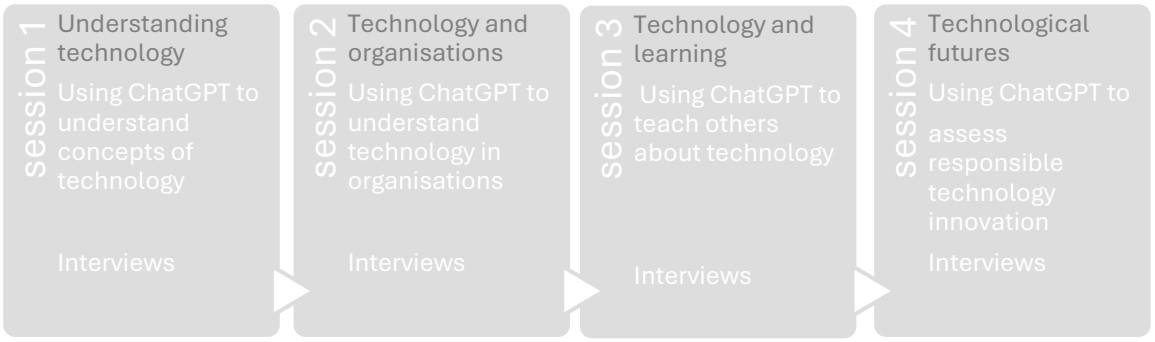

Figure 1: The 5 ECTS course Concepts and philosophical aspects of technology

The purpose of our study was to understand how ChatGPT can support students' group work and reflections on the role of technology in society and in learning. Data collections were organized as observations of group work and subsequent group interviews with students in 11 groups during a 25-minute break purposely placed near the end of the 4-hour session (Davies 1999, Halkier 2020), totaling approx 4,5 hours of interviews. Data collection and teaching was done in a team of 5 colleagues, all of which were known to the students from other modules as either teachers or supervisors[1]. One person had from the outset had the role of teacher and the others acted as interviewers and observers, usually two or three at a time. Meetings were held before, during and after the course in order to discuss common themes and frameworks for the research.

Our observations and interviews were supported by audio recordings and notes and focused primarily on students' prior experiences with GAI and the social dynamics of students' group work with ChatGPT. For both observations and interviews we had a special interest in investigating practices of inquiry, dialogue and collaboration in group work where students were asked to use ChatGPT as part of their collaborative work (Hetherington & Wegerif 2020, Miettinen 2000). We also focused on ways in which students spoke about GAI, ie ways in which the technology was anthromorphized (made human) or given specific roles in the group (Placani 2024, Mollick & Mollick 2023). This was based on the expectation that the participation of ChatGPT in problem-based group work would affect ways of interacting and engaging with knowledge, as well as possibly group dynamics and roles. For the interviews we asked students about their group work, but also their everyday uses of generative AI, ie for work and private purposes. This gave us insights into students' adoption practices and their prior knowledge about GAIs as a possible framework for using ChatGPT for learning.

In this paper we focus primarily on the interviews, as group interviews gave us significant insights into students' patterns of adoption of GAI not only in education but in their everyday lives, contributing to a holistic understanding of what characterizes students' relationships with GAIs and how this affects learning.

3. Adoption and Learning - Sociomaterial Perspectives

In the paper we focus on adoption and learning through sociomaterial perspectives that can help us capture the ways in which GAIs participate in the social dynamics of interaction and learning (Bearman & Ajjawi 2023, Godwin-Jones 2024, Johri 2022, Ou et al 2022, Suchman 2023, Sørensen 2009). Drawing on sociomaterial approaches we first of all understand relationships between students and GAIs in a posthuman perspective, ie we view GAIs and humans as collaboratively involved in producing knowledge through interaction. As described above, GAIs are often associated with human-like agency, blurring the boundaries between humans and technologies as agents in education and learning. Secondly, we use sociomaterial perspectives to focus on the materiality of learning, ie on ways in which GAIs and other materials in learning participate in forming adoption and learning activities. Sørensen (2009) describes sociomaterial relationships as patterns of relations which are particular arrangements of social and material components that make up spaces of learning. As a concept, patterns of relations point to the idea that connections are dynamic and that relationships are more than their

[1]Participating researchers were in addition to authors of this paper, research assistants Clara Laimer, and Jane Retz Jespersen

parts. GAI adoption can thus be seen as a pattern of relationships between humans and computational artefacts in a particular moment of time (Bearman & Ajjawi 2023). These are relations that often affect ecosystems of learning, ie ways in which knowledge is produced and distributed in higher education (Godwin-Jones 2024).

With regard to the materiality of learning a number of publications point to the fact that GAIs as material agents alter the way we think about education and knowledge. Peters et al (2023) for instance underline that GAIs can be understood as amplifiers of the human but also as new forms of intelligence that challenge human-centered learning. Johri (2022) similarly argues for an understanding of AI as fundamentally shifting the role of humans in learning practices, as these technologies "… can enact attributes that have largely been associated with a human and with social norms more broadly" (2022, 3). Finally, Suchman (2023) argues that the thinginess and stability of AI as a phenomenon needs to be made controversial, ie critically addressed. Thus she calls for "a keener focus on the locations, politics, material-semiotic specificity, and effects…of AI as a singular and controversial object" (2023, 4).

In addition to these theoretical insights, we build on existing research in GAI in higher education. These are studies that to a large extent focus on individual learning opportunities e.g. potentials for personalized learning, brainstorming, immediate feedback, and prompt literacies as well as ways in which GAIs challenge academic integrity, writing and assessment practices (Stöhr et al 2024, Hwuang et al 2023, Williamson et al 2023, Coeckelberg & Gunkel 2023).This research is still emerging and empirical studies, specifically with a qualitative approach, are still limited (Bruun et al 2024).

4. Analysis

Based on our data and a sociomaterial perspective we can describe different patterns of relations involved in generating GAI adoption. These are patterns in which GAIs are seen as agentic, ie we focus on what humans and AIs do together and how this contributes to forming knowledge and learning (for instance in higher education). This is an approach that differs from seeing GAIs as generalized computational artifacts with specific affordances.

For purposes of analysis and organization of our material we propose two ways of approaching patterns involving students' relationships with GAIs. These are patterns related to students' private lives and work and patterns related to education and learning. We propose that these patterns are both significantly different and interconnected as students' responses to using ChatGPT in group work is affected by relationships formed by engagements outside of the university. Thus, students' adoption of GAI is a complex pattern of relations involving ways in which GAIs enter students' lives and become part of their learning. Following our sociomaterial perspective we have chosen not to include direct student quotations, but to identify significant patterns of relations that emerge from the interviews. Our analytic approach therefore involves identifying the locations, specific uses, and effects of GAIs in education by following patterns in the interviews, ie patterns of relations between humans and computational artefacts (GAIs) in a particular moment of time. These are sociotechnical ensembles (Bearman & Ajjawi 2023) that emerge analytically from our data and involve humans and technologies, but which are also formed by eg time and efficiency restrictions as significant local phenomena.

As our study is qualitative we are focusing on specific uses of GAI and not on statistics, e.g. how many students use GAI or how often. However, we wish to underline that in our study all participating students except two had some prior experience with GAI, either from their BA-studies or through work experience. As a rule, students at our university have part time work alongside their studies to support themselves, and some students have had full time work between finishing their BA studies and enrolling in MA education, e.g. as teachers. As our data were collected in the autumn of 2024, ie within a short period of time from the launch of ChatGPT in November 2022, some students, who went directly from their BA into the master program had used GAI in their BA and others had only used it for private and work purposes. Patterns of adoption therefore involved multiple and heterogeneous relationships between humans and GAIs.

4.1 GAIs as Agents in Students' Lives and Work

Looking at patterns of relations in our data, we can point to ways in which students engaged in relationships with GAIs outside the university. First of all, students entered into relationships with GAIs that were emerging from specific needs, strategies, events or necessities in their everyday lives, including work. Some of these relationships emerged from needs and strategies where students would previously use a search engine or an app, and where they now used GAI, e.g. to plan sightseeing, routes and budgets for holidays, find recipes, plan birthdays and dates and count calories in their food. Other uses of GAI were connected to organizing activities or generating texts and tables they would previously had found elsewhere or worked out on their own. Students thus for instance talked about using GAI for creating bed-time stories for their children, organizing training

events for e.g. football and for creating speeches and finding gifts for private events such as birthdays. Several students had used ChatGPT to write job applications or improve their cvs. These were patterns of relations in which other media (search engines, apps, books) were regularly replaced or displaced by GAIs, as students discovered the value of synthesizing, organizing or generating new material with these technologies. Though students also spoke of the necessity of using e.g. Google or Wikipedia for checking and finding information, searching for and booking tickets, hotels and more, their patterns of use showed significant shifts in the ecosystem of technology usage, pointing to multiple patterns of relations in which students experimented with ways in which they could use GAIs in meaningful ways in their private lives. GAI in this way both centralized usage that had previously been associated with other technologies and simultaneously contributed to proliferating uses, e.g. for searching, organizing and generating material.

For work, students had experiences with GAI that were similar to the patterns of relations in their private lives. Thus students told us that GAIs were to a large degree integrated in their part-time jobs or had been used in prior employment, e.g. as a teacher. Students for instance told us that they had used ChatGPT or other GAIs to create content for social media, write emails or product descriptions, and create figures or images. These were generative uses where students could quickly produce text or visualisations to save time or to enhance content. Some students had also used GAIs for translations and for summarizing text, ie for organizing purposes or for simplifying or disseminating text or information at work. A student who used to be a teacher had used GAI to create scenarios for teaching German to children, another had used it for communication with parents. The general impression from the interviews was that using GAI for work was both acceptable and widespread in the companies where students have part-time jobs (or had had full-time jobs), making it necessary for them to acquaint themselves with these technologies and their uses. GAIs used by students for work were often ChatGPT, but also other platforms such as Claude and Co-pilot, and in some cases companies had created their own GAI platforms that the students used in order to comply with data regulations. One student told us that her company had initially banned the use of GAI for work, but had changed their strategy to allowing use within rules formulated by management. This tells us that companies associate uses of GAI with competitive or efficiency advantages, affecting work and thereby students' patterns of use.

4.2 GAIs in Education

In our data we see patterns of relations with GAIs in students' lives and work that are significant for their understanding of these technologies and that affect education in specific ways. Significant patterns of relations are the ways in which GAIs are enrolled into work and life practices in heterogeneous ways and without notable restrictions. In education and learning we see some of the same tendencies but also with significant differences. First of all, a number of students experience that the understanding and uses of GAI in the specific course (ie *Concepts and philosophical aspects of technology*) is significantly different from their everyday and work uses. Thus in class they were generally asked to use only ChatGPT and not other platforms and they were also sometimes required to use standardized prompt strategies defined by the teacher rather than their own strategies. For some students this contradicted their experience with GAI as a fluid and heterogeneous phenomenon, ie as a technology that has multiple and situated uses (e.g. Suchman 2023). For other students, using GAI at university and in the specific course, turned out to give them a safe learning space in which to experience with ChatGPT together with others and monitored by the teacher. This was the case for a group of two students for whom the course provided their first experience with using GAI. Initially, these students had been apprehensive of using ChatGPT due to negative media coverage and other social critiques of the technologies. In class, they therefore benefited significantly from being in a context where the teacher and other students contributed to framing uses of the technology and helped them in their reflections on how it could be used in meaningful ways.

For students who already had experience with ChatGPT and other GAIs from work or private uses, using ChatGPT in the course in many ways enhanced their uses, for instance by giving them additional knowledge and opportunities for reflection. Students for instance spoke about using ChatGPT more for learning without being stuck in the idea that using GAI is cheating. They also spoke about the fact that using it more in many cases made them more critical of specific uses. This underlines the significance of teaching as an experimental and reflective space for learning about GAI, in which students can reflect freely and critically on their experiences with the technology.

Secondly, interviews with students uncovered ways of using GAI for homework and project work, i.e. reading, writing, revising and organizing material, that emerged as highly strategic both in terms of learning and in terms of study techniques and time management. Thus, a number of students told us that they regularly used ChatGPT

for summarizing academic texts, translating difficult English texts into Danish (i.e. their first language), explaining concepts and theories, coding interviews and revising their language in project reports to make it sound more academic. These were strategies that some students had brought with them from their BA, where a number of students had initially encountered ChatGPT. For others, usage at work had initiated their experience with GAI, which had quickly spread into adoption in their studies. For reading academic texts, this to a large extent meant, according to students, that they would on a regular basis choose to prompt ChatGPT to summarize texts rather than read them. This choice was fueled both by some students' difficulties with reading English or academic texts in general, but also with time concerns, i.e. freeing up time for other activities such as analysis (e.g. of cases or their own data). Several students mentioned that they felt that prompting GAI to summarize texts gave them a better overview of theories and concepts than reading, as the time-consuming process of working through a text did not necessarily help them understand or learn. Several students also said that producing AI-generated summaries was better than not reading the texts at all, which had apparently been a strategy for some students when texts were perceived as challenging. For writing, some students would use ChatGPT to revise initial drafts, enhance their academic writing and to check orthography. Finally, for time management and study techniques students would as mentioned also save and organize summaries and explanations generated by AI for project writing, or use GAI to organize and analyze their data.

All in all these results highlight that many students have embraced uses of ChatGPT that are highly strategic and competent, though not always clearly in accordance with current rules and expectations laid down by the university. University regulations thus allow students to enhance their academic writing with GAI when they are drafting and brainstorming, but as a rule not when they are writing up the text for submission and assessment. Uses of GAI for written assignments should therefore, according to the regulations, be accounted for in submitted written work. Similarly, students are expected to read academic texts that are part of the module, however, whether they actually do so is generally their own responsibility and can possibly only be assessed through written and oral exams. We are not suggesting that students did not comply with the rules laid down by the university, only that students' practices of writing and reading were to some extent transforming and challenging ways in which we as teachers generally think about homework, research and academic writing. Significantly, in some cases we were met with claims from students that they did not use or hardly used ChatGPT for their studies, which may be the case or may signify a reluctance to disclose uses to us, their teachers. This is a methodological challenge in our investigation, as our role as teachers and supervisors (in other modules) may have affected what students communicated to us in the interviews. In any case, our results highlight that GAI has apparently in no time at all significantly changed students' literacy practices. Our results also show that reasons students give for these changes are to a large extent based on time and efficiency arguments as well as a perceived lack of academic competence in e.g. reading and writing as well as understanding texts and concepts in English. Time and perceived academic level and competence are therefore significant aspects of students' patterns of adoption that will be discussed below.

4.3 Patterns of Adoption and Learning: Summary of Results

In our interviews with students we were often told, as mentioned above, that saving time was the outcome of and the reason for using GAI for learning. In addition to this, efficiency and enhancement were significant aspects of students' GAI use, ie doing things in smarter ways, and also to some extent in better ways, specifically with regard to performing academically. With regard to time, students seemed to attach value to saving time, not only to use more time on other activities, but to increase efficiency and understanding. GAI in this sense is associated with what Sharma (2013) calls speed culture, i.e. the feeling that technology contributes to handling accelerating time in society (see also Rosa 2013). For students, the accelerated pace of reading and writing with GAI seems to have a largely positive impact on their learning, giving them a feeling of control of and access to knowledge that was perceived to be both slower and more challenging before GAI. One student even felt that she had missed out compared to fellow students who had had more extensive experience with using ChatGPT than her, i.e. she felt that they had an unfair advantage. However, distributing aspects of their reading and writing activities to ChatGPT also came with challenges, specifically challenges of cognition, engagement and pace, as students told us that using ChatGPT threatened to make them lazy, less creative and less prone to thinking independently. Relationships with GAIs in this way created new forms of agency in which students felt that they both gained and lost agentic capability.

Time, on the other hand, also figured as a restriction for students' potential to engage critically in GAI usage, according to the interviews. Thus, a number of students mentioned that time limits involved in their group work with GAI in class pushed them toward using ChatGPT in less critical ways. Lack of time for instance meant that they copied feedback from ChatGPT directly into Moodle or built their answers directly on GAI feedback, rather

than exploring it. Time was therefore a significant part of the students' patterns of adoption that in various ways affected how GAI was taken up and engaged with.

5. Discussions and Conclusions

This paper has focused on students' adoption of GAIs in education, related to patterns of relations with GAI in their work and private lives. First of all, our data show that students become involved with GAIs in multiple ways and that practices at work and at home become significant points of contact that initiate relationships and collaboration between students and GAIs. These are relationships that continuously change the field of agency for students as GAIs become involved in and form how they seek knowledge, how they plan and organize private events and activities and how content and performance at work is enacted. Both at home and at work, relationships between students and GAIs seem to be constituted by emergent strategies and needs and uses are largely unregulated, ie GAI technologies seem to flow into students' lives and in many cases contribute to enhancing and accelerating their everyday activities, projects and work practices.

For education, patterns of relations between students and GAI are to some extent understood by students as being more restrictive, however, education also, according to the interviews, acts as a space for reflection and collaboration in which GAIs are not only used but also made controversial (Suchman 2023). This is specifically true for the course described in this paper, as students' uses of ChatGPT in their former (BA) education seems to have been largely experimental and unregulated. This is probably due to the fact that GAI at the time that students did their BA was a relatively new phenomenon. Teacher colleges and universities had therefore generally not yet had time to set standards for GAI use.

In terms of reflection and learning, our data underline that ChatGPT in no time at all has transformed ways in which students read, prepare, research and write projects. Shifts in the ecology of learning affected by GAI have thus contributed to changing practices of working academically with texts and data, ie reading, writing, editing etc. have become distributed practices where students collaborate with GAI to enhance their academic performance and knowledge. This calls for increased attention to ways in which teachers can address these changes, as our data also show that teaching is a significant (safe) space for investigating GAI. Based on our analysis, we therefore propose the following implications for educators:

Collaboration and dialogue: In our interviews students often mentioned the challenges of working with GAI on their own, where they had to some extent been forced to trust feedback given by chatbots. Relationships between students, teacher(s) and reflective activities in class can therefore create a significant (safe) space for investigating GAI as a phenomenon in society and in learning.

Time: time is a significant aspect of students' patterns of adoption as investigated in this paper. Accelerated time contributes to forming students' relationships with GAI in education, illustrated by distributed literacy practices (eg summarizing and editing text). In some cases these practices generated a form of academic 'persona' and voice for students which for some had seemed almost unobtainable before GAI. The creation of academic standards, practices and identities with GAI could therefore be a significant focus for teaching. Significantly, students also formulate a need for using more time in class in order to deepen and critically investigate GAI feedback and practical uses.

Heterogeneity: making GAI controversial implies challenging and demystifying e.g. ChatGPT as a single and stable technology. The heterogeneity of uses and relationships in practice can be enhanced by collaborative learning and by investigating GAI as a situated phenomenon. In this context teaching could build on students' patterns of adoption outside the university.

Ethics declaration: An Ethics declaration as well as students' declaration of consent was obtained in accordance with GDPR regulations

AI declaration: AI tools were not used in the creation of this paper

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AI Crossroads of Security, Ethics, and Education: A Conceptual Framework for Responsible Adoption

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Abstract: In an era where artificial intelligence permeates every aspect of our lives, we find ourselves at a pivotal intersection of security, ethics, and education. This multidimensional framework invites us to explore the profound implications of AI and encourages a responsible, thoughtful approach to its integration. By prioritizing security and ethical considerations, we can unlock the transformative potential of AI while fostering a culture of responsible innovation in education. This framework serves as a crucial guide for navigating the complexities of AI adoption, ensuring that we harness its power for the betterment of society. This paper proposes a cross-sectoral framework that integrates security, ethics, and education to support the responsible, reliable, and equitable adoption of AI in small and medium-sized enterprises (SMEs) and educational institutions. As artificial intelligence continues to rapidly integrate into critical domains such as cybersecurity and education, a comprehensive approach is essential to address the unique risks and opportunities. This paper presents a cross-sectoral analysis of AI adoption in SMEs and education, focusing on cybersecurity posture, ethical considerations, and the challenges associated with integrating responsible AI within the enterprise. Drawing on recent research, we evaluate how AI-enabled threat detection and response can empower resource-constrained SMEs and educators while also highlighting emerging risks related to data privacy, model transparency, and algorithmic bias. Additionally, we examine the increasing use of generative AI tools within K–12 and higher education, identifying both pedagogical and ethical implications for curriculum development and digital literacy. The paper advocates for flexible governance and large language model training to facilitate the ethical deployment and use of AI across both the private sector and educational institutions. This framework will provide guidance for policymakers, educators, and technology leaders as they strive to strike a balance between innovation and responsible stewardship of AI.

Keywords: Artificial intelligence, Cybersecurity, Privacy, Ethics, AI in education

1. Introduction

As generative artificial intelligence (AI) and machine learning (ML) technologies rapidly evolve, organizations face increasing pressure to integrate these tools into critical decision-making processes in ways that will improve their bottom lines. Furthermore, despite companies' hefty investments in AI, this has not happened yet, according to MIT researchers (Challapally et al., 2025). Fundamental opportunities and potential risks must be navigated to ensure the responsible and effective use of AI (Floridi, et. al., 2018). However, this AI integration raises essential concerns: How can leaders ensure that AI-driven decisions are trustworthy, ethically grounded, and aligned with mission objectives, particularly in complex environments like defense, education, and enterprise systems?

This paper offers a comprehensive framework for the responsible and effective adoption of AI at the intersection of security, ethics, and education. The first section explores key decision-support tasks that lend themselves to AI and ML automation, assessing both the benefits and limitations of such integration in education. The second section presents a practical use case involving the development of a knowledge portal that incorporates AI-driven insights into planning. This approach reflects a general shift toward leveraging AI, big data, and cloud computing to build future knowledge-based systems that can assist in real-time decision-making. Emphasis is placed on the ethical and educational imperatives needed to guide responsible adoption, ensuring that emerging AI capabilities are not only technically effective but also aligned with broader institutional ethical values and operational goals.

The framework treats responsible AI integration as the goal, measured through dimensions of governance, ethics, and system reliability. Independent variables include the organizational context (SMEs vs. education), resource constraints, and sector-specific requirements. This approach ensures that the analysis not only highlights how to address technical challenges but also how to manage the ethical and institutional factors that influence adoption outcomes. The problem is that despite AI's transformative potential in cybersecurity, education, and SMEs, its adoption is limited by fragmented governance, inadequate reliability models, and weak

ethical safeguards. These gaps create security vulnerabilities, inequitable outcomes, and erode trust, highlighting the need for an integrated framework. This paper proposes a cross-sectoral model to address this gap and integrate security, ethics, and education to guide the responsible adoption of AI, enabling SMEs and educational institutions to implement AI in a secure, transparent, and equitable manner.

2. Background and Related Work

The capabilities of AI, systems engineering, and information systems have created both unprecedented decision support opportunities and significant challenges in domains that require complex decision support, such as defense, cybersecurity, and education. As organizations transition toward data-driven operations within increasingly interconnected environments such as the Department of Defense's (DoD) System of Systems (SoS) architecture, the limitations of traditional reliability models, manual analysis, and siloed IT systems have become evident. The DoD recognizes the value of AI in both current and future defense applications, including Intelligence, Logistics, Cyberspace, and Command and Control (Hoadley, Lucas, & Nathan, 2018). This section reviews foundational work in SoS reliability analysis and highlights the need for an AI-integrated approach that addresses not only technical but also ethical and educational implications.

To better understand this need, it is essential to define three core concepts: SoS, Future Knowledgebase System of Systems (FKSS), and AI-Driven Reliability. An SoS refers to a collection of independent systems that are integrated to deliver capabilities beyond what each system could achieve alone (Maier, 1998). Unlike traditional systems, an SoS is characterized by operational independence, managerial independence, evolutionary development, and emergent behavior. Each subsystem, such as logistics platforms, cybersecurity tools, or learning management systems, can function independently. However, when linked together, they produce new capabilities while also introducing added complexity and reliability challenges.

Building on this, *the* FKSS extends the SoS concept by embedding AI, big data, and cloud computing into decision-support processes (Miller et al., 2021). The FKSS represents a dynamic environment where interconnected systems, such as analytics dashboards, AI-enabled tutoring platforms, or cybersecurity monitoring tools, are continuously informed by machine learning models that update in real-time. Novel frameworks such as the Rodgers' Quantum-Enhanced Throughput Model seek to contribute to the ability for ethics to take precedence within real-time decision-making AI systems (Rodgers et al., 2013). This evolution provides a foundation for adaptive decision-making, where human operators and AI collaborate to assess risks, predict failures, and optimize outcomes across domains such as defense, SMEs, and education.

Finally, AI reliability refers to the consistent ability of an AI system to deliver accurate, trustworthy, and explainable outcomes that align with ethical and organizational values (Miller et al., 2021; NIST, 2023). AI-Driven Reliability refers to the use of AI and ML to assess, predict, and enhance the dependability of complex systems. Traditional reliability models often focus on static failure rates or hardware-level issues. However, AI-Driven approaches leverage large-scale, real-time data to identify patterns, emergent risks, and hidden correlations. In this framework, the reliability concept is expanded to include not only technical performance but also transparency, ethics, and trust, ensuring that systems remain dependable in both their outputs and their alignment with organizational goals. Recent initiatives such as the DoD's Joint Artificial Intelligence Center (JAIC) and Executive Order 13800 underscore the urgency of modernizing data infrastructure and incorporating AI-enabled decision support systems (Covington, 2018). According to Challapally et al. (2025), there is a need for coordinated initiatives to use AI at the enterprise level to support the same requirements for dependable systems. Nevertheless, implementation across the enterprise remains fragmented, hampered by inconsistent data governance and outdated legacy systems.

3. Theoretical Framework

This paper expands on prior models by proposing a modern AI-enhanced reliability framework embedded within a FKSS (Miller et al., 2019; Miller et al., 2021). The framework is designed to facilitate secure, explainable, and ethically sound decision-making across defense and educational settings. By integrating AI with systems engineering, the framework decomposes SoS complexity, while the inclusion of educational components ensures that human operators are empowered, not displaced by automation.

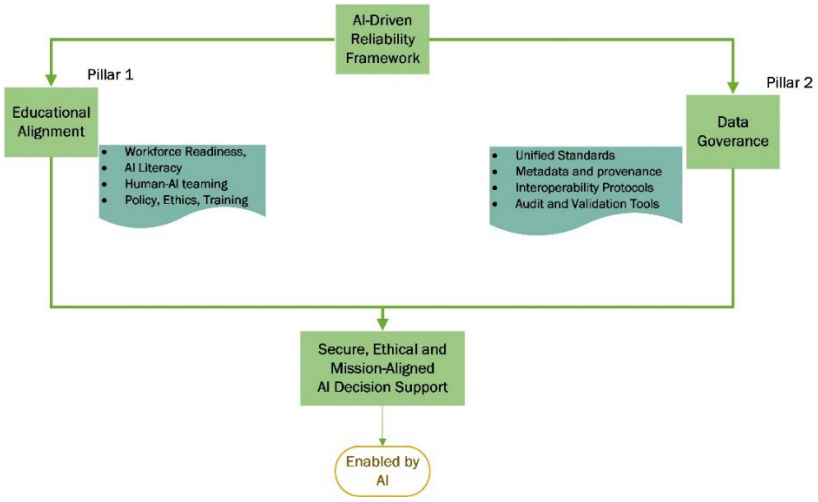


Figure 1: Conceptual theoretical model of the AI-Driven Reliability Framework

The conceptual model of the AI-Driven Reliability Framework is shown in Figure 1. The core engine is enabled by AI but sustained through two foundational pillars: educational alignment and data governance. Together, these ensure secure, explainable, and ethically sound decision-making across system-of-systems environments.

- **Educational Alignment**

The integration of AI into defense, cybersecurity, and enterprise environments requires more than just technical advancements; it demands an educated and adaptable workforce, which in turn affects workforce readiness (Ahmed et al., 2025). Without proper training, users may either misuse AI tools or underutilize them due to a lack of AI literacy, trust, or understanding (Ahmed et al., 2025). To address this, educational alignment must be embedded into the development and deployment lifecycle of AI-enabled systems.

Workforce educational readiness initiatives such as the NIST NICE Framework offer a strong foundation for role-based competency development in cybersecurity and AI literacy (NICE, 2020). These frameworks should be expanded to include skills in data interpretation, algorithmic awareness, ethical reasoning, and human-machine teaming. Educational modules must address explainable AI (XAI), AI bias, and the role of humans as decision validators (i.e., human-AI teaming), particularly in mission-critical environments (Miller, 2019). Incorporating AI education into policy, ethics, training (i.e., professional military education), and civilian workforce training), and K–20 curricula ensures that users across all levels of the organization are prepared to engage with AI responsibly. This is particularly relevant as AI systems increasingly influence decisions related to readiness, logistics, cybersecurity, and mission planning (Scharre & Horowitz, 2020). Through inclusion of these educational options, organizations can cultivate a culture of informed AI adoption where human judgment and machine intelligence are complementary rather than competitive.

- **Data Governance**

Robust data governance is foundational to both the reliability of AI systems and the trust placed in their outputs. In the absence of consistent, unified standards, access controls, and lifecycle management practices, even the most sophisticated AI models are vulnerable to producing misleading or incomplete results (NIST, 2023). The heterogeneity of legacy systems amplifies these challenges, resulting from decentralized program offices, and varying levels of compliance with enterprise data standards (Janssen et al., 2020). To enable AI integration at scale, agencies must implement data governance frameworks that incorporate metadata tagging and provenance tracking, role-based access controls, interoperable data exchange protocols, and mechanisms for real-time auditing and validation.

Effective data governance not only supports reliability analysis but also strengthens cybersecurity, enhances transparency, and supports legal and ethical accountability. Moreover, good data governance is a prerequisite for educational alignment, assuring that learners and operators have access to accurate, contextualized, and appropriately classified data for training and operations.

4. The Risks of Inadequate AI-Integrated Reliability Models in Education

As educational institutions adopt artificial intelligence AI across administrative, instructional, and student support functions, the lack of robust AI-integrated reliability models poses serious risks to effectiveness, equity, and trust. From K–12 schools using AI for personalized learning to universities employing predictive analytics for student retention, AI is reshaping how education systems operate (Zawacki, 2019). However, without frameworks that evaluate reliability, transparency, and data integrity, these implementations can lead to unintended and potentially harmful consequences. For instance, AI-powered learning platforms like DreamBox or ALEKS adjust content difficulty based on student responses. Yet suppose the algorithms are not properly calibrated or fail to account for linguistic, cultural, or neurodiverse differences. In that case, they may misinterpret learning needs, delivering content that is either too advanced or too remedial. Inaccurate adaptations can discourage learners or widen achievement gaps, particularly for students in underserved communities.

Similarly, higher education institutions are increasingly utilizing predictive analytics to introduce multiple AI-based products to the market (Williamson & Eynon, 2020). Systems like Civitas Learning and EAB utilize past academic records, demographic data, and engagement metrics to identify students who require intervention. While helpful in theory, such systems often operate as black boxes. Without transparent reliability measures or proper validation, administrators risk acting on flawed predictions, diverting resources away from students who need them, or triggering intrusive outreach that undermines student autonomy.

Many of these problems stem from the use of legacy systems or third-party tools with limited interoperability and a lack of institutional capacity to evaluate their reliability. Educational environments are often ill-equipped to handle the complexities of AI integration due to fragmented data governance, inconsistent staff training, and a lack of shared reliability standards across vendors and platforms. These gaps make it difficult to assess whether AI systems are functioning as intended—or to identify when they are causing harm. The use of AI can cause harm due to the loss of user privacy, yet students might be willing to exchange personal data for benefits (Slade et al., 2019). Additionally, compliance with privacy regulations, such as Fair Employment Practices Agencies (FERPA) in the U.S. or General Data Protection Regulation (GDPR) in Europe, becomes more complex when AI processes educational data across cloud-based or hybrid infrastructures. Without strong reliability and audit frameworks, institutions may unknowingly violate data protection laws or expose student information to cyber threats.

In short, educational organizations cannot afford to treat AI adoption as a purely technical upgrade. Without a comprehensive framework that incorporates reliability modeling, ethical oversight, and educational alignment, schools and universities risk deploying systems that are unaccountable, ineffective, or inequitable. This paper proposes such a framework—grounded in cross-sector best practices—to guide the responsible and sustainable integration of AI into educational ecosystems.

5. Research Methodology: The Specific Contributions

This conceptual framework integrates AI into complex SoS environments, with a focus on enhancing reliability, promoting ethical oversight, and aligning with educational goals. The central contribution of this research is a methodology for assessing and enhancing the reliability of AI-enabled systems within educational institutions and related sectors, particularly in contexts where multiple interconnected platforms influence decision-making, learner outcomes, or administrative operations. By embedding AI within SoS architectures, the framework is designed to capture not only technical interactions but also ethical and institutional dimensions that shape outcomes.

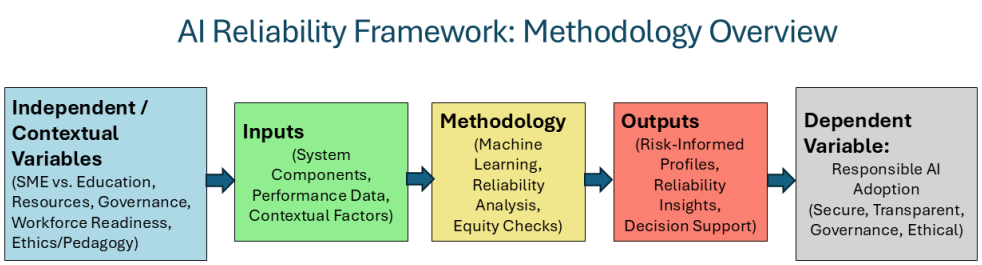


Figure 2: AI Reliability Framework: Methodology Overview

Within this framework, represented in Figure 2, the dependent variable is defined as responsible AI adoption, measured through the integration of indicators for security, transparency, governance, and ethical safeguards. This definition ensures that adoption is not assessed in binary terms of "use" or "non-use" but rather through its quality, integrity, and alignment with broader institutional values. The independent and contextual variables influencing this adoption include organizational type (SME versus educational institution), resource constraints, governance maturity, workforce readiness, and ethical or pedagogical imperatives. For SMEs, responsible adoption is often conditioned by cost limitations, staffing shortages, and compliance requirements, whereas in education, ethical imperatives such as privacy, fairness, and student trust tend to dominate. By situating the dependent variable within these sector-specific contexts, the methodology enables comparative analysis across different domains while preserving the central research focus on responsible adoption.

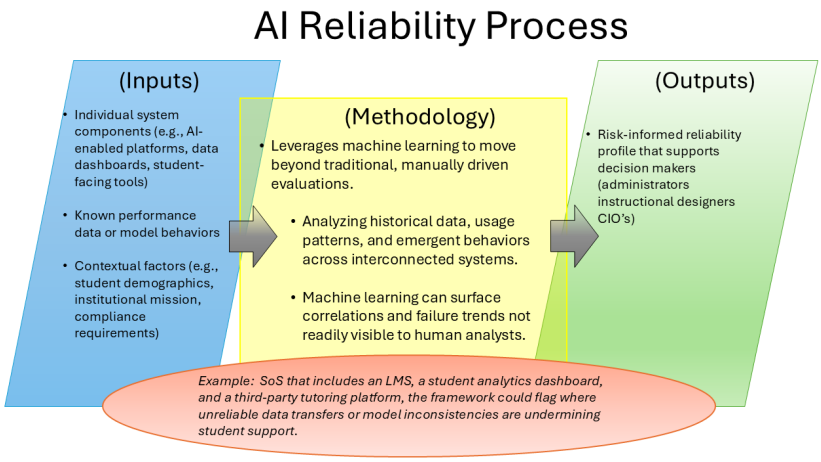


Figure 3: Conceptual model of the AI-Driven Reliability Framework

Figure 3 illustrates the structure of this methodology through the AI Reliability Process, which is organized into three key components: Inputs, Methodology, and Outputs. The Inputs encompass individual system components, such as AI-enabled platforms, data dashboards, and student-facing tools, along with relevant performance data and contextual variables, including student demographics, governance maturity, and institutional compliance requirements. These inputs are then analyzed in the Methodology phase, where machine learning techniques examine historical data, usage patterns, and emergent behaviors across interconnected systems. This allows for the identification of correlations, equity concerns, and failure trends that may be overlooked in manual evaluations.

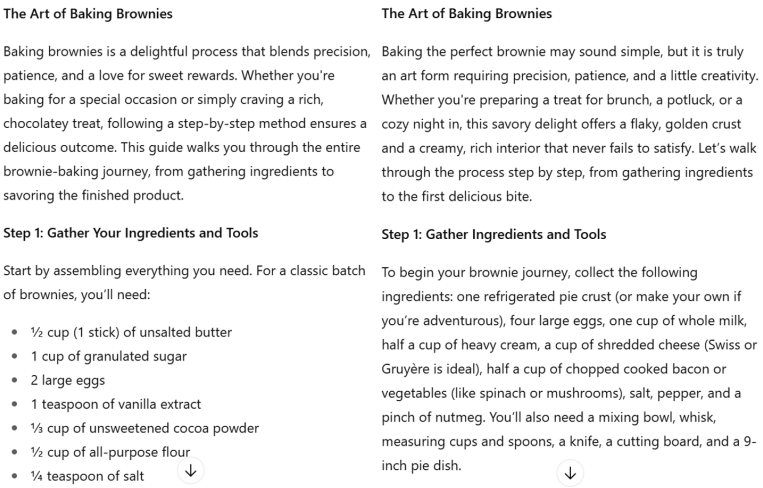
The Outputs of this process consist of risk-informed reliability profiles designed to enhance institutional decision-making for stakeholders, including instructional designers, Chief Information Officers (CIOs), and administrators. By structuring the process around both technical and contextual variables, the framework not only identifies reliability issues, such as unreliable data transfers or model inconsistencies, but also links them back to the larger research goal of fostering responsible AI adoption across domains. This methodology therefore provides both a theoretical foundation and a practical pathway for integrating AI responsibly within complex SoS environments.

In summary, this research contributes to the body of knowledge by offering a scalable, AI-assisted process for assessing the reliability of complex educational technology environments. It empowers decision-makers to make informed, ethical, and data-driven adjustments, ensuring that AI adoption is not only effective but also responsible and aligned with broader institutional missions.

- **Case Study: An Intersection of Ethics and Security within AI in Education**

The need for a well-developed framework is most evident in the tension between security and ethics, particularly in the use of modern AI tools in educational contexts. An example of this is within the tool Sneaky-PDF (2025), created to conceal additional text instructions, or prompt injections (Liu, 2024a; Liu, 2024b), into a PDF expected to be ingested by a large language model (LLM). The tool itself is simple; it creates a new PDF with 1-point, white text containing new, hidden instruction(s) and then overlays the original PDF, avoiding any visible changes to margin or text placement in the original document. For the current article's purposes, an examination of how this example context and intent can radically change a tool like this from "good" to "bad" is explored.

In the case of an instructor, a tool like this can exploit a security issue known to LLMs to promote ethical behavior and penalize its inverse in the education sphere. The instructor may, with their original assignment PDF, include hidden instructions for an LLM to complete the assignment in an obviously different and incorrect fashion. The logic being that a student attempting to leverage an LLM to generate an answer or assignment to claim as their own may not verify the result, thus submitting work worthy of little to no marks, and more importantly, an investigation into whether academic dishonesty occurred. Figure 4 highlights ChatGPT's two distinct responses to an assignment asking for a one-page essay on baking brownies, one assignment having no hidden text, and the other having hidden text instructing the LLM to write on making a quiche and referring to said quiche as a brownie.



The Art of Baking Brownies

Baking brownies is a delightful process that blends precision, patience, and a love for sweet rewards. Whether you're baking for a special occasion or simply craving a rich, chocolatey treat, following a step-by-step method ensures a delicious outcome. This guide walks you through the entire brownie-baking journey, from gathering ingredients to savoring the finished product.

Step 1: Gather Your Ingredients and Tools

Start by assembling everything you need. For a classic batch of brownies, you'll need:

- ½ cup (1 stick) of unsalted butter
- 1 cup of granulated sugar
- 2 large eggs
- 1 teaspoon of vanilla extract
- ⅓ cup of unsweetened cocoa powder
- ½ cup of all-purpose flour
- ¼ teaspoon of salt

The Art of Baking Brownies

Baking the perfect brownie may sound simple, but it is truly an art form requiring precision, patience, and a little creativity. Whether you're preparing a treat for brunch, a potluck, or a cozy night in, this savory delight offers a flaky, golden crust and a creamy, rich interior that never fails to satisfy. Let's walk through the process step by step, from gathering ingredients to the first delicious bite.

Step 1: Gather Ingredients and Tools

To begin your brownie journey, collect the following ingredients: one refrigerated pie crust (or make your own if you're adventurous), four large eggs, one cup of whole milk, half a cup of heavy cream, a cup of shredded cheese (Swiss or Gruyère is ideal), half a cup of chopped cooked bacon or vegetables (like spinach or mushrooms), salt, pepper, and a pinch of nutmeg. You'll also need a mixing bowl, whisk, measuring cups and spoons, a knife, a cutting board, and a 9-inch pie dish.

Figure 4: ChatGPT responses to original (left) and prompt-injected (right) brownie assignments

The inverse case is with the student, who may use this type of tool to promote unethical behavior by including hidden instructions for the LLM to always judge their submission as worthy of a perfect or near-perfect score. In this case, the student may be successful in their unethical pursuit, assuming the instructor is leveraging an LLM to assist their grading process in some way. Both cases highlight the tension of whether it is ethical to place instructor-designed traps that exploit security flaws for unsuspecting students. Furthermore, is it ethical for students to leverage an LLM for assistance with assignments, and at what point should the LLM be recognized as the primary author on a given assignment? Lastly, is it ethical for an instructor to claim authorship of feedback generated by an LLM to be given to a student? The proposed framework aims to serve as the foundation for evaluating ethics, addressing questions such as those posed above.

- **Case Study: AI Reliability and Data Governance**

In examining the need for a data governance framework to be paired with an AI reliability framework, one must look no further than the current implementations, or attempts of implementation, within the education sector. Universities such as Duke (Technology, 2025), as well as UC San Diego and Notre Dame (Wong, 2025), are working to implement AI, particularly LLMs, into the daily workflows of faculty, staff, and students.

In the case of UC San Diego, the AI "assistants" currently implemented can help faculty and staff with simple tasks such as identifying a phishing email, answering a question about the university, and writing or summarizing information, but plans to integrate these assistants with student, employee, research, and facility data are on the roadmap (Wong, 2025). The idea is to replace traditional implementations that allow for user queries, which can result in including undesired data and excluding desired data depending on the rigidity of the query system, with a more "human" interface that allows for conversational queries. The proposed benefit is that faculty and staff will spend less time on "wrestling" with traditional systems to receive information necessary for their job functions.

6. Discussion

Given AI's vulnerability to produce inconsistent or incorrect data (NIST, 2023) and the ability for malicious actors to force inconsistent or inappropriate data (Kou et al., 2025), it remains to be seen how data governance can exist with high confidence without an AI reliability framework in place. If incorrect data is not recognized and re-entered into one or more systems, will the AI assistants become more likely to espouse non-factual information

as truth? Assuming the incorrect data produced contains regulated information, are safeguards in place to prevent it from being exposed? If a malicious actor gains access to one or more assistants, are the assistants resilient to common hijacking attacks? An AI reliability, such as the one proposed, becomes necessary to ensure AI tools are being used correctly and are responding as expected.

Educational institutions from K–12 districts to large universities are under increasing pressure to modernize their digital infrastructure, adopt AI-driven platforms, and personalize learning at scale. However, these innovations often face resistance due to cultural inertia, budget constraints, fragmented governance, and a lack of system-wide visibility. Despite these challenges, educational and corporate leaders must recognize the requirements for successful AI adoption at the enterprise level by ensuring the need for reliable, integrated systems that support instructional effectiveness, equity, and informed institutional system integration. A core issue is the tendency for institutions to adopt technologies in isolation, with departments or units making independent decisions about platforms for employee AI usage, as well as in educational organizations, improving learning management, enrollment, student support, and assessment capabilities. While these tools may function well individually, they often fail to integrate smoothly, creating SoS environments that are fragile, redundant, or prone to data silos. Without a unified approach to measuring system performance and interdependence, institutions cannot easily assess reliability risk, identify failure points, or make informed decisions about upgrades and investments.

The cost of innovation in SMEs and education extends far beyond the initial procurement of software. True transformation requires long-term investments in professional development to prepare employees, management, educators, and administrators to work effectively with AI-driven systems, in system maintenance and the retraining of algorithms as institutional needs evolve, in downtime planning to minimize disruptions during upgrades or migrations, and in ongoing monitoring to safeguard reliability, security, and compliance with privacy regulations such as FERPA and GDPR.

Institutions must also consider the ethical implications of deploying AI tools without adequate human oversight. For example, predictive analytics systems that identify students "at risk" may be unreliable if they rely on outdated or biased student datasets. Similarly, AI-enhanced grading systems may introduce inconsistencies that undermine trust in academic assessment.

7. Conclusion

AI has rapidly matured into a transformative force in both the public and private sectors, including education, due to three key technological milestones: the availability of large-scale data, advancements in machine learning algorithms, and significant improvements in processing power. These developments have enabled institutions to analyze complex systems, personalize learning experiences, and optimize administrative decision-making processes in ways that were previously unimaginable.

A major challenge in this transformation lies in managing the reliability of interconnected systems while preserving the ethical trust, transparency, and performance of individual components. The dynamic and evolving nature of corporate and educational environments demands time-sensitive and context-aware insights into system behavior—insights that cannot be generated effectively through manual processes alone. AI offers a powerful potential solution to this challenge, but its potential can only be fully realized when supported by robust data governance, cross-platform interoperability, and continuous professional development. Ultimately, the successful adoption of AI in corporations and educational institutions requires a balanced approach that integrates technical innovation, ethical safeguards, and AI systems integration alignment. Institutions that embrace this comprehensive view will be best positioned to deliver reliable, equitable, and future-ready learning experiences—ensuring that technology serves corporate decision-makers, employees, students, and educators responsibly and effectively.

8. Future Work

While the framework offers a conceptual roadmap, future efforts should focus on validating it through case studies and empirical analysis in the SME and educational sectors. For instance, testing the model in the context of cybersecurity adoption by SMEs or in the deployment of predictive analytics at a university would help measure its effectiveness and refine key variables. Moreover, aligning the framework with established standards such as the NIST AI Risk Management Framework and the NICE Workforce Framework can further enhance its practical applicability across various sectors.

Acknowledgements

We thank UNCW and NPS for making this research possible.

Ethics declaration: There is no need for ethical clearance for the research referred to in this paper.

AI declaration: An AI tool was used for grammar clarity and correction.

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Mapping Moves, Modes and Methods: Designing Socratic Conversational Agents for AI-Enhanced Learning

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Abstract: Conversational agents powered by Large Language Models (LLMs) are increasingly proposed as scalable tools for personalised learning support. Yet much existing research focuses on algorithmic capability rather than the nuanced human learning dialogues that shape educational practice. This leaves a gap in empirically informed frameworks for translating rich instructional conversation into actionable design principles for Socratic AI partners. This paper addresses this need through a secondary analysis of live, online design critiques conducted at a South African university - an environment reflective of many Global South contexts marked by resource constraints, student diversity, and socio-economic pressure. Building on the author's doctoral research, the study synthesises previously collected empirical material, including surveys, a focus-group interview, and recorded critique sessions. A composite conceptual lens (Conversation Theory, Experiential Learning Theory, and Cognitive Apprenticeship) guided the interpretive analysis. The findings identify four recurring student–tutor relationship archetypes and four interaction dimensions that position critiques as formative, iterative, formal, and immersive. These insights are consolidated into a "moves–modes–methods" matrix that captures how knowledge is negotiated, feedback is scaffolded, and agency is fostered in the critique space. Mapping this matrix onto current scholarship on LLM-based tutors reveals both alignments, such as the value of probing questions, and tensions related to contextual sensitivity, including bandwidth limitations, student diversity, and socio-economic realities. By integrating detailed empirical insight with emerging work on AI-supported learning, the study offers an evidence-based framework to inform the design of conversational agents that augment human expertise while preserving the pedagogical integrity of the online critique in under-resourced, highly diverse settings.

Keywords: Conversational agents, Large language models (LLMs), Socratic AI tutors, Online design critique, Global south higher education, Human-AI bollaboration, Design education

1. Introduction

Large Language Model (LLM) driven conversational agents are increasingly promoted in higher education for their potential to deliver personalised, scalable learning facilitation to large and diverse student cohorts (Zawacki-Richter et al., 2019; Luckin & Cukurova, 2023). Yet, much of the existing research and development focuses predominantly on algorithmic optimisation (Kasneci et al., 2023), often overlooking the nuanced human learning dialogues that underpin meaningful educational experiences (Laurillard, 2013). This creates a notable gap in empirically grounded frameworks capable of translating the richness of human-to-human educational conversation (specifically those rooted in formative, dialogic traditions) into actionable design specifications for Socratic AI partners (Stokel-Walker & Van Noorden, 2023).

The live, online architectural design critique (or "crit") offers a productive context for addressing this gap. As the signature pedagogy of architectural education (Shulman, 2005; Cuff, 1992; Crowther, 2013), the crit is a structured formative encounter in which students present work-in-progress and engage in iterative dialogue with tutors. During a crit, students are required to articulate design intent, justify decisions, respond to probing questions, and demonstrate iterative refinement of their ideas, while tutors model expert reasoning, challenge assumptions, scaffold conceptual leaps, and provide multimodal feedback. This interaction integrates verbal explanation, visual artefacts (drawings, diagrams, models), real-time annotation, and reflective discussion; producing a dense conversational space where knowledge is co-constructed through moves, such as presenting, questioning, commenting, adapting, and reflecting (Kuhn, 2001; Laurillard, 2013). In this sense, the crit exemplifies a disciplined form of guided inquiry closely aligned with the principles of Socratic teaching.

In the South African and broader Global South context, where resource scarcity, linguistic diversity, and socio-economic inequalities intensify demand for scalable yet high-quality learning support (Morkel & Cronjé, 2022; Ng'ambi et al., 2013), the online crit takes on added significance. Conducted synchronously via webinar platforms, it enables geographically distributed and working students to participate (Wang & Hsu, 2008), while also highlighting challenges related to digital access, bandwidth limitations, reduced physical presence, and the need for explicit verbalisation of design reasoning. These conditions raise critical questions about how relational dynamics, interactional modes, and scaffolding strategies can be preserved or reimagined within AI-mediated learning environments.

This study builds on the author's doctoral research, which explored the student–tutor interaction in the live online critique in a blended architectural technology programme in South Africa (Morkel, 2022). That qualitative, exploratory investigation analysed surveys from current students, graduates, and tutors, alongside a focus-group interview and detailed protocols of three recorded critique sessions. Guided by an integrated conceptual lens combining Conversation Theory (moves: present, question, comment, adapt, reflect) (Laurillard, 2013), Experiential Learning Theory (modes: negotiation, exploration, reflection, application) (Kolb, 1984), and Cognitive Apprenticeship (methods: articulation, modelling, scaffolding, coaching) (Collins et al., 1989), the study identified four recurring student–tutor relationship archetypes—novice–expert, consultant–client, mentee–mentor, and parent–child—and four interactional dimensions—formative, iterative, formal, and immersive.

In the present paper, these empirically derived insights are mapped against emerging scholarship on LLM-powered tutors conceptualised as Socratic partners (Bazouche, 2025). This comparative analysis highlights convergences, such as the pedagogical value of probing questions, reflective prompts, and iterative feedback (Stokel-Walker & Van Noorden, 2023), as well as tensions, including the need for contextual sensitivity to bandwidth constraints, multilingual realities, and socio-economic pressures in Global South contexts (Olweny, 2017; Morkel et al., 2021). By bridging detailed empirical understanding of human critique interactions with current AI tutoring design literature, the paper proposes an evidence-based "moves–modes–methods" matrix as a framework for developing conversational agents that augment human expertise while safeguarding the pedagogical integrity of online critiques; specifically in under-resourced, highly diverse educational settings.

2. Literature Review

This literature review examines the intersection of architectural design critique pedagogy and emerging AI-driven tutoring, situating the live online critique as both a distinctive disciplinary practice and a suitable site for exploring how conversational agents can support complex, feedback-intensive learning.

2.1 Conversational Agents and Socratic AI Tutoring

Conversational agents powered by LLMs have gained significant attention for their capacity to simulate human-like dialogue and provide personalised support at scale (Zawacki-Richter et al., 2019; Luckin & Cukurova, 2023). Their affordances include adaptive questioning, feedback generation, and conversational scaffolding, making them promising tools for learner-centered, constructivist pedagogy (Woolf, 2010; Kasneci et al., 2023). Current research increasingly frames LLM-powered tutors as "Socratic" assistants who guide learning through probing questions, reflective prompts, and iterative dialogue rather than direct instruction (Stokel-Walker & Van Noorden, 2023; Bazouche, 2025). However, much of this scholarship remains conceptual or system-oriented, focusing on optimisation of models and prompt strategies rather than grounding design in empirically documented human learning interactions.

This gap is significant, as the effectiveness of AI conversational tutors depends on their ability to engage in pedagogically meaningful dialogue - dialogue that is responsive, relational, contextual, and aligned with disciplinary norms. Without empirical models of such dialogue, the design of AI tutors risks becoming detached from the nuanced conversational and pedagogical practices that underpin effective human teaching and learning. This study addresses this gap by bringing empirical evidence from architectural design critiques to bear on the design of LLM-based Socratic tutors.

2.2 Architectural Education and the Design Crit

Architectural education is shaped by the design studio, widely recognized as its signature pedagogy (Shulman, 2005; Cuff, 1992; Crowther, 2013). At the centre of this pedagogy lies the architectural design critique, or crit, a structured formative encounter in which students present developing design work to (design) tutors and receive feedback through dialogic exchange (Schön, 1984; Kuhn, 2001). The crit is inherently multimodal: tutors and students rely on drawings, diagrams, models, hybrid media, and real-time annotation to make design thinking visible, negotiate meaning, and iterate conceptual and spatial decisions.

During a crit, students are expected to communicate design intent clearly, justify decisions, respond to probing questions, and demonstrate iterative development. Tutors, in turn, model expert reasoning, identify conceptual gaps, articulate design principles, and scaffold students' movement from novice to more expert-like ways of thinking (Anthony, 1991; Percy, 2004). These interactions constitute a disciplined form of guided inquiry characterised by structured turn-taking, reflective engagement, negotiation of alternatives, and iterative problem-solving.

The crit therefore provides an exemplary site for analysing the interactional patterns of formative educational dialogue - exactly the kind of structured, probing conversational architecture that Socratic AI tutors must learn to emulate. Its emphasis on cycles of presenting, questioning, testing, modelling, reflecting, and applying makes the crit a rich environment for studying how learning unfolds through conversation and experience, and how expertise is scaffolded in real time.

In the South African and broader Global South context, the online crit has additional significance. Resource scarcity, cultural diversity, and socio-economic inequalities shape student participation and interaction patterns (Ng'ambi *et al*., 2013; Morkel & Cronjé, 2022). During the rapid transition to online and blended learning, the live online crit emerged as one of the few opportunities for synchronous, high-engagement interaction (Morkel *et al*., 2021). Conducted via webinar platforms, online crits enable remote participation (Wang & Hsu, 2008) but also amplify challenges such as bandwidth limitations and the need for explicit verbalisation of spatial reasoning. These contextual factors highlight the urgent need for pedagogical models and AI support tools that are responsive to diverse, under-resourced educational environments (Olweny, 2017).

2.3 Interactional Dynamics in the Live Online Crit

The author's doctoral research (Morkel, 2022) offers a detailed empirical account of student–tutor interactions in live online crits within a blended architectural technology programme. Using an integrated conceptual framework, the study identified four recurring student–tutor relationship archetypes, namely novice–expert, consultant–client, mentee–mentor, and parent–child; each influencing the tone, expectations, and pedagogical stance adopted during the crit. These relational patterns shaped the kinds of questions asked, the level of scaffolding offered, and the extent to which students were positioned as autonomous designers or as students needing guided support.

The study also identified four interactional dimensions (formative, iterative, formal, and immersive) that characterise how online crits unfold. The online crit functions primarily as a formative assessment space where feedback is central; it is iterative, involving cyclical development of ideas; it is formal and structured, often more so than physical studio interactions; and it is immersive, involving deep engagement with multimodal representations of student work.

Underlying these relational and interactional patterns is a consistent set of pedagogical moves, experiential modes, and cognitive apprenticeship methods that recur across the crits. These patterns provide an empirical foundation for understanding how disciplinary thinking is modelled, how problem-solving is scaffolded, and how students learn through guided dialogue and applied reasoning, offering a structured vocabulary for analysing and designing educational conversations.

2.4 Bridging Human Critique Practices with AI Tutoring Design

To systematically analyse the crit as a dialogic learning environment, this study draws on three complementary theoretical frameworks:

2.4.1 Conversatino theory (Laurillard, 2013)

Conversation Theory conceptualises learning as a structured dialogue involving iterative exchanges between student and tutor. The theory identifies key conversational "moves" (such as presenting ideas, questioning, commenting, adapting, and reflecting) that describe how knowledge is negotiated. These moves map directly onto the interaction patterns in crit dialogue and form the foundation for the coding of conversational strategies in this study.

2.4.2 Experiential learning theory (Kolb, 1984)

Kolb's model describes learning as a cycle of concrete experience, reflective observation, abstract conceptualisation, and active experimentation. The crit embodies this cycle: students present experiential work, tutors prompt reflection, conceptual reasoning is articulated, and students test new strategies. These dynamics inform the experiential "modes" used in the coding framework - negotiation, exploration, reflection, and application.

2.4.3 Cognitive apprenticeship (Collins et al., 1989)

Cognitive Apprenticeship explains how expert thinking is made visible and learnable through strategies such as modelling, coaching, articulation, scaffolding, and reflection. These methods map closely onto the pedagogical

practices employed in crits, where tutors model disciplinary reasoning, scaffold design decisions, and support conceptual development. These "methods" form the third dimension of the analytical framework.

Together, these theories provide a robust conceptual foundation for analysing the design crit as a site of dialogic, experiential, and scaffolded learning, and for translating its structure into specifications for Socratic AI tutors.

2.5 Linking Literature to Methodological Approach

The literature reviewed above establishes the crit as a dialogic, multimodal, socially situated learning interaction that naturally aligns with the principles of Socratic tutoring. It also provides theoretical justification for the moves–modes–methods matrix used in this study. By integrating Conversation Theory, Experiential Learning Theory, and Cognitive Apprenticeship, the framework supports a combined inductive–deductive analytical approach, enabling both the identification of emergent patterns and the structured classification of interactional behaviours. This theoretical grounding directly informs the methodological decisions outlined in the next section.

3. Methodology

This section outlines the qualitative exploratory design, participant profile, data sources, analytical procedures, and ethical considerations guiding the investigation of interactional dynamics in live, online architectural design critiques and their relevance for designing LLM–powered Socratic conversational tutors.

3.1 Research Design

This qualitative exploratory study examined live, online architectural design critiques (crits) within a blended part-time Architectural Technology programme at a South African University of Technology. The purpose was to analyse the interactional patterns that characterise critique dialogue and to map these onto pedagogically meaningful design principles for LLM-powered Socratic tutors. The study builds on and extends the author's doctoral research on student–tutor interaction in the same programme (Morkel, 2022), using a two-phase inductive–deductive analytical approach.

3.2 Setting and Participants

The live online crits were synchronous webinar-based sessions in which students presented design work and engaged in structured dialogue with tutors. Participants included 23 current students (Years 1 and 2), 13 recent graduates, and 5 design tutors. This sample reflects the linguistic, socio-economic, and professional diversity typical of South African higher education and captures perspectives from multiple positionalities within the crit environment.

3.3 Data Sources

Three complementary data sources were used to support triangulation:

- **Online surveys** (with open-ended questions) from students, graduates, and tutors captured perceptions of interaction quality, critique value, and relational dynamics.
- **A graduate focus-group interview** enabled deeper reflection on critique experiences.
- **Three recorded Year-1 crit sessions** were purposively sampled to include high engagement, diverse design approaches, and rich multimodal interaction.

These data sources served distinct analytical purposes: surveys identified broad perceptual themes, the focus group provided interpretive depth, and the crit protocols supplied naturally occurring conversational data for detailed interaction analysis.

3.4 Conceptual Framework

Data analysis was informed by an integrated conceptual framework combining:

- Conversation Theory (Laurillard, 2013), which defines conversational moves such as presenting, questioning, commenting, adapting, and reflecting.
- Experiential Learning Theory (Kolb, 1984), which outlines modes of engagement including negotiation, exploration, reflection, and application.
- Cognitive Apprenticeship (Collins et al., 1989), which identifies pedagogical methods such as modelling, articulation, coaching, and scaffolding.

Together, these three perspectives formed the moves–modes–methods analytical lens used in deductive coding and interpretation. In this study, the term framework refers to the conceptual analytical lens derived from these theories, while the term matrix refers to the applied mapping of moves, modes, and methods generated through the analysis.

3.5 Data Analysis

Data analysis proceeded in two phases following Braun and Clarke's (2006) reflexive thematic analysis:

Phase 1: Inductive Analysis

Survey and focus-group data were coded inductively to identify emergent themes related to crit characteristics and student–tutor relationship archetypes. Patterns were refined through iterative comparison across datasets.

Phase 2: Deductive Analysis

All three datasets were then deductively coded using the moves–modes–methods framework. This allowed for systematic classification of conversational moves, experiential modes, and pedagogical methods across interactional turns.

For the crit recordings, the unit of analysis was the interaction turn: each discrete contribution by a student or tutor, segmented according to verbal utterances and associated screen-based actions (e.g., drawing, pointing, or switching views).

Credibility was strengthened through:

- Data triangulation (surveys + focus group + crit protocols)
- Method triangulation (inductive + deductive coding)
- Peer checking of a sample of coded extracts to enhance dependability
- Maintenance of an audit trail documenting coding decisions
- Reflexive memoing during theme development

This multi-layered approach allowed comparison of perceived interactional patterns with observed conversational behaviours.

3.6 Ethical Considerations

Ethical clearance for the original doctoral research on which this paper is based was obtained from the Cape Peninsula University of Technology (Reference: CPUT/HW-REC 2018/H15). Participation in the earlier surveys and focus groups was voluntary, with informed consent obtained from all participants. Crit recordings were collected with institutional approval and were anonymised prior to analysis. No identifiable information has been included in this paper.

The current study involves a desk-based mapping and secondary analysis of previously collected data. No new data were generated from human participants, and the work therefore falls under the general ethical provisions for research conducted for teaching and learning purposes at the author's current institution. The study adheres to established ethical guidelines relating to confidentiality, secure data storage, and responsible reporting.

4. Findings

Drawing on survey responses, focus-group insights, and detailed analysis of live online critique protocols, the findings reveal distinct interactional patterns and pedagogical dynamics that not only shape the student–tutor relationship in the crit but also offer transferable principles for designing context-sensitive, Socratic AI tutors.

4.1 Student–Tutor Relationship Archetypes

Analysis of the survey, focus-group, and crit protocol data revealed four recurring relationship archetypes:

- Novice–Expert: The tutor acted as the authoritative source of disciplinary knowledge, directing the student towards established norms (Schön, 1984; Morkel, 2022).
- Consultant–Client: The tutor responded as a design consultant, treating the student's work as a brief to be improved (Anthony, 1991).
- Mentee–Mentor: The interaction extended beyond the immediate project, emphasising professional growth (Collins et al., 1989).

- Parent–Child: The tutor adopted a protective, directive stance, especially when students showed uncertainty (Blair, 2006).

These archetypes reflect the fluid, situational nature of teaching in the crit, with tutors shifting roles depending on student needs, project stage, and interactional cues. For AI Socratic tutor design, this implies the need for adaptive persona-switching (Bazouche, 2025), where the AI can modulate tone, questioning style, and feedback depth dynamically. Unlike static rule-based agents, LLM-powered systems can be trained to recognise cues signalling when to shift from directive guidance to exploratory mentoring (Stokel-Walker and Van Noorden, 2023; Luckin & Cukurova, 2023). Holmes *et al*. (2019) further argue that effective AI tutors must be capable of adjusting their pedagogical stance in real time to support learner agency while maintaining scaffolding appropriate to the learner's developmental stage.

4.2 4.2 Interactional Dimensions of the Live Online Crit

The student–tutor interaction in the live online crit was characterised by four dimensions:

- Formative – Resembling a formative assessment rather than a collaborative design session (Milovanovic & Gero, 2018; Morkel, 2022).
- Iterative – Cyclical revisiting of ideas and feedback (Laurillard, 2013).
- Formal – Structured turn-taking and reduced spontaneity (Maher, Simoff & Cicognani, 2012).
- Immersive – Intensive engagement with multimodal inputs such as drawings, 3D models, and verbal commentary (Ceylan et al., 2021).

These dimensions show that the online crit supports depth and focus but at the cost of informal, serendipitous interaction (Lotz et al., 2015). For AI tutor design, balancing formality and informality is critical — too rigid, and engagement suffers; too loose and learning outcomes may dilute. AI conversational agents could intentionally embed prompts for social exchange or reflective pauses to counteract the transactional nature of online sessions, fostering rapport while maintaining academic rigour (Luckin & Cukurova, 2023; Holmes et al., 2019). Designing such AI-mediated dialogue flows requires sensitivity to the balance between instructional control and student autonomy (Woolf, 2010).

4.3 The Moves–Modes–Methods Matrix in Practice

Using the integrated framework, interaction patterns were coded as:

- Moves – Presenting dominated early phases, questioning and commenting mid-session, with reflection primarily in closing stages.
- Modes – Negotiation and application were most frequent; reflection was often tutor-led (Percy, 2004; Morkel, 2022).
- Methods – Modelling and scaffolding were common; coaching was less frequent, and articulation tended to be tutor-driven.

This structured mapping confirms that effective crits blend multiple pedagogical strategies in a temporal sequence, echoing Laurillard's (2012) conversational model. For AI tutors, the moves–modes–methods logic can serve as a dialogue architecture, ensuring sequences include problem presentation, exploratory questioning, reflective synthesis, and application (Stokel-Walker and Van Noorden, 2023). Holmes et al. (2019) note that AI tutors that explicitly embed such conversational scaffolding can better emulate the responsive, iterative nature of expert teaching. LLM-based systems, in particular, could be fine-tuned to maintain this sequence while adapting language, timing, and questioning depth to individual students' responses (Luckin & Cukurova, 2023).

4.4 Implications for AI Socratic Tutor Design

Mapping findings to AI tutoring literature suggests key design priorities:

- Adaptive Role-Shifting – Emulating fluid movement between archetypes.
- Dimension Balancing – Combining the depth of formal engagement with moments of informality (Maher, Simoff & Cicognani, 2012).
- Dialogue Structuring – Embedding moves–modes–methods sequencing in conversation flow.
- Contextual Sensitivity – Accounting for bandwidth constraints, multilingual communication, and socio-economic diversity (Olweny, 2017; Morkel et al., 2021).

These priorities underscore that while many aspects of crit pedagogy (such as probing, modelling, and iterative refinement) are transferable to AI tutoring systems, relational and socio-cultural elements are harder to

replicate. Designing for pedagogical integrity means ensuring that AI tutors function not only as information providers but as strategic partners in thinking (Luckin & Cukurova, 2023; Holmes et al., 2019). Such systems should be evaluated not just on algorithmic accuracy but on their capacity to sustain the depth, adaptability, and relational quality that underpin effective human-led critiques.

5. Discussion

5.1 Bridging Human Critique Practices with AI Tutoring Design

The findings of this study offer a grounded empirical basis for informing the design of LLM-powered Socratic tutors. The moves–modes–methods matrix derived from live online crits provides a structured vocabulary for describing the conversational strategies, experiential engagements, and pedagogical interventions that characterise effective formative dialogue. These patterns highlight not only how design knowledge is negotiated between students and tutors, but also what kinds of conversational behaviours an AI tutor would need to emulate to support deep, iterative learning. This aligns with Pratschke's (2024) argument that meaningful learning (especially in AI-rich environments)requires shifting assessment focus from final outputs to the scaffolded processes through which students reason, iterate, and construct knowledge.

First, the distribution of conversational moves across crit sessions (early-session presenting, mid-session questioning and commenting, and closing-stage reflection) suggests that effective tutoring requires dynamic modulation of stance over time. Rather than supplying generic prompts, a Socratic AI tutor would need to recognise the student's stage in the design cycle and adjust its questioning, feedback, and reflective cues accordingly. This has direct implications for conversational flow modelling in AI systems, particularly those relying on sequence-based or state-based dialogic scaffolds.

Second, the dominance of experiential modes such as negotiation, exploration, and application indicates that design learning is fundamentally iterative and problem-centered. An AI tutor designed for such environments should therefore prioritise prompts that promote student reasoning, test alternative interpretations, and foster exploratory iterations rather than provide prescriptive solutions. The crit demonstrates the value of iterative cycles of "explain-probe-revise," which align strongly with contemporary framings of AI tutors as partners in guided discovery learning (Stokel-Walker & Van Noorden, 2023; Bazouche, 2025).

Third, the presence of cognitive apprenticeship methods (modelling expert thinking, scaffolding complex decisions, coaching strategic moves, and encouraging articulation, exploration and reflection) highlights the relational and pedagogical depth required for effective AI support. These methods underscore the need for conversational agents that can not only prompt reflection but also demonstrate disciplinary ways of thinking, manage cognitive load, and gauge support to the student's emerging capability. Importantly, the shift between mentoring, consulting, and directive guidance observed in crit tutors suggests that an AI tutor may need to adopt flexible personas or scaffolding levels to align with student needs.

Contextual factors also play a crucial role. In Global South settings where bandwidth limitations, diverse cultural realities, and socio-economic pressures shape student participation, AI tutors must operate with heightened sensitivity to diverse communication styles and variable levels of prior knowledge (Olweny, 2017; Morkel et al., 2021). The online crit exposes how tutors compensate for these constraints through explicit verbalisation, multimodal redundancy, and affective support - features that AI systems must be designed to replicate if they are to function equitably in under-resourced environments.

Overall, the alignment between crit interaction patterns and the aspirations of Socratic AI tutoring suggests that human critique practices provide a valuable empirical template for designing pedagogically credible conversational agents. By grounding AI design in the moves, modes, and methods observed in real educational dialogue, it becomes possible to develop systems that augment rather than oversimplify the complex cognitive and relational work of teaching. The empirically derived framework presented in this paper offers a pathway towards AI tutors that not only emulate the structure of Socratic inquiry but also honour the contextual, experiential, and relational nuances that define effective design critique pedagogy.

5.2 Implications for the Design of Socratic AI Tutors

The findings of this study offer several implications for the design of LLM-powered Socratic tutors that aspire to support reflective, dialogic, and contextually responsive learning. The moves–modes–methods matrix provides a structured foundation for translating human critique practices into AI-mediated tutoring behaviours. These implications span pedagogical design, conversational architecture, and contextual adaptation, each of which is critical for developing AI tutors that are both educationally credible and socially responsive.

Pedagogically, the results highlight the need for AI tutors to facilitate learning through iterative cycles of explanation, probing, and refinement, rather than through directive content delivery. The crit demonstrates that learning is driven by structured questioning that promotes students' reasoning, challenges assumptions, and prompts the exploration of alternative strategies. AI tutors should therefore prioritise open-ended, generative questions that mirror the conversational moves observed in crit dialogue – specifically questioning, commenting, and reflective prompting. Pratschke (2024) similarly notes that the conversational affordances of generative AI make it well-suited to dialogue-driven pedagogies and assessments, reinforcing the value of modelling critique-based inquiry within AI tutor design.

Additionally, the prominence of cognitive apprenticeship methods in tutor behaviour suggests that AI tutors must be capable of modelling expert thinking in transparent ways, offering scaffolded hints, and guiding students through increasingly complex tasks while preserving student autonomy. These pedagogical patterns imply the need for LLMs to balance epistemic authority with strategic restraint, avoiding both over-direction and superficial encouragement.

From an interaction design perspective, the study underscores the importance of AI tutors adopting flexible conversational stances that shift according to the student's stage in the task and the nature of their responses. The moves–modes–methods matrix provides a usable model for structuring such adaptivity, enabling AI systems to modulate their prompts based on conversational state (e.g., presentation, exploration, or reflection). This may involve incorporating state-based dialogue models, persona switching, or hierarchical prompting structures to ensure that feedback is appropriately timed and pedagogically purposeful. Furthermore, the multimodal nature of the crit, where sketches, diagrams, and models play a critical role, points to the need for AI tutors capable of interpreting and responding to visual artefacts, or at least, prompting students to externalise visual reasoning through descriptive language. Such capabilities align with current developments in multimodal LLMs and interaction design for AI-supported creative disciplines.

Contextually, the Global South learning environment foregrounds additional design considerations. Bandwidth limitations, device constraints, and other resource challenges shape how students participate in online learning spaces. AI tutors must therefore be designed to function effectively in low-resource settings, leveraging lightweight interactions, text-first modes, or offline-compatible models where needed. The relational dynamics observed in the crit, especially the parent–child and mentee–mentor archetypes, highlight the importance of dialogic warmth, empathy, and affective support. AI tutors should therefore incorporate socio-emotional sensitivity, culturally aware phrasing, and adaptive encouragement to foster psychological safety and learner confidence, particularly for students experiencing socio-economic or epistemic marginalisation.

Finally, these implications suggest that the design of Socratic AI tutors cannot rely solely on prompt engineering or generic instructional strategies. Instead, AI tutors must be grounded in empirical evidence of how disciplinary learning unfolds through conversation, how expert reasoning is made visible, and how contextual constraints shape educational interaction. The moves–modes–methods matrix developed in this study provides a structured foundation for such design, enabling the development of conversational agents that are pedagogically rigorous, interactionally adaptive, and contextually inclusive.

5.3 Contextual Considerations for global South Learning Environments

The contextual realities of Global South higher education exert a significant influence on how online critique practices unfold and, by extension, on how AI tutors should be designed to support such environments. The live online crit analysed in this study illustrates the ways in which students and tutors navigate structural constraints shaped by limited digital infrastructure, cultural diversity, and socio-economic inequalities. These contextual factors do not simply form the backdrop to learning; they actively shape interactional patterns, influence pedagogical decisions, and determine the accessibility and meaningfulness of learning experiences.

Digital infrastructure constraints represent a key consideration. Bandwidth instability, device limitations, and uneven access to reliable internet directly affect students' participation in online crits, often requiring tutors to compensate through heightened verbalisation, redundancy in explanation, and careful pacing of dialogue. As a result, AI tutors intended for these contexts must be designed to operate effectively under low-bandwidth or intermittent connectivity conditions, with a prioritisation of text-based or compressed interactions over high-volume multimodal exchanges. This includes the ability to maintain conversational coherence across connectivity disruptions and provide adaptive responses when students re-engage after losing access; capabilities not commonly prioritised in AI tutoring research conducted in well-resourced environments.

Socio-economic diversity adds an additional layer of complexity. Students may balance work and study responsibilities, face unpredictable living or environmental conditions, or experience varying levels of exposure to digital tools. These conditions influence confidence, willingness to participate, and ability to sustain engagement in synchronous online learning environments. The online crit reveals how tutors frequently adopt mentoring, coaching, or even protective relational stances to support students' persistence and emotional wellbeing. This underscores the need for AI tutors that integrate affective support; providing encouragement, normalising uncertainty, and offering validation that aligns with principles of care and inclusion. Such sensitivity is essential to avoid unintended reproduction of inequities of students.

Cultural and relational norms also play a pivotal role. In many Global South contexts, hierarchical educational cultures and respect for authority influence student participation, often leading to hesitation in questioning tutors or expressing uncertainty. Human tutors adjust their relational stance accordingly, using humour, reassurance, or strategic self-disclosure to reduce power distances and foster dialogue. AI tutors must similarly be capable of modulating tone and relational posture to ensure that interactions are experienced as supportive rather than evaluative or punitive.

Overall, the contextual considerations emerging from this study demonstrate that the design of AI tutors cannot rely on generalised assumptions derived from Global North learning environments. Instead, they must explicitly incorporate responsiveness to infrastructural, linguistic, socio-economic, and cultural conditions that shape learning in the Global South. By doing so, AI-supported critique practices can contribute to widening access, enhancing epistemic justice, and supporting meaningful participation for diverse student cohorts.

6. Conclusion

This paper set out to explore how interactional dynamics in live online architectural design critiques can inform the design of LLM-powered Socratic conversational tutors. Drawing on data from surveys, a graduate focus group, and three recorded critique sessions, and guided by an integrated framework of Conversation Theory, Experiential Learning Theory, and Cognitive Apprenticeship, the study identified the relational, pedagogical, and conversational structures that underpin critique dialogue. These include four student–tutor relationship archetypes, four interactional dimensions, and a moves–modes–methods matrix that captures how design knowledge is articulated, negotiated, scaffolded, and iteratively refined in practice.

By mapping these empirically grounded patterns against current scholarship on Socratic AI tutors, the study demonstrates that the crit provides a rich and structurally coherent model of pedagogically meaningful dialogue; one characterised by probing questions, reflective prompts, modelling of expert reasoning, and iterative cycles of reflection and exploration. The moves–modes–methods matrix offers a theoretically robust and practically usable framework for translating these human critique practices into AI-mediated tutoring behaviours. In doing so, the study contributes to the emerging field of AI-based conversational pedagogy by providing concrete, evidence-based specifications for how LLM-powered tutors might emulate, support, or extend expert human facilitation.

Importantly, the findings highlight that effective AI tutoring design must be sensitive to the contextual realities of Global South learning environments. Bandwidth constraints, socio-economic pressures, and hierarchical educational cultures shape the nature of online interaction and the forms of support students require. The crit illustrates how human tutors compensate for these conditions through explicit verbalisation, multimodal scaffolding, and affective support. AI systems intended for these contexts must therefore embed lightweight interaction modes, and culturally responsive feedback strategies to ensure equitable and meaningful learning experiences.

Overall, this study positions architectural design critique pedagogy as a productive empirical lens for designing Socratic AI tutors that are pedagogically rigorous, interactionally adaptive, and contextually inclusive. The moves–modes–methods matrix provides a foundation for AI systems that can participate in structured, reflective, and exploratory dialogue while preserving the relational integrity and epistemic complexity of human–human critique. Future research should explore multimodal extensions to support visual reasoning, evaluate learner experiences with AI-augmented critique environments, and investigate how hybrid human–AI facilitation models might enhance learning in design and other feedback-intensive disciplines. By grounding AI design in authentic educational practice, this work contributes to developing conversational agents that augment (rather than replace) the expert pedagogical judgement at the heart of meaningful learning facilitation.

AI declaration: Artificial intelligence (AI) tools were not used to generate data, conduct analysis, or produce any part of the study's findings. All coding, interpretation, and synthesis were carried out by the author using

established qualitative research methods. AI assistance was used only for editorial support (such as grammar refinement and text clarity), and all AI-assisted text was critically reviewed, verified, and edited by the author. Responsibility for all content, arguments, and interpretations presented in this paper remains with the author.

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Exploring Generative AI for Personalized Engagement in Therapy Adherence Contexts

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Abstract: This study explores the use of generative AI to create personalized virtual companions, referred to as "Tamagotchis," aimed at fostering emotional engagement and supporting therapy adherence. A prototype system was developed that generates individualized 2D image sequences representing symbolic objects or characters in different states, such as weakened, neutral, or improved. Through a mixed-methods evaluation involving a quantitative survey (n=78) and qualitative interviews (n=10), the study assessed the visual clarity, emotional resonance, and perceived relevance of the generated images. Results indicate that personalized objects were more emotionally engaging than predefined versions, and user involvement in the creation process significantly enhanced identification and motivation. These findings suggest that emotionally adaptive virtual companions may hold promise as a supportive element in long-term therapeutic interventions.

Keywords: Generative AI, Therapy adherence, Personalization, Virtual companion, Tamagotchi effect

1. Introduction

Lack of adherence to treatment presents a substantial challenge to healthcare systems (Religioni et al. 2025). Research indicates that a significant proportion of patients fail to consistently follow medical recommendations. On average, only about half of all patients adhere to long-term treatment regimens (Castillo et al. 2021). This not only compromises the effectiveness of medical interventions but also leads to increased healthcare costs (Ehlken et al. 2020). Therapy adherence is particularly critical in the treatment of chronic illnesses, which require consistent and often complex long-term management strategies (Anghel, Farcas, and Oprean 2019). According to the World Health Organization, noncommunicable diseases (NCDs) were responsible for over 43 million deaths globally in 2021, approximately 75% of non-pandemic-related deaths (WHO 2024). Given the global burden of chronic diseases, effective and sustainable measures to support patient adherence are needed.

Digital technologies are playing an increasingly important role in addressing this challenge. Mobile health applications, telemonitoring tools, virtual assistants, and AI-supported platforms offer novel ways to engage patients and support continuous self-management (Rejula *et al.*, 2021; Lavine, 2020; Scholz and Teetz, 2021). Practical examples include digital diaries for oncology patients, remote monitoring systems for diabetes or chronic obstructive pulmonary disease (COPD), and interactive pain management apps that incorporate biofeedback and psychotherapeutic elements (Vitodata, n. d.; Wechsler and Mühlberger, 2024). However, many of these digital health interventions rely on standardized, one-size-fits-all solutions. They frequently neglect individual differences in personality, emotional needs, and motivational drivers (Baumel et al. 2019). This lack of personalization can result in diminished user engagement and limited long-term effectiveness (Midyett 2023). One emerging direction is the integration of emotionally engaging, personalized digital entities into therapeutic contexts (Moser and Keller 2025). Inspired by the "Tamagotchi effect", this paper investigates how generative AI (genAI) can be used to create personalized virtual companions that symbolically represent a patient's therapeutic journey.

2. Research Objectives

This study explores how generative AI can be used to create personalized virtual companions, referred to in the context of this research as "Tamagotchis", that foster emotional attachment and support therapy adherence. It is based on the assumption that emotionally resonant, individualized virtual objects which symbolically represent a patient's therapeutic journey can strengthen engagement and motivation over time. The central research question is:

How can generative AI be leveraged to create personalized virtual companions (Tamagotchis) that effectively foster emotional attachment and enhance therapy adherence, while ensuring distinct visual progression and stylistic coherence for intuitive user comprehension?

To address this question, the study focuses on the development and evaluation of a prototype that generates personalized 2D image sequences depicting a symbolic object or companion in different stages of a therapeutic

or developmental journey. The use of 2D imagery was selected as a technically accessible and conceptually focused starting point to explore the feasibility and perceived impact of this approach.

3. Methodology

This research is grounded in the Design Science Research (DSR) framework, which emphasizes both scientific rigor and practical relevance through an iterative, cyclic process (Hevner 2007). The development and evaluation of the research artifact followed the Design Science Research Methodology as outlined by Peffers et al. (2007). This study begins at the design and development phase, as both the underlying problem and the research objectives were predefined: to explore how generative AI can be used to design personalized Tamagotchis that promote emotional attachment and therapy adherence, while ensuring their visual stages are clearly distinguishable and stylistically consistent for intuitive understanding. The research was structured into three main phases:

First, technical and functional requirements were defined, focusing on visual consistency, recognizable transitions, and semantic coherence. This involved evaluating language models, image generation platforms, and prompt strategies through literature review, testing, and iteration.

Second, the artifact was iteratively developed to support collaboration between patients and health care professionals, offering two personalization modes—*TamaPersona* and *Create-a-Gotchi*—with a focus on functionality, visual quality, and reliability.

Third, the prototype was validated through a mixed-methods study: a quantitative online survey (n=78) and qualitative interviews (n=10). Quantitative data were analyzed descriptively and exploratively (Döring & Bortz, 2016), while qualitative data were thematically analyzed using verified interview transcripts and structured coding (ibid.).

4. Related Work

Digital interventions have become increasingly important in managing chronic diseases and supporting therapy adherence. A wide range of tools, including mobile health applications, remote monitoring systems, and patient-facing platforms, are designed to provide continuous support and integrate data into clinical workflows. Projects like the Digital Companion combine practice management software with patient apps, enabling seamless communication between patients and healthcare providers (Färber et al. 2023, Yoker 2023). Condition-specific solutions such as monitoring systems for diabetes and COPD, or software for inflammatory bowel disease, exemplify the diversity of applications currently in use (Scholz and Teetz 2021). For cancer patients, interactive therapy diaries offer additional guidance throughout treatment (ibid.). Many of these tools aim to promote therapy adherence directly, offering features such as medication reminders, symptom tracking, and progress visualization. Apps like MyTherapy and Medisafe have shown measurable improvements in adherence, yet their impact often remains limited to functional support, lacking deeper emotional engagement with users (Vervloet et al. 2012). In an effort to enhance motivation, gamification-based applications such as SuperBetter and Habitica incorporate reward systems and playful challenges. While effective in stimulating short-term engagement, these strategies often fall short in sustaining long-term behavioral change (Johnson et al. 2016).

Text-based virtual assistants such as Woebot and Wysa provide psychological support and reminders through natural language interaction, enabling a basic level of personalization (Fitzpatrick, Darcy, and Vierhile 2017). However, these systems typically lack visual or interactive depth, limiting their emotional resonance. XR-based therapies using virtual or augmented reality have demonstrated clinical potential, particularly in the treatment of pain and anxiety disorders. Notable examples like SnowWorld show significant effects on pain reduction in acute settings (Hoffman et al. 2011). Despite their promise, these interventions are typically confined to specific therapeutic scenarios and are not designed for continuous or adherence-focused support. Overall, while digital tools in healthcare are advancing, most current approaches fall short of fostering sustained emotional connection, a factor increasingly recognized as critical for long-term engagement and adherence.

Beyond functional design, recent research highlights the growing importance of emotional connection and personalization in digital health tools. Mental health apps have been shown to reduce depressive symptoms effectively; however, the inclusion of gamification elements does not significantly enhance their effectiveness (Six et al. 2021). This suggests that long-term engagement may require more than surface-level interactivity and instead depend on meaningful emotional alignment. Additional findings indicate that virtual agents perceived as visually similar to users can increase identification, positive affect, and motivation (Ashrafi et al. 2024). Furthermore, AI-driven coaching tools capable of analyzing user input and providing emotionally attuned

feedback have been found to foster a stronger sense of engagement and support (Alazraki et al. 2021). These insights underscore the value of personalized and emotionally resonant interactions in the design of future therapeutic technologies.

Generative AI is increasingly being adopted in healthcare, particularly in areas such as diagnostic assistance, screening processes, and the interpretation of medical data (Yim et al. 2024, McKinsey 2025). Alongside its technical potential, however, ethical considerations ranging from data security and emotional manipulation to algorithmic bias have become central to discussions about its responsible integration into clinical practice (The Lancet Regional Health – Europe 2023, Ning et al. 2024). While current applications primarily aim at improving clinical efficiency, the potential of genAI to facilitate emotionally engaging experiences in therapeutic settings remains largely unexplored.

Concepts from adjacent fields such as marketing and psychology suggest that emotional resonance plays a decisive role in shaping user experience and long-term engagement (Forrester 2015). Applying this insight to healthcare, the idea has emerged to develop emotionally appealing, personalized virtual companions to support therapy adherence. Building on this vision, early-stage concepts have been formulated and adapted to immersive environments such as extended reality (Moser 2024, Moser and Keller 2025). In addition to prior empirical work, theoretical models such as Self-Determination Theory (Deci and Ryan 1985) and the COM-B model of behavior change (Michie, van Stralen, and West 2011) emphasize the importance of autonomy, competence, and relatedness in sustaining engagement. The proposed Tamagotchi approach aligns with these frameworks by offering a sense of personal agency and emotional resonance, thereby situating this work within a broader theoretical foundation for understanding digital adherence support.

However, realizing such concepts in practice requires foundational exploration of their technical feasibility and psychological impact. This study addresses this need by investigating how generative AI can be used to create personalized 2D virtual companions, representing an initial step toward emotionally adaptive and personally meaningful digital health interventions.

5. The Conception of the Tamagotchi Creator

The goal of the technical implementation was to develop a system that uses generative AI to create personalized visual objects functioning as symbolic companions in a therapeutic context. To support this goal, a modular system architecture was designed, comprising four core components: a user-friendly frontend interface, a logic-driven backend structure, a prompt generation engine, and an image generation interface powered by DALL·E 3 (available in GitHub; see Lauria, 2025). The prototype offers two distinct modes of interaction, each reflecting a different personalization logic: *TamaPersona* and *Create-a-Gotchi*. These two pathways accommodate varying user needs and therapeutic contexts (see Figure 1). To ensure both expressiveness and usability, each Tamagotchi can be generated in three or four visual stages: three stages provide the minimum for a meaningful progression, while a fourth tests whether clarity, consistency, and emotional resonance hold with added visual complexity.

5.1 TamaPersona

TamaPersona enables health care professionals to generate Tamagotchis based on individual personality traits, preferences, or motivational profiles of patients. The process begins with a free-text description of the person, such as: “Leonie is curious, sensitive, and grows through challenges.” This input is processed by GPT-4o, which interprets the personality and proposes a symbolic object—e.g., a fox—along with a brief narrative and a set of typical states such as “sleeping,” “waking up,” “running,” and “resting.” The model’s output is returned in a structured format, enabling automated processing.

In a second step, GPT-4o generates three or four consistent image prompts corresponding to the suggested object and states. These prompts are then passed to DALL·E 3, which produces the respective images. The resulting visuals are stored and displayed in the frontend, allowing for immediate feedback and reflection. This approach supports an interpretive, therapist-led personalization pathway.

5.2 Create-a-Gotchi

Create-a-Gotchi offers a more user-driven alternative. It is intended for users who already have a concrete idea of the object that best represents them. In this mode, individuals directly input the object, its visual characteristics, and associated states. For example, a user might describe a “white mug with golden trim” and specify the states “empty,” “steaming,” and “ideal drinking temperature.”

These inputs are automatically structured and processed by GPT-4o to generate precise, stylistically coherent image prompts. As in *TamaPersona*, the prompts are then rendered into images by DALL·E 3. The images are stored and immediately presented in the user interface. This path allows for greater autonomy and aesthetic control, reflecting a co-creative personalization approach.

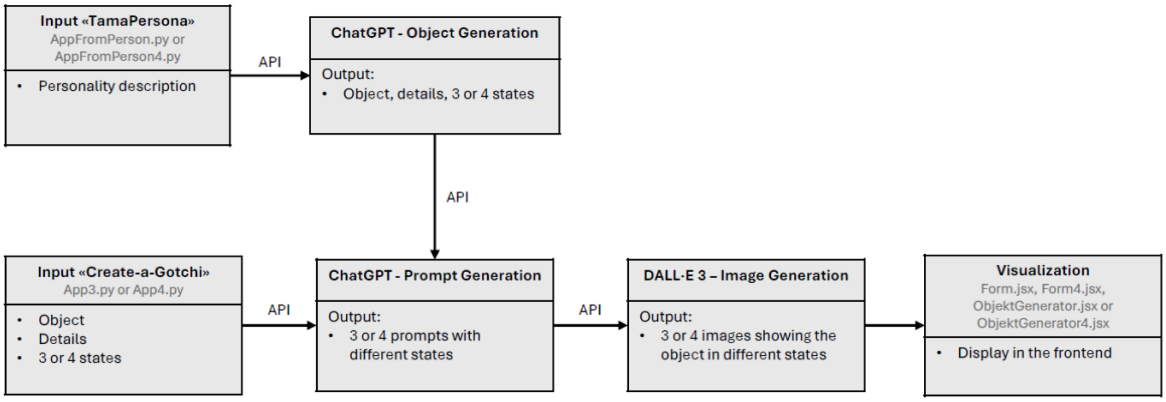


Figure 1: System Architecture

5.3 Prompt Engineering

To ensure consistent visual representation of personalized Tamagotchis across multiple states, a well-defined prompt strategy was essential. Two approaches were explored: an initial manual method using a morphological box to systematically combine visual attributes (e.g., object type, mood, background, style), and an automated semantic approach using ChatGPT.

While the manual strategy was helpful for early testing and analyzing model behavior, it was not scalable for practical use. In the final prototype, prompts were generated automatically. Based on a free-text personality description provided by healthcare professionals, ChatGPT produced three or four prompts, each corresponding to a distinct state such as calm, anxious, or joyful. These prompts (available through OSF; see Lauria, Moser and Keller, 2025) preserved the object's core features while adjusting parameters like lighting, color, or posture to reflect emotional variation.

6. Evaluation

6.1 Study Design

This study used a mixed methods approach to evaluate both the technical feasibility and user acceptance of personalized Tamagotchi-like visual artifacts in a therapeutic context. Combining quantitative and qualitative methods enabled the assessment of measurable visual perception alongside deeper emotional and subjective responses (for additional material and detailed results see Lauria, Moser and Keller, 2025).

The *quantitative* component consisted of an online survey assessing whether AI-generated images were perceived as visually and emotionally distinct across intended states (e.g., neutral, positive, negative). It also examined user acceptance of personalized, expressive visual objects in therapy. Participants (n=78) viewed ten image sequences from five categories—*Animals*, *Plants*, *Objects*, *People*, and *Fantasy*—each depicting three or four states (for a selection of sequences see Table 1). They arranged states in a logical order and rated the visual progression and stylistic coherence on Likert scales.

The *qualitative* component involved semi-structured interviews (n=10) exploring emotional resonance, comprehensibility, aesthetics, and therapeutic relevance. Participants first discussed attitudes toward digital Tamagotchis, emotional attachment, and AI. They evaluated four image sequences, answered open-ended questions, and created a personalized Tamagotchi using the *TamaPersona* tool. If needed, *Create-a-Gotchi* was used to refine results. Participants assessed fit, expression, quality, and preferences between personalized and pre-generated images. All inputs and outputs were documented for analysis.

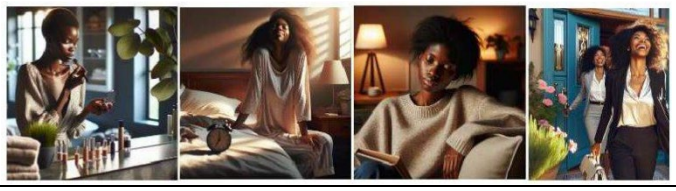
6.2 Sample Description

A total of 78 individuals took part in the quantitative online survey, the majority of whom were in young to middle adulthood. The largest proportion belonged to the 25–34 age group (37%), followed by 18–24-year-olds (23%) and 35–44-year-olds (20%). Older age groups were only sporadically represented. The gender distribution

was nearly balanced, with 53% identifying as male, 46% as female, and one participant identifying as non-binary. Approximately half of the participants had prior experience with therapeutic interventions, mainly in the form of psychotherapy or physiotherapy. Experience with digital therapy was uncommon; some respondents mentioned familiarity with mindfulness applications, online psychotherapy platforms, or tools such as ChatGPT or Fitbit.

The ten participants in the qualitative interviews represented a heterogeneous sample with respect to age, gender, and educational background. The largest age group was again between 25 and 34 years, with individual participants ranging in age from 18 to 84 years. Six participants identified as female and four as male. Approximately half of the interviewees reported previous experience with therapy. Digital therapeutic approaches were largely unfamiliar. Attitudes toward digital support tools varied from cautious to open, depending on personal experience and technical affinity.

Table 1: Selection of Tamagotchi sequences

No.	Image Category *Correct sequence*	Image Sequence
1	Animals (Part 1) *1 → 3 → 2*	
2	Animals (Part 2) *1 → 3 → 4 → 2*	
3	Plants (Part 1) *3 → 2 → 1*	
4	Plants (Part 2) *2 → 4 → 3 → 1*	
6	Objects (Part 2) *2 → 4 → 3 → 1*	
8	Humans (Part 2) *3 → 2 → 1 → 4*	

9	Fantasy (Part 1) *1 → 2 → 3*	

6.3 Survey Results

The quantitative survey revealed that participants largely perceived the AI-generated image series as visually coherent and developmentally logical. Across all responses, 67% agreed or strongly agreed that the visual development between image states was clearly recognizable, while 71% agreed that the visual style was coherent (see Figure 3).

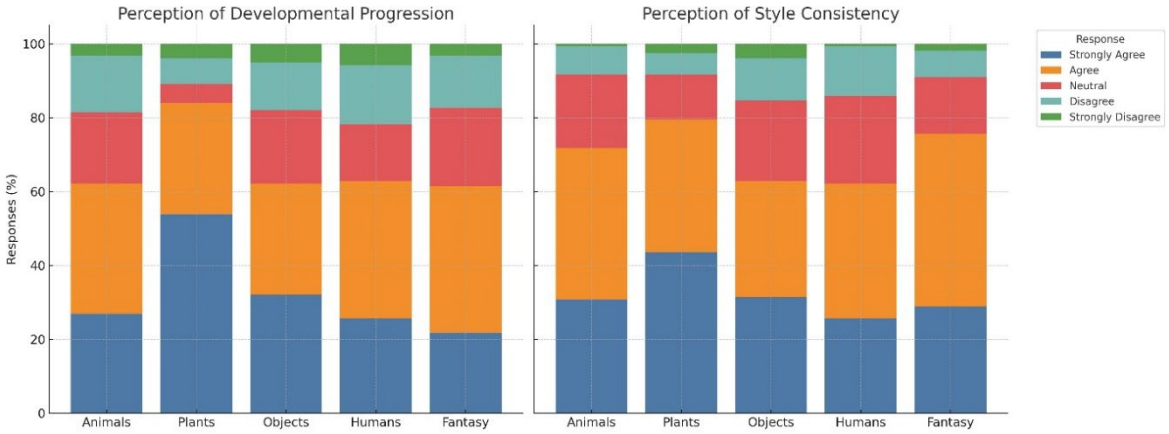


Figure 2: Perception of Developmental Progression and Style Consistency

Recognition accuracy varied by image category (see Figure 4). The *Animals* category showed the highest agreement with the intended state sequence, particularly in Sequence 1 (88.5%) and Sequence 2 (60.3%). In contrast, the *Plants* category had the lowest recognition rates, with only 25.6% and 23.1% correctly ordering Sequence 3 and 4, respectively. Despite this, subjective ratings of visual progression and style coherence remained high. Other categories showed mixed results. In the *Objects* category, Sequence 5 was correctly ordered by 87.2% of participants, while Sequence 6 dropped to 29.5%. The *Humans* category followed a similar pattern, with 76.9% correct in Sequence 7, but only 23.1% in Sequence 8. The *Fantasy* sequences were moderately successful, with correct orderings of 67.9% and 80.8%, respectively, and were generally well received in terms of narrative plausibility and visual consistency.

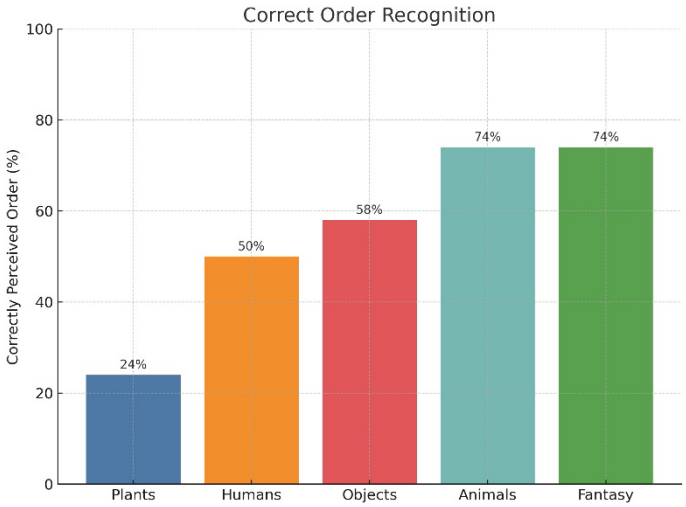


Figure 3: Correct Order Recognition by Image Category

Regarding concept perception, 72% of respondents expressed a positive view of using a personalized, AI-generated Tamagotchi as a motivational tool in therapy. 65% indicated they could imagine using or recommending such a system. However, critical feedback was also collected in open questions, grouped into the following themes:

- Conceptual Clarity: Some participants struggled to understand how the Tamagotchi system would function in therapy.
- Target Group Suitability: The concept was perceived as more appropriate for younger or tech-savvy users.
- Emotional Engagement: Concerns were raised about the depth or appropriateness of emotional attachment to digital objects.
- Privacy and Ethics: Questions emerged about data handling and ethical implications of visualizing personal health data.
- Sustained Motivation: Several respondents questioned whether engagement could be maintained over the long term.

6.4 Interview Results

Reactions to Pre-generated Image Sequences

In the initial phase of the interviews, participants were presented with four pre-generated image sequences, each representing a different virtual Tamagotchi object progressing through various emotional or health-related states. Overall, responses were cautiously positive. Many participants expressed openness to engaging with such imagery in a therapeutic context, noting that the sequences conveyed symbolic narratives of development, change, and motivation. These terms recurred frequently and indicate that the visual transitions were broadly interpreted as metaphors for therapeutic progress. Sequence 1 (*Animals*) stood out as the most emotionally engaging, often described as “cute,” “charming,” or “uplifting,” and elicited spontaneous identification and positive affect. In contrast, Sequence 3 (*Plants*) was frequently perceived as emotionally distant or visually unappealing, with some participants describing it as “too dark” or “not motivating.” This diversity in reception underscores the subjective nature of visual aesthetics and emotional resonance. Despite these variations, most participants identified at least one sequence with which they felt a personal connection, highlighting the potential of even standardized images to evoke emotional and motivational responses. However, a minority found none of the images compelling, which points to the limitations of pre-designed visuals in addressing diverse user preferences.

Reactions to Personalized Tamagotchis

The second, interactive part of the interviews focused on the creation of personalized Tamagotchi objects. Based on short self-descriptions, the *TamaPersona* tool generated visual representations intended to reflect individual traits or self-perceptions. In cases where the output was not satisfactory, particularly due to stylistic or aesthetic misalignment, participants used *Create-a-Gotchi* to modify elements such as shape, color palette, or thematic content. Most participants responded positively to the personalized objects, frequently describing them as appropriate, emotionally resonant, and even self-representative. Statements such as “It fits me well,” or “The phoenix really represents me” illustrate the emotional depth of identification that personalization can enable. This effect was strengthened by participants’ active involvement in the creation process, which was commonly described as enjoyable, creative, and meaningful. Only in isolated cases was the generation process perceived as frustrating or exhausting, typically due to multiple iterations being needed to reach a satisfying result. Crucially, eight out of ten participants preferred their personalized Tamagotchi over the standardized image sequences, attributing this preference to greater emotional fit, the ability to co-create the visual content, and a stronger sense of ownership.

Subjective Impressions and Suggestions for Improvement

In the final section of the interviews, participants were asked to reflect on the process as a whole and to offer suggestions for further development. Emotional responses were overwhelmingly positive: participants frequently described the experience as motivating, fun, stimulating, or empowering. Several remarked that the process had prompted reflection on personal traits and emotional needs, indicating that the prototype had some exploratory and introspective impact even outside a formal therapeutic context. Participants offered numerous suggestions to improve the emotional accessibility and functional depth of the system. A central theme was the desire for emotional interactivity, such as having the Tamagotchi respond to user input, simulate empathy, or

communicate basic emotional states. Many also wished for more personalizable visual elements, including the ability to select preferred animals, styles, or symbolic motifs. Features such as naming, sound integration, motion, or seasonal variations were suggested to enhance engagement and foster long-term identification with the virtual companion. Participants also voiced concerns: some feared that overly strong emotional attachment to a digital figure could lead to dependency, while others worried that abstract or stylized images might trigger unintended negative associations. Ethical considerations such as data protection, transparency of AI-generated content, and clinical framing were also raised. Furthermore, the need for clearer integration into therapeutic settings—for instance, as part of an established treatment plan or in collaboration with therapists—was mentioned repeatedly.

6.5 Discussion

The evaluation results underscore the central importance of personalization in fostering emotional engagement and therapeutic relevance. Crucially, emotional resonance was not solely linked to the final visual output, but also to the co-creation process itself. Participants frequently described the interactive design of their Tamagotchi as meaningful, enjoyable, and motivating. The ability to shape visual attributes and iteratively refine the outcome significantly enhanced their sense of ownership and connection. This indicates that the personalization process plays a critical role in building engagement, beyond the symbolic or aesthetic qualities of the resulting image. Most participants preferred their personalized Tamagotchis over the pre-generated ones and often described them as emotionally fitting, supporting the conceptual foundation of the prototype.

The study also demonstrated the technical feasibility of the approach, even though further refinement is needed to ensure consistent output quality and semantic accuracy. Some categories were more intuitively interpretable than others. Sequences featuring animals were generally easier to understand, likely due to familiar symbolism and clearer visual cues. In contrast, abstract or plant-based imagery posed greater challenges. Furthermore, image series with three states were generally interpreted more successfully than those with four, suggesting that increased complexity may reduce clarity in perceived progression.

The overarching idea of a personalized, AI-generated Tamagotchi as a therapeutic tool was positively received by the majority of participants. Most appreciated the symbolic representation of change and motivation, though some raised concerns. These included doubts about emotional depth, questions about sustained motivation over time, and a perceived mismatch for certain user groups. Some participants also expressed ethical reservations, particularly around emotional dependency and data privacy.

7. Conclusion

This study explored the use of generative AI to create personalized virtual companions aimed at fostering emotional engagement and supporting therapy adherence. The findings underscore that personalization is central to the effectiveness of such interventions, not only in the creation of tailored outputs, but also in the co-creative process itself.

Future work should focus on advancing the technical aspects of the system. This includes moving beyond static 2D representations to more complex formats, such as 3D visuals and dynamic behavioral states. Additionally, the ability to simulate Tamagotchi-like behaviors and integrate such companions into healthcare systems in a secure and scalable way remains an important development goal.

While the results highlight the promise of generative AI for fostering engagement, they also underscore unresolved challenges that extend beyond technical refinement. Longitudinal research is needed to determine whether emotional attachment to virtual companions can be sustained over time and meaningfully influence adherence outcomes. Equally important are the ethical implications: designing companions that motivate without fostering unhealthy dependency, ensuring transparency in how AI-generated representations are created, and safeguarding user data in clinical contexts. Addressing these concerns will be critical for translating the concept of personalized Tamagotchis into responsible, clinically relevant practice.

Ethics Declaration: This research did not involve sensitive personal data, medical interventions, or vulnerable populations. Therefore, formal ethical clearance was not required. Participation in the study was voluntary and anonymized. Informed consent was obtained from all participants.

AI Declaration: AI tools, specifically ChatGPT and DALL·E 3, were used in the design and implementation of the research prototype. Additionally, ChatGPT was used as a writing assistant for drafting and editing parts of this paper under the full direction and review of the authors. The interpretation of findings and all critical assessments were carried out by the authors.

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AI Generated Images for Education and Work Life: On Bias and Guardrails

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Abstract: The rapid multimodal development of Generative AI (GenAI) tools has opened up possibilities for content creation in many fields. This paper presents a study that had a focus on image generation for educational contexts and professional development in a course on artificial intelligence for education and work life. In an assignment, participants used different GenAI tools for image generation. Moreover, course participants analysed and discussed their AI generated images in essays. In the wide variety of GenAI tools two different image generation software were suggested, one from a big established IT company and the other from a small independent software developer. Both these tools were chosen because they are free to use without any licence fees, and that there are not any complex login procedures before using them. This was seen as important criteria for a group of course participants with relatively low pre-knowledge of GenAI and image generation. On the other hand, course participants with earlier experience of were allowed to use other and more advanced tools. Images could be generated individually or in groups, but the final analysis essays had to be written individually without any AI assistance. Four portraits should be generated with each tool of two world-wide well-known persons, one locally known person and a portrait of the course participant that wrote the essay. 61 essays were thematically analysed with the use of open coding and axial coding. Results were divided into the categories of Age, Gender and Ethnicity, Language, Guardrails, and Training data, with Training data as the central or axial category. Findings show that the results to a certain degree are depending on prompting and the language, but that the found bias is depending on the training data.

Keywords: Image generation, Biased data, Artificial intelligence, GenAI, AIED

1. Introduction

Humans have created sophisticated images since way back, with Palaeolithic cave art by Cro-Magnon artists 40 000 years ago (Gray, 2010). In the year of 1826 or 1827, the exact date is not verified, the French inventor Nicéphore Niépce preserved the first photo copy from a camera obscura and a new technique for generating images was created (Mcquire et al., 2024). During the following 150 years until the introduction of the first prototype for a digital camera in 1975 to 1976, an estimated 15 billion of images were created. This could be compared to the 15 billion images that were AI generated during the first year after the first accessible AI image generator was released in September 2022. (Attie, 2023; Tensetti and Rangsjö, 2024)

With this new possibility to generate more or less photorealistic images with user-friendly online tools, it is tempting to replace traditional image generation in many professional fields. As brought up in Göring et al. (2023), the use of image generating tools has rapidly increased in popularity, despite the facts that they may be of low quality, look artificial, and be less appealing when compared to real images. There are yet no objective quality models for AI-generated images, and that research studies indicate that there are huge variations in quality between different AI image generators (Göring et al., 2023; Lu et al., 2023).

There are several reasons to believe that the image quality has improved during 2023 to 2025, with Midjourney and DALL-E as two promising tools in iterative development (Adetayo, 2024). The study by Berg et al. (2024), concluded that the integration of AI generated images could add value to active and student-centred learning with creation of portraits of historical persons. This study had a focus on AI supported image generation for educational contexts and the creation of portraits of existing persons. The study was conducted in a course on artificial intelligence for education and work life where course participants generated images, analysed the images and wrote essays about their results and reflections. The majority of the course participants are working as teachers in different educational contexts, but there were also course participants that are university students or working in private companies.

At the same time as Generative AI (GenAI) has opened up new and rich possibilities for image generation in educational contexts, research studies have reported on a low AI literacy among educators. Another motivation for this study is the discussion on bias in the AI models and how that affects AI generated images. The aim of the study is to explore the potential of using AI generated images to illustrate existing persons in educational content. Two research questions were formulated to guide this exploration:

RQ1: In what ways could the use of AI-generated images contribute to richer and more multimodal teaching and learning content?

RQ2: What are the main challenges to consider when involving AI generating images in teaching and learning activities?

2. Extended Background

Synthetic data have been produced and used for more than 60 years, but developments in machine learning and GenAI have hugely increased the use (Resnik et al., 2025). Another change during the last years is the spread of AI generated images to many new contexts such as tourism (Zhu et al., 2024), art, and education (Shen et al., 2025). In some contexts, this has added creativity and value, but there are also research studies reporting on how AI generated images reinforces existing stereotypes (van Kolfschooten & Pilottin, 2024; Zhu et al., 2024).

2.1 AI Models and Training Data

In the training of AI models, it is important to enhance the diversity and representativeness of the used training data (Sharma et al., 2025). However, when this is done by web scraping that involves all kind of biased image presentations, this will also be reflected when the AI model is used for image generation. The ethical problem to address is that while synthetic GenAI data can be used to correct for biases in datasets, they can at the same time perpetuate and amplify biases in the training data. If the AI models that are used to generate synthetic data are not thoroughly evaluated and tested, the ingoing biases can lead to discrimination and inequity (Resnik & Hosseini, 2024). In contexts such as health care this is an identified problem that biased models could have serious consequences (El Emam et al., 2020; Mehrabi et al., 2021).

2.2 AI Models and Guardrails

Except for propagating societal stereotypes uncensored AI models sometimes also generates, among other offending things, strongly discriminatory language and racist argumentation. The mitigating solution is called guardrails, using the metaphor of physical guardrails we use when we cross a bridge or when we are descending steep stairs, for filtering inappropriate AI-generated output. Since AI models are vast, multi-dimensional entities using billions of parameters the implementation of guardrails in GenAI tools is more complex than constructing guardrails in traditional real-world settings (McDermid et al., 2024). As highlighted in the previous section, AI generated content reflects the bias and misalignment in the used training data. The early AI bots without any filtering frequently produced harmful and discriminating content. Today, guardrail mechanisms are no longer an optional feature, but a mandatory must (Akheel, 2025).

During the last years, an entire ecosystem of different guardrails mechanisms for constraining inappropriate LLM behaviour has emerged. Except for mere content gating guardrails can also include: 1) Real-time content moderation, where sophisticated classifiers detect and transform or remove problematic content before it reaches the end-user, 2) Privacy-preserving strategies, involving features for anonymization to prevent inadvertent disclosure of sensitive information, 3) Bias mitigation, to minimize the risk of perpetuating harmful societal stereotypes or discriminatory language in GenAI output, and 4) Value alignment, ensuring that the output harmonising with organisational and community norms. Guardrail features that have to be balanced between a guardrail that aggressively censors all risky terms, and a guardrail that allows legitimate queries, do not disturb the end-user's workflow, for a AI tool that generates useful output (Akheel, 2025).

3. Method and Materials

The overall research approach was pedagogical action research involving the idea of a concrete and systematic approach "that enables teachers to investigate their own teaching and their student's learning" (Nolen & Putten, 2007, p. 401). Pedagogical action research also comprises the dual roles where an author also has had the role of a teacher (Norton, 2009). In the research context described below, the author has had the roles of being a teacher, a facilitator, a content developer and the course developer. These multiple roles bring in the ethical issue of having a more subjective opinion toward the investigated assignment, compared to a researcher and author without any other involvement in the educational context. The quotes in 4. Findings and discussions have been translated from Swedish to English by the author. Finally, course participants have been kept as anonymous as possible.

3.1 Research Context

The course was designed and developed to be given as a nation-wide 7,5 ECTS standalone distance course. A course that should be open for all persons with general entry requirements for higher education, but with pre-service teachers and persons working in educational as a main target group. The 97 course participants that have submitted a solution to the assignment have a wide geographical nation-wide spread around Sweden and

also with some participants from Norway. Moreover, the average age of the course participants has been higher than in a standard university course and somewhere around 40 years. In the two first course iterations the majority of participants have been working in different educational contexts, and many of them are working on a full-time basis. In the moment of writing the third iteration is given as a summer course, and with a more heterogeneous group of participants and with a slightly lower average age.

Since it is a course that is given at a department of education, it ought to have a focus on pedagogical and didactical aspects of AIED. However, to better understand some of the general aspects of AIED, the course also comprises technical, administrational and ethical aspects of AI. The course is divided into the four main sections:

1. Introduction and tool testing
2. AI in Education
3. Multimodal AI
4. Discussion webinars as knowledge cafés

To introduce and support the course sections above the course was outlined to involve a mix of teacher led synchronous activities, online workshops, online and onsite group discussions, and asynchronous self-studies. These activities were built around six mandatory assignments created to assess the learning objectives that are listed below:

The overall aim of the course is to present, discuss and apply fundamental tools and theories in the field of AIED. After a completed course the participant should be able to:

- Understand and explain the history and development of AI and AIED
- Analyse and discuss the main opportunities and challenges of AIED
- Evaluate and discuss different tools for detection of AI generated texts
- Explore and apply different GenAI modalities such as text, images, sound and music
- Compare, discuss and reflect over how GenAI could affect and enhance teaching and learning activities and assessment in various educational contexts

A course that was built around the overarching idea of combining practical and theoretical aspects of AI for a deeper understanding of AIED that should be useful, not only during, but also after the course. (Mozelius, 2025)

3.2 Data Collection

There is today, a wide variety of GenAI tools for image generation. The two different image generation software used in this study were, one from a big established IT company and the other from a small independent software developer. Two tools that were chosen, and because they are free to use without any licence fees, and that there are no complex login procedures before participants with low IT-skills could start using them. This was seen as important criteria for a group of course participants without any training in computer science with relatively low pre-knowledge of GenAI and digital image generation. Participants with earlier experience of image generation were allowed to use other and more advanced AI-tools.

Course participants did, individually or in groups, generate 4 images in each of the chosen image generating tools. To solve the assignment these 8 images should later be described, analysed and reflected upon. Finally, to complete the assignment course participants had to wrote individual essays about their image generation process, their results, and their reflections. In two course iterations a total of 97 essays were submitted and analysed as described in the section here below. Course participants were allowed to generate and analyse more images, but the 4 mandatory images that had to a part of every submission were:

- Two images of Greta Thunberg
- Two images of Boris Johnson
- Two images of the course participant
- Two images of the university Vice-chancellor / Rektor

Course participants were allowed to choose their tools for image generation, but the two given and cost-free suggestions were:

- Perchance Image Generator
- CoPilot / DALL-E

3.3 Data Analysis

The submitted essays have been analysed according to the Grounded theory analysis process of data being 1) fractured and labelled, and 2) conceptualised around a central category (Moghaddam, 2006). In the first analysis phase, also known as Open coding, data were split into units of meaning that later were aggregated to categories as described in Khandkar (2009). The second analysis phase, also known as Axial coding, was guided by the Grounded theory concept of "coding that treats a category as an axis around which the analyst delineates relationships and specifies the dimensions of the category" (Bryant & Charmaz, 2007, p. 603). In the Axial coding process the preliminary categories from the Open coding phase, were reassembled into more abstract conceptual categories around the central axis category of ''Training data''. Larger Grounded theory studies often comprise a third phase that could be referred to as Confirmatory coding (Cleveland-Innes and Campbell, 2012), or as Selective coding (Walker and Myrick, 2006). This third phase where the identified categories in the second phase should be revised put in context is future work, and not a part of this study.

4. Findings and Discussions

After four text-based assignments many course participants found it both enjoyable and frustrating. Enjoyable since image generation is fascinating and creative, but frustrating since the images often did not meet the participants expectations. All the 4 image themes involved several types of surprising results. The analysis and discussion below were based on 97 submissions from 2 course iterations.

4.1 Two Images of Greta Thunberg

In the submissions from the first course cohort both DALL-E and Perchance Image Generator generated images of Greta. However, it is very hard to associate Image 1 below with a portrait of Greta Thunberg.

Image 1. Greta Thunberg in DALL-E

Image 2. Greta in Perchance IG

Image 3. Greta in real life 2025

It is definitely easier to recognise Greta in Image 2 but as one of the course participants wrote in his submission: *"She looks like 10 years old"*. Another course participant prompted Perchance IG to make Greta a bit older, but the result was not particularly good. This illustrates the first category 'Age' that also was appearing in the generation of the 3 other images, but most obvious here since Greta is younger than the other persons. There were also other pictures in the submissions where she looked younger than in Image 2. The probable explanation is that training data for the tools were scraped from the web and contains images that were captured some years ago. In the second course cohort DALL-E refused to create any images of Greta and almost all course participants were meet by the standard response: *"I cannot create images of contemporary political candidates or elected officials, including Greta Thunberg. Let me know if i can help you with something else!"*. However, one course participant in the second course cohort succeeded, with smart and iterative prompting, to create a portrait of Greta in DALL-E with much better resemblance than Image 1.

4.2 Two Images of Boris Johnson

An obvious difference between DALL-E and Perchance IG is that DALL-E has much more of inbuilt guardrails. The results differ, but already in the first course cohort a course participant did, instead of an image get the response: *"I can't directly show you a photo, but you can find many images of Boris Johnson on Getty Images. Here are some links where you can browse through a large collection of his photos"*. However, the results differ and one course participant in the same course cohort generated the portrait shown in Image 4 below. When she asked DALL-E to make the hair thinner, it got instead thicker and the resemblance with the real Boris in Image 6 is poor.

Image 4. Boris Johnson in DALL-E	**Image 5. Boris in Perchance IG**	**Image 6. The Official Portrait 2019**

The image generated by Perchance IG is definitely more look-alike than the one created in DALL-E. On the other hand, Perchance IG did sometimes make caricatures of Boris and other persons. Moreover, the lack of guardrails in Perchance IG sometimes generates images of a sexual or pornographic nature. Something that also can be explained by the axial category Training data, when the web was scraped for as much data as possible, some images were gathered from fashion and porn sites as well.

4.3 Two Images of the Course Participant

According to the Pedagogical action research principle of keeping informants as anonymous as possible no images of course participants were inserted in the paper. Probably that would not have been a big issue, since very few course participants could recognise themselves in the generated images. However, this could instead be illustrated by two images of the author generated in DALL-E before the first course iteration in 2024.

Image 7. The author in DALL-E with simple prompting	**Image 8. In DALL-E with complex prompting**

There is nothing offending in the pictures, but on the other hand nothing is right either, and none of the images can break the rule of an anonymous conference submission. In the complex prompting details such as that the author works as a senior lecturer and researcher at a university were added. The different prompts lead to the category of language, where the role of prompt engineering is a factor. Other findings for this category are the differences between prompting in English and prompting in other languages. The choice of language does not make a big difference in DALL-E, but definitely in Perchance IG, and some other tools used in the course. Male course participants were mainly surprised and disappointed over the poor resemblance in the images. Female course participants have more comments on that they "Look like movie stars", with the long neck and with the 'plastic' look that can be found in Image 1. There are also comments on sexism in the generated images, and lack of sense in the image generators regarding what was selected for the category of Gender and Ethnicity.

4.4 Two images of the university Vice-chancellor / Rektor

Finally, the images of the university's seemed on beforehand to be the least complicated task, since he is an official person that easily can be found on the Internet. However, and once again the dependency on training data and that most persons are not close to the numbers of images that have been published on Greta Thunberg and Boris Johnson. Regarding guardrails they seem to have been strengthen during 2025 in DALL-E and also in ChatGPT. An example of a response to a course participant was*: "I am sorry, but I can't generate an image of the*

Vice-chancellor since it goes against our content policy. If you like I could instead create a generic image of a Vice-chancellor or an academic leader".

Image 10. Generic image in ChatGPT	**Image 11. Generic image in DALL-E**	**Image 12. Generated with Perchance**

Where none of the images could be used in any educational context, or neither in any other context. Regarding the category of Gender, one course participants generated a series of generic Vice-chancellors where 5 out of 6 images depicted a male Vice-chancellor. Some submissions report that the image generators recommended links to web pages where images of the Vice-chancellor could be found. However, this was not a default answers and maybe something that was depending on the prompt that was entered. In a summarisation of all the 97 submissions there are many reports on surprising variations that confirm the fact that GenAI tools work stochastically and not algorithmically.

4.5 Data Analysis

After a two-step Grounded theory analysis process findings have been divided into the categories of Age, Gender and Ethnicity, Language, Guardrails, and Training data. Since all the other categories are depending on Training data, this was the obvious choice for the central or axial category. How the other found categories depicted in Figure 1 are aggregated and related to the central category of Training data is described here below, category by category.

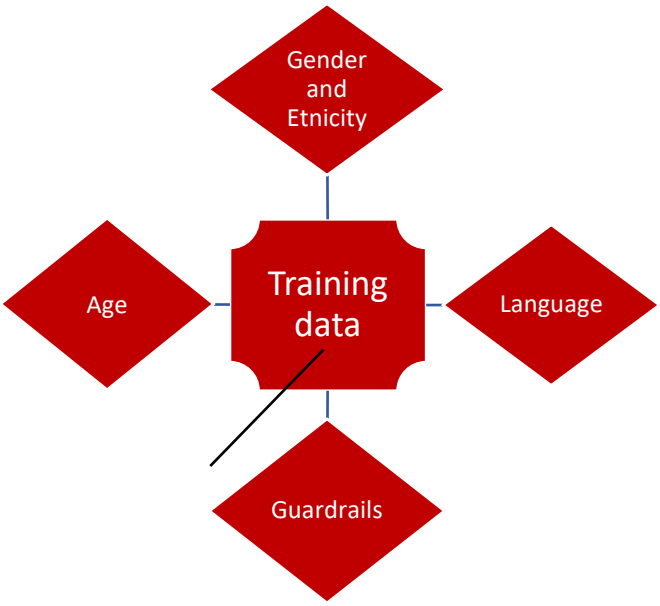

Figure 1: Found categories and their relation to the axial category of 'Training data'

Category 1: Age

There are many comments on Age in the submissions and that both the well-known official persons and the self-portraits of the course participants often look younger and sometimes inexplicably younger. This got even more extreme when course participants used the 'Painted Anime Filter' that was the default setting in Perchance IG during the first course iteration. As an example, Image 14 is a self-portrait prompted by a woman in her forties.

Image 13. A young Greta	**Image 14. A young course participant**	**Image 15. A young Boris**

This can partly be explained by the fact that training data consist of images from the past, and that the results are depending on the training data. However, as some course participants brought up in their submissions, there seems to be instructions for choosing a younger depiction, than the opposite. A solution that seems to work in the new version of DALL-E is to prompt the year of when the image should from, and that DALL-E now can link to existing images to base the generation on.

Category 2: Gender and Ethnicity

As mentioned earlier, five out of six Vice-Chancellors were depicted as men, when the prompting only consisted of Vice-Chancellor. This might represent the gender distribution in the training data, which is hard to check since the transparency is not there. The reports on sexism and ethnical bias seem also to be strongly related to the training data. When the web unconditionally was scraped for training data, this gave a US-centred focus with several types of bias. In areas such as medicine this is a serious problem where the biased impact of ethnicity and sex disturbs the prediction models (Ravindranath et al., 2025). As found in the cross-sectional study by (Gisselbaek et al., 2025) images generated by ChatGPT DALL-E and Midjourney repeats existing stereotypes regarding ethnicity, sex, and age.

Category 3: Language

This category consists of the two sub-categories 'Natural language' and 'Prompting language'. Regarding the first, the output from the AI-tools depended on which language that was used in the conversations. Especially for Perchance IG, there was a significant difference between course participant using English, and the ones that used other languages. Small languages are, more than by proportion, less represented in the training data and gives more unexpected outcomes. Prompting language could be seen as a synonym for prompt engineering, but at the same time as it matters how you prompt the tools, it is hard to see this as engineering. How, clever and iterative prompting could generate a different result is illustrated in the next category.

Category 4: Guardrails.

Without any guardrails at all the outcomes could, depending on the prompting language, be very offending and that the bias reported under 'Gender and Ethnicity' would be much stringer. On the contrary, the guardrails are what makes the outcomes from the image generation more or less useless in educational contexts. However, with smart, clever, or provocative prompting some course participants generated quality and identifiable images of persons without using their names.

Category 5: Training data

Without a substantial data set the AI-models would not perform well, but without a thorough curation of the training data will be biased in aspects such as age, gender, and ethnicity.

Finally, old training data contains a huge amount of historically interesting content, and as an example, guardrails do not stop you when generating images of Winston Churchill.

Image 16. Winston Churchill 1945 generated in DALL-E

5. Conclusion

Despite the poor and frustrating outcomes, the two research questions could be answered:

RQ1: AI-generated images could enrich learning content when it comes to abstract illustrations and historical, no longer living persons. To compare with the frustrating task of trying to depict living persons, or persons that are sparsely represented in the training data. Regarding what the guardrails in DALL-E mentioned as "contemporary political candidates or elected officials, including Greta Thunberg", they can often be retrieved from the Internet without violating any copyrights.

RQ2: The main challenges to consider are the presented categories of Age, Gender and Ethnicity, Language, Guardrails. Since they all are depending on Training data, the brief and generalised solution would be to curate the training data, as suggested in several other studies.

As pointed out by (Zhu et al. (2024), AI-generated images have their own limitations that need to be discussed, and as concluded by Hsu et al. (2024) due to the bias in training data, GenAI is today unable to fully present the nuances of socio-cultural diversity. Addressing biases in training data to ensure fairness in model outputs is essential for the ethical deployment of generative models. Future research should address bias detection and mitigation strategies to promote ethical AI practices as suggested in Sharma et al. (2025). Finally, the pedagogical action research idea of making changes should be considered, and based on the finings in this study, the described assignment and its related activities should be revised in the next course iteration. This paper will also be a part of the additional reading in the next course iteration.

Ethics declaration and AI declaration: Data have been collected with informed consent, and course participants have been kept as anonymous as possible. AI tools were used in the described image generation, but the essays and all parts of this paper, have been written without any use of AI.

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Interpersonal Trust Development in GenAI-augmented Organisations

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Abstract: Generative artificial intelligence (GenAI) is being increasingly adopted across organisations, where its integration into work has been shown to significantly enhance efficiency and productivity. However, GenAI's use introduces greater uncertainty about the reliability and quality of work. This uncertainty, combined with potential changes in social interaction as an outcome of GenAI use, may directly impact interpersonal relationships, especially trust, among employees. Yet, remarkably few studies explore GenAI's impact on interpersonal relationships within organisations. This study, therefore, seeks to explore the impact of GenAI on interpersonal trust in organisations that have integrated GenAI to assist in the conduct of work, referred to here as GenAI-augmented organisations. In this study, we apply the organisational trust model, defining trust as the willingness to be vulnerable in response to perceived trustworthiness based on evaluated ability (skills and competencies), integrity (adherence to shared values and norms) and benevolence (concern for others). We explore how this response evolves in the context of GenAI use. We conducted nine qualitative semi-structured interviews in April-May 2025 with managers from knowledge-intensive, GenAI-augmented organisations. Our findings suggest that in GenAI-augmented organisations, managers tend to place greater trust in employees demonstrating ability requiring higher cognitive effort, such as critical GenAI use, asking questions, understanding, and explaining GenAI outputs. Integrity, described through the manner of GenAI use, particularly by demonstrating responsibility, maintaining transparency, providing evidence, and aligning with organisational policies, is also critical for developing interpersonal trust. Moreover, uncritical GenAI use that may burden others with more work can lead to a reduction in trust. In response to uncertainty, managers often increase supervision; however, this is not necessarily a sign of distrust but a strategy to manage uncertainty. To our knowledge, our study is one of few qualitative studies exploring GenAI use in organisations. It provides a novel perspective that connects GenAI and interpersonal relationships. The findings have implications for management practices, organisational culture, and aligning GenAI to enhance trust and collaboration within organisations.

Keywords: Trust, Generative AI, Workplace environment

1. Introduction

The rapid adoption of generative artificial intelligence (GenAI) is transforming the nature of work in organisations that have integrated GenAI to support employees in conducting their work. In this study, we refer to these as GenAI-augmented organisations. Despite these changes, interpersonal relationships among employees remain central to work (cf. Bankins et al, 2024). Trust, which emerges through social interaction, is recognised as one of the most important interpersonal relationships for organisational performance (Mayer, Davis & Schoorman 1995). Recent research found that GenAI may foster conditions that promote social interaction (Marimon, Mas-Machuca & Akhmedova 2024) but may also lead to a decline in it (Retkowsky, Hafermalz & Huysman 2024) and erode interpersonal trust (Pavleska 2025; Schilke & Reimann 2025). Therefore, it is increasingly important to understand how GenAI influences interpersonal trust within organizations, leading to the research question: *How does the use of GenAI affect the development of interpersonal trust between managers and their team members within GenAI-augmented organizations*?

GenAI refers to a subset of artificial intelligence systems that autonomously produce content, such as text and images, in response to prompts (cf. Retkowsky, Hafermalz & Huysman 2024). GenAI-augmented organizations commonly apply it to support decision-making, automate routine tasks, enhance communication, and deliver performance-related feedback (Bankins et al, 2024). Our study seeks to explore how managers in these organisations develop interpersonal trust in their team members. To address this, we draw from the organisational trust model that defines interpersonal trust in organisations as the willingness to be vulnerable to another's actions, based on perceptions of their ability, benevolence, and integrity (Mayer, Davis & Schoorman 1995). As GenAI alters the nature of work (Bankins et al, 2024), it may influence how these dimensions are enacted and perceived.

2. Literature Review

Prior research suggests that evaluation of trustworthiness is a necessary antecedent to trust. Mayer, Davis, and Schoorman (1995) propose a trust model in which trustworthiness is evaluated along three dimensions:

ability (skills and competencies), integrity (adherence to shared values and norms), and benevolence (concern for others). This model is widely applied in exploring interpersonal trust in contemporary organisational settings (e.g., Bentzen 2023). Notably, context influences how trustworthiness is evaluated and perceived (Mayer, Davis & Schoorman 1995). Blomqvist and Ståhle (2000) extend this model by distinguishing between interpersonal trust (trust among individuals) and organisational trust (trust in systems, structures, and norms) and by emphasising that trustworthiness is evaluated iteratively through observed competence, goodwill, and behaviour. Their work highlights the important role of competence, defined as professional skills, expertise, and judgment, as a necessary condition for trust development. In relationships between managers and employees, perceptions of competence, benevolence, and integrity are central to the evaluation of trustworthiness (Bentzen 2023). When trustors perceive trustworthiness as low and are unwilling to take risks, different forms of supervision are often used as substitutes for trust (cf. Mayer, Davis & Schoorman 1995). However, recent research suggests that meaningful supervision may enhance rather than reduce trust (cf. Bentzen 2023).

Research has shown that technologies can significantly shape how trust is developed (Lumineau, Schilke & Wang 2023). Communication tools like email, messaging, and video conferencing have been shown to enhance social interaction, thereby supporting trust (Lumineau, Schilke & Wang 2023). Unlike these earlier technologies, GenAI is not a communication tool (cf. Retkowsky, Hafermalz & Huysman 2024). Instead, by generating content in the background as the basis for social interaction, it alters the conditions under which such interaction takes place (cf. Retkowsky, Hafermalz & Huysman 2024). GenAI use can enhance employees' access to and processing of information and reduce misunderstandings. It also supports collaboration, creativity, and knowledge sharing by retrieving and synthesising large volumes of data, improving written consistency, and serving as a learning tool (Florea & Croitoru 2025; e.g., Yeon, Lee & Park 2024). However, by performing work tasks more independently and reducing employee interdependence, GenAI use may reduce interpersonal interaction, and may contribute to individualisation and isolation (Retkowsky, Hafermalz & Huysman 2024). GenAI use may also reinforce inequality and insecurity, as high performers are often better positioned to use GenAI for high-quality output, thus extending their abilities (Humlum & Vestergaard 2025). All this can constrain social interaction.

GenAI outputs raise reliability and data quality concerns (cf. Bankins et al, 2024). Therefore, critical GenAI use, such as verifying outputs rather than blindly accepting them, is central to mitigating the risks of overreliance on GenAI (Marimon, Mas-Machuca & Akhmedova 2024). Moreover, research shows that GenAI use may unintentionally negatively affect evaluations of trustworthiness and trust development (Pavleska 2025; Schilke & Reimann 2025), a phenomenon referred to as the "AI Penalization Effect" (Kim et al, 2025, p. 6).

Although research increasingly explores the use of and trust in GenAI (cf. Bankins et al, 2024), less is known about how GenAI, operating in the background and embedded in employees' work, may influence interpersonal trust, especially between managers and team members.

3. Method

We conducted a qualitative study to explore how GenAI use impacts the development of interpersonal trust in GenAI-augmented organisations. Semi-structured interviews were chosen to capture participants' experiences. To answer our research question, we recruited nine managers working in GenAI-augmented organisations in Norway, Denmark, Germany, the UK, and the USA. We focused on managers because they are uniquely positioned to evaluate the trustworthiness of employees within organisations. Therefore, this provides important insights into the nature of interpersonal trust in GenAI-augmented organisations.

Participants were recruited through purposive sampling via a LinkedIn announcement targeting managers in GenAI-augmented organisations. This approach ensured a relatively homogeneous group with relevant GenAI experience, enabling rich insights into its impact on interpersonal trust. The nine recruited managers (M1–M9) described themselves as experienced GenAI users. Three participants worked in consulting, four in software research, and two in IT services; seven had direct reports, while two did not. One was a C-level executive in a large international consulting firm; the others were middle managers. Their responsibilities typically included planning, task assignment, team communication, and performance reviews. The sample size of nine was considered sufficient for a qualitative interview study, allowing for in-depth exploration of diverse perspectives while achieving thematic saturation (cf. Saunders & Townsend 2016).

The data collection, conducted in April-May 2025, adhered to the dedicated data management plan and followed the principles of responsible research conduct. Each interview lasted approximately one hour and

was conducted digitally via Microsoft Teams. The interview guide included questions grouped into five sections: (1) participant background (e.g., job role, responsibilities), (2) use of GenAI (e.g., work tasks, integration into workflow), (3) organisational context (e.g., organisational policies), (4) impact on work and trust (e.g., transparency, performance evaluation), and (5) interpersonal relationships and communication (e.g., changes in collaboration, communication patterns). Interviews were audio-recorded using Microsoft Teams recording function with participants' consent and transcribed both automatically and manually verbatim to ensure accuracy.

The interview data were analysed using thematic analysis (Braun & Clarke 2006). NVivo 15.0 was used for thematic analysis alongside exploring code relationships. Transcripts were read multiple times to gain familiarity, and initial codes were generated inductively to capture recurring patterns related to GenAI and trust. The final themes reflect how trust is developed in GenAI-augmented organisations, focusing on employees conducting their work using GenAI, managers evaluating trustworthiness and developing trust, and GenAI usage, boundaries, and effects.

4. Findings

The analysis revealed a strong relationship between how work is conducted and how trust is developed in GenAI-augmented organisations. Findings reveal that participants' trust in team members was shaped by the critical use of GenAI, the ability to ask questions, understand, and explain GenAI outputs, and behaviours such as demonstrating responsibility, maintaining transparency, providing evidence, adhering to policies, and avoiding overburdening others as a result of GenAI use.

4.1 GenAI use and Increased Uncertainty

Participants described extensive use of GenAI when conducting their work. Employees use GenAI for tasks such as meeting transcription, summarisation, and drafting emails and reports. It also supports performance reviews, document translation, and synthesising internal documentation across languages and regions. In their organisations, GenAI is used for both routine administrative tasks and more complex work, such as stakeholder communication and business architecture planning. In consulting, GenAI processes large volumes of meeting data to produce workshop content, reports, and specifications. In software development research, it supports data collection and analysis. In some of these organisations, GenAI is also applied to support dyslexic employees and non-native English speakers. In several domains, such as consulting and software development, internal GenAI platforms have been developed and tailored to organisational needs.

All participants observed that GenAI use was a source of increased uncertainty regarding work reliability and quality. They explained that while GenAI produces impressive outputs, verifying them is challenging. As a result, employees often struggle to determine whether these outputs are reliable. As one participant elaborated: "We often get very, I shall not say, cool things, very good things out, but we are not sure if they are real things, if they are really good and it is very difficult to verify" (M3).

Although all organisations in this study had implemented company-wide policies for GenAI use, participants noted that these did not help mitigate uncertainty. Several participants explained that the policies focused on legal compliance and information security, resulting in vague guidance that failed to address practical uncertainties. As one participant explained: "We have standard guidelines mostly around legality... but it's not giving you guidelines on what can go wrong" (M7). Another participant echoed: "They might say, use it where you think it makes sense..." (M1). This further contributed to uncertainty resulting from GenAI use. Still, most participants observed that the majority of their team members adhered to these policies, which contributed to their trust in them.

4.2 Ability and Integrity: Critical GenAI use and Trust

All participants expressed trust in team members who used GenAI in ways that added value to their work. As participants noted, GenAI outputs were considered "really smart logical output" (M1) when it made "sense in the wider context" (M1).

This trust was particularly evident when their team members demonstrated critical GenAI use, especially by taking responsibility and actively verifying GenAI outputs. As one participant noted: "It [critical use] certainly affects trust' (M1). Another participant trusted her team members when they acted as an "interrogator" (M2), ensuring that the insights generated were real and "not AI's hallucinations" (M2). This emphasis on verification stemmed from participants' concerns about personal responsibility in GenAI use. As participants put it: "You have to stand by what you produce" (M3) and "The responsibility for the deliverable lies with the person

producing it" (M4). Reinforcing this, one participant in a consulting company noted: "You can't write something without understanding it. You can't write something without having control over your sources" (M4). Another participant echoed this, urging: "Please review it before sending it out, verify and double-check that it's correct... if you generate information and plan to send it to others, read it over, verify it!" (M6).

All participants noted that being "critical thinkers" when using GenAI required even greater cognitive effort from employees. As one participant told, "It actually requires more ability or a greater capacity for critical thinking than ever before. Precisely because we can't necessarily be 100% certain that what's being suggested is the only correct answer" (M8). Another participant explained that she trusted her team members when they demonstrated planning, synthesised information, and formulated complex instructions to achieve meaningful results with GenAI, while also verifying its outputs. She elaborated: "[They] had a strategy in their head. They had—for their tasks—they need to combine multiple types of data and information and documents. And they have to write very specific prompts to get—like, usually—an instruction this long, sometimes even a couple of pages long, to spit this output that they have" (M7).

Moreover, several participants emphasised the importance of team members asking questions for critical GenAI use. As one participant elaborated, asking questions reflects intentionality and planning: "Another important thing is that they ask questions, because that's one of the indicators for me that they have a plan in their head—they know what they're doing" (M2).

Most participants trusted their team members when they demonstrated an understanding of their work processes and context, as GenAI outputs were seen to lack contextual depth and could reduce reliability and quality if used without such understanding. Participants exemplified this concern. One stated: "In my head, I'm screaming like you're not allowed to use AI, you need to figure out the design process first, you need to be able to navigate it up and down" (M2). Another participant elaborated: "It [GenAI] only has text, and it needs to extrapolate context from text. Like, the transcription doesn't tell you what's the problem, who's the user, why we're talking to them, and what we're trying to extract from the situation. It just gives me a lot of text that it's going to summarise in a bunch of bullet points that don't address my assumptions or initial hypothesis that I came in with" (M7). A third participant echoed this concern, highlighting the importance of "understanding the content and the consequences of something that is more advanced than what you normally work with" (M3).

4.3 Ability, Integrity, and Benevolence: "It Only Decreases Trust if you Blindly Follow it"

While participants generally stated that their trust remained unchanged following GenAI adoption in their organisations, many acknowledged that uncritical GenAI use by team members could reduce it. All participants have experienced situations of uncritical GenAI use by their team members. One participant described this uncritical GenAI use as a very linear process: work goes into Copilot and comes out without any verification (M1). Similarly, another participant elaborated: "AI tells them something and they're like, OK, well, I guess that looks legit to me" (M2), while another remarked: 'It only decreases trust if you blindly follow it' (M7).

Moreover, uncritical use of GenAI affected how participants assigned work tasks. One participant explained that, after a team member delivered low-quality work, he became reluctant to assign tasks requiring autonomy: "For him, certainly, you know, I really have to be careful about what I assigned him… So, certainly it does affect the work that I can assign to him" (M1).

Uncritical GenAI use also led to a burdening with more work, signalling the lack of consideration for others in their team. One participant shared how this uncritical GenAI use required him and other team members to: "step in by discarding everything that had been created and rewriting it all from scratch ourselves" (M6). Another participant described a situation where a team member used GenAI to quickly produce a first draft and then passed it to others for revision. This left the participant with more work: "Then we find that it's myself or the other person in the team that are the ones doing all of the critical thinking, and the manual work to improve something that he had only just sort of put through ChatGPT or Copilot. So, it is certainly between team members, it is, and between team, it is affecting people when it's not being used correctly, absolutely" (M1).

However, participants noted that uncritical GenAI use is often associated with team members who are generally low performers. One participant emphasised that a decline in trust stems from a broader pattern of low performance, with GenAI use being just one example (M1). Another participant explained that low performers' general tendency to avoid asking questions was reflected in their uncritical GenAI use: "My lower performers—you know, as a manager, you always encourage your people to ask questions—but they don't.

They can't. And if they don't have questions for me, they won't have questions for AI either" (M2). Notably, some participants observed that GenAI use actively worsened the quality of certain team members' work, making their low performance more visible (M2).

4.4 Integrity: Transparency and Evidence

Participants were not concerned about the disclosure of GenAI use but emphasised that their trust was affected when GenAI use was not disclosed in the cases of low-quality work: "He didn't tell me that it was with AI, but I saw it and the quality was really bad, and I could tell he hadn't read through it, and that did make me lose trust in the work" (M1). Participants also noted that disclosure was often left to team members, making it harder to evaluate how GenAI was applied. As one participant explained, at present, "it's up to an individual to say when they use it and when they don't" (M1). Another added: "I see the traces, but it's hard for me to see it systematically and comprehensively" (M4).

In contrast, participants trusted team members who used GenAI transparently and supported their outputs with evidence: "She's using it a lot, she's also pretty careful in kind of like structuring it... showing her work, like showing evidence... even if you know AI did something that still she has the evidence that is supporting it" (M2). These team members were seen as trustworthy, as one participant explained: "She will always put a caveat or a little asterisk saying, you know, like, I created this synthesis using AI. So, she does full disclosure" (M9).

4.5 Increased Managerial Supervision

All participants noted that the increased uncertainty around work reliability and quality, rooted in uncritical GenAI use, required increased supervision. Moreover, the complexity of verifying GenAI outputs significantly increased the need for quality assurance. Participants emphasised that supervision was important for ensuring quality. As one participant elaborated: "Previously, it was difficult to formulate something if you didn't understand it. But now, you can formulate something without understanding it, and that creates new demands for both control and follow-up" (M4). He further stressed that: "[GenAI use] mean we have to be more vigilant, of course, in terms of quality assurance and the responsibility placed on each employee and each leader" (M4). Another participant echoed this concern, stating: "Our trust issue is more about quality assurance and the methods the tools use" (M3).

Moreover, most participants experienced situations in which uncritical GenAI use resulted in serious negative consequences. These incidents led to tighter supervision of certain team members. For example, one participant experienced how one of his team members sent a GenAI-produced report directly to top management without verifying it (M1). This participant elaborated regarding such negative experience: "From then on, I was always checking the work that he was doing..." (M1). He concluded that until his team members demonstrate critical GenAI use: "Maybe it does require more managerial oversight until people are more comfortable with it and know how to use it appropriately" (M1).

4.6 Summary

In GenAI-augmented organisations, GenAI use together with vague organisational policies introduces greater uncertainty regarding work reliability and quality. Therefore, managers' trust in their team members is shaped not only by how critically GenAI is used but also by team members' ability to ask questions, understand, and explain GenAI outputs. According to participants, this requires a higher level of cognitive effort than before. Moreover, demonstrating responsibility and transparency in GenAI use, providing evidence, and alignment with organisational policies are also important to managers for developing trust. In contrast, uncritical use of GenAI can burden others with more work and reduce trust. When uncertainty is high and/or evaluated trustworthiness is low, managers tend to increase supervision. Thus, in GenAI-augmented organisations, trust is developed and reinforced when employees are perceived as trustworthy based on behaviours such as demonstrating the results of cognitive effort, which reflects their ability, and the manner in which work including GenAI use is conducted, which reflects their integrity; and using GenAI in ways that do not burden others, which reflects their benevolence (see Figure 1).

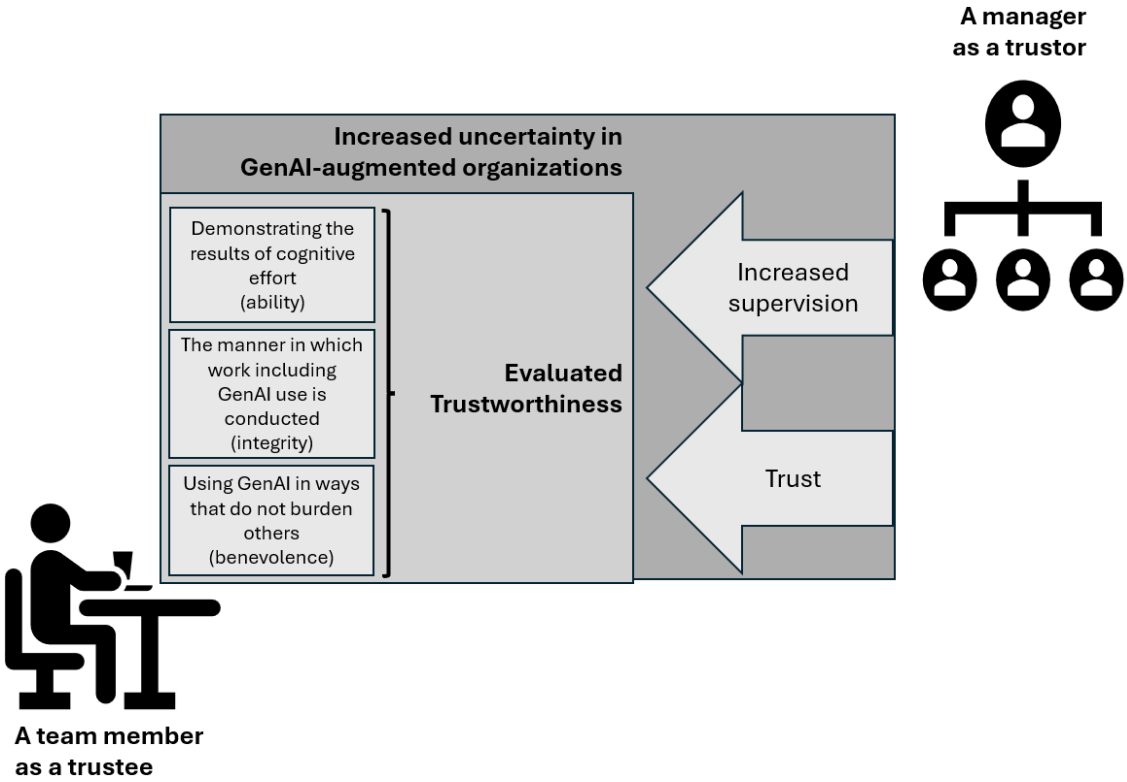

Figure 1: Managers' trust development in GenAI-augmented organisations

5. Discussion

Drawing from the trust model proposed by Mayer, Davis and Schoorman (1995), this study advances the understanding of how GenAI use affects the development of interpersonal trust between managers and their team members within GenAI-augmented organisations. It appears that ability and integrity are particularly important in evaluating trustworthiness for developing trust in these organisations, compared with the central role of all three dimensions in relationships between managers and employees in non-GenAI-augmented organisations (cf. Bentzen 2023). The emphasis on cognitive effort, reflected in ability, aligns with the view that competence is a necessary condition for trust development (cf. Blomqvist & Ståhle 2000). Moreover, employees who take responsibility, through critical GenAI use, particularly by verifying GenAI outputs, demonstrate ability and, through this, integrity. These intertwined dimensions shape how managers evaluate trustworthiness and develop trust, thereby specifying Mayer, Davis, and Schoorman's (1995) model by showing how responsibility and cognitive effort, when intertwined through GenAI use, amplify their influence. Notably, our findings reveal that uncritical use of GenAI, especially when it creates more work for others, may be perceived as a lack of consideration, which negatively impacting evaluations of benevolence. In such cases, benevolence is evaluated based on the consequences of GenAI use rather than the employee intent. However, its influence on trust development appears less prominent than that of ability and integrity. This may be explained by the context in which trust is evaluated (cf. Mayer, Davis & Schoorman 1995), as GenAI-augmented organisations are described by uncertainty and/or reduced social interaction and employee interdependence (cf. Retkowsky, Hafermalz & Huysman 2024). These conditions may make benevolence, such as empathy or helpfulness, less observable and therefore less influential.

Our findings align with prior research emphasising the increased uncertainty, reliability concerns, and risk of overreliance on GenAI, which in turn necessitate greater cognitive effort to verify GenAI outputs (Marimon, Mas-Machuca & Akhmedova 2024; Retkowsky, Hafermalz & Huysman 2024). This also helps explain why the manner in which work is conducted, especially the demonstration of responsibility and the provision of evidence, influences trust development. Moreover, the increased uncertainty necessitates increased supervision. This increase in supervision does not necessarily indicate a decline in trust; rather, it is a strategy to manage uncertainty. This aligns with research suggesting that supervision, when perceived as meaningful, does not erode trust (cf. Bentzen 2023). However, our findings differ from those of Schilke and Reimann (2025) and Pavleska (2025), possibly due to our participants' emphasisis on responsibility, evidence and verification.

This suggests that the relationship between disclosure of GenAI use and trust is complex and context-dependent.

Our findings indicate that uncritical GenAI use is often associated with employees already known as low performers. This uncritical use appears to amplify performance inequalities, consistent with Humlum and Vestergaard's (2025) findings. Moreover, reduced social interactions, which can constrain peer support and informal learning (cf. Retkowsky, Hafermalz & Huysman 2024), may further increase these performance inequalities by limiting opportunities for low performers to improve. This, especially alongside the emphasis on cognitive effort and reduced observability of benevolence in a GenAI context, may present a significant organisational challenge. If high performers are better equipped for critical GenAI use, managers may place greater trust in them over low performers. Thus, GenAI use may contribute to uneven distribution of trust, leading to a more polarised or inequitable workplace if not mitigated.

These findings can be integrated into practical recommendations for GenAI-augmented organisations. Managers may need to provide targeted training to support employees in critical GenAI use. Such training should be tailored to specific workflows, as generalised training is often of limited value. To prevent GenAI from reinforcing existing inequalities, organisations should ensure that all employees receive adequate support. Finally, trust development is an ongoing process, requiring regular managerial reflection.

This study has several limitations. First, the relatively small number of participants may affect the generalisability of the findings. Second, the study focused exclusively on managerial perspectives and did not capture the experiences of non-managerial employees. Third, by focusing on interpersonal trust between managers and their team members, the study does not explore how interpersonal trust may interact with organisational trust, such as trust in structures, processes, and policies in GenAI-augmented organisations. Fourth, the data was collected at a single point of time, providing a snapshot rather than longitudinal view. Finally, while interviews provided rich data, they are subject to self-reporting biases and may reflect socially desirable responses, particularly in discussions of trust.

6. Conclusion and Further Research

This study explored how interpersonal trust between managers and their team members develops in GenAI-augmented organisations. Our findings reveal a potential shift in how trust is developed in these organisations, driven by the intertwining of ability and integrity, and by the reduced observability of benevolence in contexts of increased uncertainty related to work reliability and quality. Our study further contributes to the literature as one of the few to qualitatively explore interpersonal trust in GenAI-augmented organisations, specifically by showing how GenAI use influences managers' evaluation of these dimensions and providing deeper insight into interpersonal trust development in these settings.

Future research should explore the risk of GenAI-driven workplace polarisation and the role of benevolence.

Expanding beyond managerial perspectives to include diverse roles and industries, alongside longitudinal studies, would provide a more comprehensive understanding of how trust develops as GenAI becomes more embedded in work. Further research into the interplay between interpersonal and organisational trust would also enrich this understanding.

Ethics declaration: Ethical clearance was not required for this study.

AI declaration: The authors used Microsoft Copilot to assist with language editing of the manuscript. After using Microsoft Copilot, the authors reviewed the manuscript and take full responsibility for the content of the publication.

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AI-Driven Cyber Deception in FinTech: An Adaptive Defense Strategy

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Abstract: FinTech platforms clear high-value transactions in milliseconds, making them lucrative targets for adversaries who increasingly weaponize artificial intelligence. Once an attacker bypasses the perimeter, via credential stuffing, supply-chain malware, or deep-fake social engineering, traditional defenses often alert too late to prevent loss. We present an Adaptive Deception Defense Framework (ADDF) that intertwines AI-orchestrated honeypots, honeytokens and decoy micro-services within everyday banking and payment workflows. A recurrent-neural threat profiler classifies live attacker behavior; a Proximal-Policy-Optimization agent then selects actions such as spawning a shadow login API, cloning a database or injecting synthetic ledgers, thereby misdirecting intruders while harvesting telemetry. In a controlled "FinBank" test-bed featuring a vulnerable Flask-and-MySQL stack, ADDF shortened mean time-to-detect from 3 min 42 s to 29 s, increased attacker dwell-time inside decoys to 12 min 18 s and prevented all real data exfiltration across ten attack trials. False-positive alerts remained below 1% per run and added resource use averaged 14% CPU/RAM on mid-range servers. The framework also produced high-fidelity indicators of compromise, password lists, malware binaries and lateral-movement scripts, that would have been unavailable under baseline controls. These findings indicate that AI-driven cyber deception can transform FinTech security from passive monitoring into proactive engagement, mitigating breach impact while supplying rich threat intelligence. The paper details system architecture, reinforcement-learning policy training, empirical evaluation and operational implications—showing how defenders can regain initiative in the AI-to-AI cyber arms race without disrupting legitimate customers or breaching regulatory duties. FinTech platforms process high-value transactions at internet speed, making them prime targets for advanced cyber-criminals who now weaponize artificial intelligence. Traditional controls detect many incidents yet remain reactive; once adversaries bypass the perimeter, defenders struggle to contain damage fast enough to prevent data loss or fraud. We present an AI-driven cyber-deception framework that inserts a dynamic layer of honeypots, honeytokens and decoy services into a live FinTech environment. A learning engine classifies attacker behaviour in real time, then deploys or adapts decoys to misdirect adversaries while capturing rich telemetry. In a controlled banking testbed, the system cut mean time-to-detect from minutes to seconds, confined intruders to fake assets in every trial, and prevented exfiltration of real customer data. Adaptive deception also generated high-quality threat intelligence with negligible false positives and modest resource overhead (<15% CPU/RAM on a mid-range server). Findings from this study suggest that the use of AI-powered deception methods can shift or otherwise redirect Fintech defence posture from passive monitoring configurations to that of proactive engagement. This can reduce risk for defensive teams and potentially boost incident-response agility without significantly disrupting legitimate users within a system where the novelty lies in orchestrating established AI components (RL, anomaly classification, and generative decoys) into a closed-loop deception system for real-time FinTech operations.

Keywords: AI-riven, Deception, ADDF, Honeypots, Machine learning, Adaptive, Proactive, Defense, Fintech

1. Introduction

Digital finance now moves trillions of US dollars annually through mobile wallets, real-time gross-settlement rails and open-banking APIs (World Bank 2025). The same connectivity and agility that enable more convenient customer interactions create ever-wider attack surfaces. In 2024 the financial sector recorded a 53% year-on-year rise in confirmed breaches, driven largely by credential-stuffing bots, ransomware campaigns against payment processors and AI-assisted social-engineering scams (Bonini 2025). FinTech firms face asymmetric risk. Adversaries need only one foothold (phished credentials, a misconfigured S3 bucket or a single zero-day) to pivot laterally and exfiltrate sensitive data. Regulators such as the European Union and the Payment Card Industry fine institutions heavily for breaches and mandate near-real-time incident response (European Union 2016; PCI Security Standards Council 2024). Meanwhile, defenders wrestle with alert fatigue: a modern Security Operations Centre (SOC) may review millions of daily events but still miss the handful that matter (Crandall 2025). Standard safeguards (firewalls, multi-factor authentication, fraud-scoring models) remain essential but inherently reactive. Once an attacker phishes valid credentials or finds a zero-day vulnerability, lateral movement can occur in seconds, threatening funds, personally identifiable information and market reputation. Operators need mitigations that buy time, mislead adversaries and reveal their tools of trade before damage occurs.Cyber deception answers that need. By scattering decoys indistinguishable from production systems, defenders turn the network into a minefield: attackers waste effort on fake assets, while defenders observe every move. Early honeypots proved the concept but suffered from static content and high upkeep. Recent

advances in artificial intelligence (especially reinforcement learning (RL) and generative models) enable adaptive deception: decoys that spawn, mutate or retire in response to live attacker cues. Cyber deception offers a complementary strategy. Defenders can use cyber deception to frustrate and create a hostile environment for intruders through the use of realistic decoys, in the form of honey pots, honey tokens, fake micro-services, and more, within production networks. Hints of decoys alone are inherently suspicious, and these can produce a high-fidelity signal that cuts through logging noise (Ferguson-Walter, 2025). Early honeypots, however, were static: attackers could fingerprint stale banners, implausible directory trees or isolated IP subnets (Moric et al. 2025). Artificial intelligence applied to defensive cybersecurity maneuvers, especially through the application its subset, machine learning, changes the equation of defense strategy outcomes. Machine learning, itself, can be utilized to high success in improving defense through uses in (i) *detecting anomalies* in high-volume telemetry (Nobre et al. 2023); (ii) *optimizing decisions* under uncertainty via reinforcement learning (Ngo et al. 2023); and (iii) *generating synthetic artefacts* that pass human or machine scrutiny (Ahmed et al. 2025). Combining these capacities with deception yields adaptive honeynets that spawn, mutate or retire in real time, mirroring genuine customer activity and data schemas. Attackers are lured into a responsive "hall of mirrors," wasting effort while defenders observe tactics, techniques and procedures (TTPs) in a safe sandbox.

This paper makes four contributions:

1. **An ADDF Architecture,** an end-to-end AI-driven deception framework purpose-built for FinTech micro-service meshes is presented
2. **A Reinforcement-Learning Policy** wherein a PPO agent trained to maximize attacker engagement and minimize risk to genuine assets is given.

- *The authors recognize that PPO is not a new concept; rather, we encourage the reader to view this work as an innovative integration of established AI techniques that can be applied within critical contexts. This can be applied to any industry that seeks to utilize fintech as part of their models; this is itself relevant to Industry 4.0 (Ferraro et al, 2024).*
- *However, it can be an orchestration policy that integrates reinforcement learning with real-time anomaly classification and generative decoy synthesis for FinTech micro-services. We use PPO as a robust optimizer (not as a novelty in itself) to decide when and where to deploy, mutate, or retire decoys under live resource, latency, and regulatory constraints. The contribution is the design and integration of this control loop in a high-stakes financial setting, not the PPO algorithm per se.*
- *An RL-driven orchestration policy (implemented with PPO as a stable optimizer) that fuses anomaly classification and generative decoying to make real-time placement decisions under FinTech resource and regulatory constraints (our novelty lies in the integration and operational design, not in PPO itself).*

3. **Generative Data Pipelines**, tools that create synthetic customer records, KY-C documents and transaction streams indistinguishable from production baselines, are demonstrated.
4. **Empirical Validation** through controlled experiments showing that ADDF cuts detection latency an order of magnitude and blocks breach objectives at modest cost is given.

Section 2 surveys threat trends and related research. Section 3 details the architecture, RL training and synthetic-data generation. Section 4 outlines our banking test-bed and attack scenarios. Section 5 reports quantitative and qualitative results. Section 6 discusses trade-offs, limitations and comparison with prior art. Section 7 explores operational and regulatory implications for FinTech. Section 8 concludes and sketches future extensions, including large-language-model (LLM) decoy chatbots and cost-aware cloud auto-scaling.

2. Background and Related Work

2.1 FinTech Threat Landscape

Typical FinTech stacks comprise web front-ends, RESTful gateways, cloud databases, blockchain nodes and vendor APIs. Prominent attack avenues include:

- **Credential abuse:** Botnets replay leaked username–password pairs against login APIs, bypassing multi-factor where SMS intercept or session riding is viable.
- **Data-layer exploits:** SQL injection, insecure deserialization or Server-Side Request Forgery against micro-services expose customer PII and payment tokens.
- **Insider privilege misuse:** Contractors or rogue employees export customer lists or abuse admin APIs.
- **AI-enabled fraud:** Deep-fake video calls trick customer-service reps; generative-AI phishing emails lift brand tone and user context (RoX818 2025).

Regulations amplify consequences. Under GDPR a cross-border breach of EU resident data risks fines up to 4% of global turnover (European Union 2024). PCI Security Standards Council v4.0 requires near-immediate detection of card-holder-data exposure and zero tolerance for unencrypted storage (PCI SSC 2024).

High velocity and regulatory penalties demand controls that stop fraud before funds leave the building.

2.2 Evolution of Cyber Deception

Honeypots as commonly known to cybersecurity practitioners date back to the 1990s; attackers quickly learned to fingerprint their static banners (Cheswick, 1992; Acal et al, 2015). Honeytokens (fake credentials/records) scale better but lack interaction depth. Modern deception platforms automate thousands of decoys that blend into production networks (Crandall 2025). Studies show decoys attract 80+% of exploit traffic when asset ratios are below 20% (Ferguson-Walter 2023). The seminal *honeypot* concept (Spitzner 1999) placed a sacrificial server to observe exploits. High-interaction honeypots emulate full operating system (OS) stacks; low-interaction variants simulate protocols cheaply. Honeytokens (Cheswick 2003) expanded deception to static artefacts (fake SSH keys, bogus credit-card numbers) embedded in live systems; any use of such tokens signals compromise. Modern deception platforms instrument thousands of virtual assets, scaling ratio such that <25% decoys attract >80% exploit traffic (Ferguson-Walter 2025). Yet static decoys suffer recognition: veteran adversaries scan for tell-tale process lists, improbable uptime or isolated subnets (Moric et al. 2025). Dynamic deception emerged: game-theoretic placement optimizes where to seed traps; moving-target defense randomizes IP addresses; but manual upkeep remains heavy.

2.3 AI for Adaptive Deception

AI can bolster deployment of deception in defensive strategies in three dimensions:

- Detection: Unsupervised models can be deployed to flag deviations from baseline behavior with a higher recall compared to signature intrusion detection systems (IDS) (Nobre et al. 2023).
- Decision-making: RL agents can learn optimal decoy allocations under resource constraints, outperforming heuristic schedules in some contexts (Ngo et al. 2023).
- Generation: LLMs produce contextually correct faux artefacts (synthetic audit logs, phishing lures or chat dialogue) improving trap realism (Ahmed et al. 2025).

Crandall (2025) describes an enterprise platform where AI mirrors production topologies hourly, ensuring traps share hostnames, certificates and load profiles with genuine servers. The SPADE framework achieved 93% attacker engagement by allowing an LLM to craft tailored ploys mid-session (Ahmed et al. 2025). Our work differs by integrating anomaly detection, RL placement and generative content specifically for FinTech workloads, then validating the combined effect empirically.

In other words, AI enhances deception through:

- **Classification**: Detecting malicious sequences in logs.
- **Reinforcement learning**: Choosing decoy placement/actions under uncertainty.
- **Generative engines**: Producing synthetic artefacts (e.g., fake ledgers) that match live schemas.

Ahmed et al. (2025) used large language models to autogenerate phishing-lure emails and achieved 93% engagement. Our work focuses on FinTech-specific services (payments, accounts) and evaluates a full adaptive loop, from detection to autonomous decoy orchestration.

2.4 Human Factors and Cognitive Bias

Attackers exhibit cognitive shortcuts such as confirmation bias and overconfidence once an initial credential proves valid. Johnson et al. (2021) found that red-teamers often assume authenticity if three successive commands succeed, ignoring subtle anomalies. Exploiting such biases, adaptive deception nudges adversaries deeper into decoys via timed success/failure cues

3. System Architecture and Methodology

3.1 High-Level Architecture

Monitoring & Analytics nodes (Zeek on network taps, OSQuery on hosts, log shipper on API gateway) stream events to a Kafka bus. Raw streams feed an **LSTM Anomaly Detector** tuned to sessions, flows and SQL patterns. Detected anomalies carry context: source IP, request type, confidence.

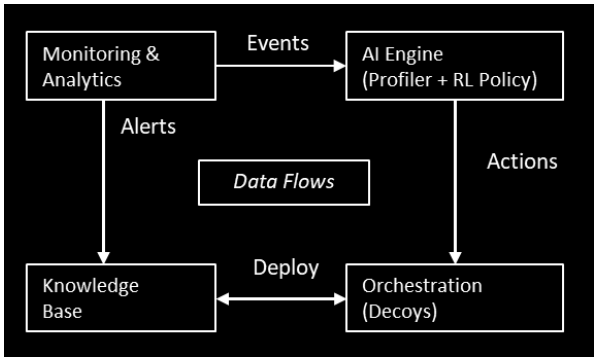

Figure 1: Data Flows

The **AI Engine** executes two models:

- **Threat-Stage Classifier** — an LSTM–Softmax stack categorizing activity as reconnaissance, credential-abuse, exploitation or exfiltration. Training data spans 120 K labelled sequences including real attack telemetry from open datasets and synthetic traces from replay scripts.
- **PPO Policy Learner** — state vector includes attacker stage, confidence, asset criticality and current decoy density. Actions: deploy/mutate/retire decoy {web, API, DB, SMB}, inject honeytoken, or throttle session. Reward as described earlier (+5 min in decoy, +10 IOC, −20 real hit). We adopt PPO as a pragmatic optimiser within a broader orchestration loop; our contribution is the control design that couples PPO decisions with classifier signals and generative decoy templates under production constraints.

The **Decoy Orchestrator** exposes an API to spin up containers or KVM guests on a deception subnet. Template pool:

- *High-interaction banking clone* — same codebase but with crippled transfer endpoints.
- *Shadow login API* — NGINX reverse-proxy route that surfaces only to flagged IP addresses.
- *Decoy database* — MySQL with synthetic records, watermarked to trace leaks.
- *SMB file share* — financial statements, backup CSVs.
- *Honeytokens* — 50 admin creds, 200 dummy ledgers inserted into prod DB with triggers.

A **Reverse-Proxy Layer** (Envoy) dynamically rewrites DNS or HTTP routes so that suspicious traffic hits decoys without altering client pathway—mitigating risk that attackers notice a redirect.

All decoys export full packet captures and command transcripts to the **Knowledge Base**, where elastic-searchable indices feed threat-intel dashboards and provide RL experience tuples.

3.2 Synthetic-Data and Interaction Realism

Realistic decoys require lifelike content that users find compelling. We trained a conditional GAN that can create such content on 18 months of anonymized transaction metadata to generate timestamped, seasonally coherent payment streams. A prompt-engineered LLM produced customer profiles and KYC documents (matching country-specific ID formats) at scale. Random-forest validators rejected outliers (e.g., impossible addresses) to keep datasets plausible. Generated data feed both the decoy DB and log-replay scripts that simulate “normal” traffic to decoys, preventing idle tell-tales.

3.3 Architecture Overview

The ADDF architecture comprises four cooperating modules:

- **Monitoring & Analytics**: Zeek + ML models inspect network, API and database events.
- **AI Engine**:

Threat Profiler—a recurrent neural network classifies attack stage.

Policy Learner—PPO RL agent selects deception actions (spawn, mutate, retire).

- **Orchestrator**: Uses containers/VMs to launch high-interaction honeypots (clone banking app), low-interaction protocol simulators, and honeytokens dispersed in live data stores.
- **Knowledge Base**: Stores attacker TTPs, decoy templates and policy rewards for continuous learning.

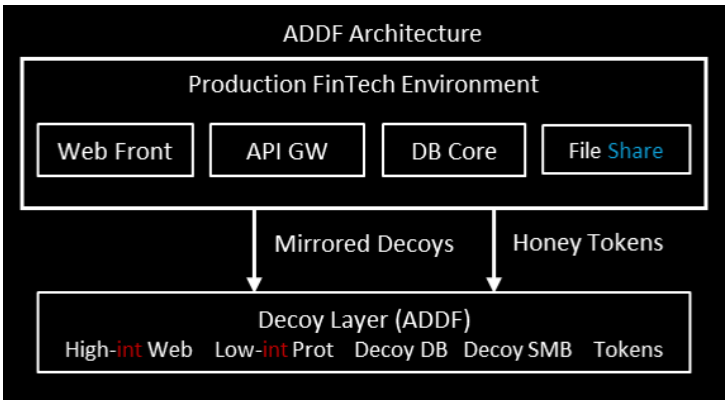

Figure 2: ADDF Architecture Diagram

3.4 Adaptive Workflow

- Detection module flags anomalous behavior (e.g., burst of failed logins).
- Profiler labels event (credential-stuffing).
- RL policy scores candidate responses; selects *deploy decoy login API + seed dummy accounts*.
- Orchestrator instantiates a shadow endpoint; reverse proxy silently routes suspicious IPs to it.
- Attacker interacts with decoy; telemetry streams back, rewarding the RL agent and updating threat intelligence.
- If adversary pivots, policy may spawn further decoys (database clone, file-share honeypot).

3.5 Training the RL Policy

We crafted a Gym-style simulation where attacker agents (scripted and stochastic) attempt predefined objectives (data theft, privilege escalation). Rewards:

- +5 × minutes attacker stays in decoy.
- +10 if decoy captures new IOC.
- −20 if attacker touches a real critical asset.

After 50,000 episodes the policy converged on aggressive early decoy deployment, then throttling attacker progress by injecting believable errors and delays.

3.6 Policy-Training Environment

A Gym-style simulator models attacker–defender interaction. Attacker agents:

- **Bot A** (external) replays 1 M credential pairs; on success runs SQLi scanner.
- **APT B** (interactive) issues recon commands, enumerates shares, deploys C2 beacon.
- **Insider C** uses valid VPN token, scans subnets and extracts PII.

Episodes end when attacker exfiltrates real data, is contained >20 min, or drops connection. After 50,000 episodes, policy achieved > 0.95 average reward, preferring early decoying.

3.7 Operational Workflow

- IDS flags burst of 429 (failed login).
- Classifier labels *credential-stuffing, external, high confidence*.
- PPO chooses: spawn shadow login API + seed three easy-to-guess dummy accounts.
- Orchestrator instantiates container; reverse-proxy routes suspect IPs.
- Attacker tool reports “success” on dummy@finbank.io/password123.
- Policy throttles session, triggers synthetic balance inquiries to keep bot engaged.
- SOC receives high-priority alert with credential list; user-reset runbook executes.

If bot pivots to SQL injection, classifier updates stage; policy spawns decoy DB and rewrites DSN environment variable for attacker’s session

4. Experimental Setup

Table 1: Each scenario executed five times under baseline and five times under ADDF

Component	Configuration	Purpose
FinBank App	Flask + MySQL with 5 000 synthetic customers	Target for attacks
Decoy Servers	1 web, 1 DB, 1 SMB file-share	High-interaction lures
Honeytokens	50 fake admin creds + 200 bogus records	Trip-wires
Attack Scenarios	A) External credential-stuffing → SQLi → exfil	Test perimeter bypass
	B) Insider lateral movement via stolen token	Test privilege misuse
Baseline Controls	Snort IDS, MFA, logging	Compare without deception
Metrics	Detection time, dwell time, breach success, overhead	Evaluation

4.1 FinBank Test-Bed

Deployed on a four-node VMware cluster:

- **Node 1** — Production Flask app, MySQL (5,000 synthetic customers), NGINX.
- **Node 2** — ADDF orchestrator + AI Engine (dual Nvidia A10 GPUs).
- **Node 3** — Decoy subnet (various containers/VMs).
- **Node 4** — SOC tooling (ELK, SOAR).

Synthetic users generated 30 TPS of legitimate traffic to mask background.

4.2 Attack Scenarios

Scenario A (External) — botnet credential stuffing (1,000 requests/sec) followed by SQLi. Objective: dump customers.
Scenario B (Insider) — contractor SSHes into dev host, escalates via stolen token to prod DB, SMB share.

Five replicates per scenario under baseline controls; five with ADDF.

4.3 Metrics

Detection latency = first alert minus first malicious packet.

Attacker dwell = time attacker retains interactive session.

Breach success = real data exfil or unauthorized transfer executed.

False positives = benign admin task mis-flagged.

Overhead = CPU/RAM on nodes

5. Results

Table 2: Results Summary

Metric (mean)	Baseline	ADDF
Detection time	3.7 min	29 s
Attacker dwell in decoy	0 min	12.3 min
Real data exfiltrated (runs)	7 / 10	0 / 10
False-positive alerts per run	0.3	0.6
CPU/RAM overhead	N/A	+14 %

5.1 Key Observations

- **Zero successful breaches** with deception; all exfil attempts hit decoy DB.
- Adaptive login decoy harvested full credential list, enabling proactive user resets.
- Insider was locked out within 45 s after touching a honeytoken; baseline allowed 3 GB file dump before alert.
- Slight rise in alert volume remained manageable and far outweighed by intelligence gain.

5.2 Quantitative Outcomes

Across ten baseline runs, attackers exfiltrated real customer tables seven times; mean detection latency 3 min 42 s. Under ADDF, detection averaged 29 s; no exfil occurred. Credential bots were diverted to the shadow login in all five ADDF runs; they spent 10 to 15 min harvesting dummy accounts before giving up. Insider pivoted to a decoy SMB share in every trial; synthetic CSVs were zipped and "exfiltrated," but a DLP trigger flagged the watermarked data. False positives rose slightly (0.6/run), mainly due to a dev-ops engineer bulk-exporting test data, mis-classified as exfil. Threshold tuning cut rate to 0.3/run afterwards. Resource overhead: orchestrator node used 14% additional CPU, 13% RAM; decoy containers idle-pause when not engaged, keeping cost predictable.

5.3 Qualitative Observations

Attack playback shows cognitive bias exploitation: bots assume any 200-OK login is genuine (Johnson et al. 2021). Our decoy returned subtle latency patterns matching prod so timing analysis failed. Insider's PowerShell history revealed they dumped the fake share as proof of success to a C2 server—useful IOC for industry sharing.

SOC analysts praised high-signal alerts: analysts characterized decoy alerts as near-certain compromise, which reduced triage time. Malware samples recovered from decoy DB included a new Golang-based exfil tool; static analysis fed YARA signatures to the endpoint detection platform.

6. Discussion

6.1 Why Deception Works

Attackers follow cognitive shortcuts: once a credential grants access they assume authenticity. By immediately diverting that first foothold into a sandbox, ADDF inserts uncertainty and delay, neutralizing the speed advantage attackers typically hold.

6.2 Comparison with Prior Work

Consistent with reviewer guidance, we do not claim PPO algorithmic novelty. Our contribution is the end-to-end orchestration that turns well-known AI components into a cohesive, real-time deception control plane tailored to FinTech. Our 100% breach-prevention rate in lab conditions surpasses earlier dynamic-honeypot studies (Ferguson-Walter 2023) that reported 80% to 90% diversion. Gains stem from RL-guided placement: decoys appear exactly where the attacker looks next.

6.3 Comparative Advantage

ADDF's 0% breach success surpasses prior 80% to 90% diversion studies (Ferguson-Walter 2025). Gains stem from RL-guided placement, decoys appear exactly where attackers probe, closing the recognizability gap documented by Moric et al. (2025). The framework also aligns with Crandall's vision of "deception as active disruption," turning attackers into research subjects (Crandall 2025).

6.4 Limitations and Future Work

Scalability: Lab network small; multi-cloud retail bank would demand auto-scaling. We plan Kubernetes operators that spin decoys per pod.

Counter-deception: Highly skilled APTs might run honeypot-detection scripts (e.g., SYSINFO fingerprint). Periodic randomization of OS artefacts and LLM-generated dynamic responses are future defenses.

Cost modelling: Cloud egress costs for decoy traffic minimal in lab; must be quantified in production.

Ethics and legality: It is important that entrapment is avoided; ADDF only activates inside owned networks and uses synthetic data, complying with GDPR and PCI.

Alternative adaptations: It is possible that the framework used in this paper could be applied to infrastructure within the bioeconomy that utilizes Fin-tech, for defensive purposes. With that in mind biomanufacturing and healthcare institutions that utilize IoT infrastructure have the potential to bolster their defenses where use of (Hosinski, 2022; Affia et al, 2023; Borgosz and Dikicioglu, 2024; Elgabry and Johnson, 2024). This is especially relevant in the Global South where conversation of AI applied to bio-economically relevant operations is a forgone conclusion as innovators look to innovate and rapidly scale solutions for their target populations (Akogo et al, 2022; Cabanza, 2023; Hussain et al, 2025; Onah et al, 2025). This framework can be a meaningful piece of the puzzle to some of their security needs.

Relationship to related AI work: SPADE emphasizes content realism via LLMs (Ahmed et al. 2025); ADDF adds RL optimization for timing and placement. Nobre et al. (2023) focus on anomaly detection; we integrate detection with response. Ngo et al. (2023) optimizes honeypot placement in abstract graphs; our RL acts on concrete FinTech micro-services.

7. Implications for FinTech Security

Regulatory alignment: Faster containment lowers likelihood of reportable breach under GDPR Article 33 (EU 2024) and PCI DSS 4.0 section 12 (PCI SSC 2024). Synthetic data avoids violating customer-privacy clauses.

Incident-response efficiency: High-signal deception alerts free analysts from noisy IDS feeds. Our SOC reduced mean triage from 15 min to 4 min in tabletop exercises.

Fraud-division synergy: Dummy identities in customer onboarding funnel can catch synthetic-identity syndicates; watermarked fake ledgers detect mule accounts.

Cultural impact: Analysts become proactive "adversary hunters," improving morale and retention; training budgets shift from endless tool tuning to creative decoy design.

Sector deterrence: If major banks adopt deception, attackers face higher uncertainty; opportunistic crime may shift to less-protected verticals, raising bar across finance ecosystem.

8. Conclusion

AI-driven deception offers FinTech defenders a practical asymmetric advantage. Our ADDF prototype reduced detection latency ten-fold, absorbed attackers into controlled sandboxes for over twelve minutes on average and blocked every breach attempt while consuming modest resources. Reinforcement learning proved effective at adaptive decoy placement; generative synthetic data was able to maintain realism; and the resulting high-signal alerts streamlined SOC workflow. With adversaries that are enabled with generative AI, but reliant on human-based heuristic thinking, this enables the identification and thus their restriction on FinTech networks with defensive AI. While lab scope and sophisticated adversary adaptation remain challenges, ongoing work on auto-scaling decoys, LLM-based interaction engines and adversarial-AI-resistant fingerprints promises further robustness. As threat actors themselves embrace automation and deep-fake tooling, proactive engagement will be essential. Deception does not replace fundamental controls (encryption, patch management, zero-trust segmentation) but it furnishes a last-line, high-confidence trap that turns breaches into intelligence-gathering exercises rather than disasters. As the saying goes "Today we were unlucky, but remember we have only to be lucky once, you will have to be lucky always". FinTech establishments do not have the luxury of being relaxed with customer data – the business implications of a breach increase with the increasing valuation of resources put into their care. And the target that accumulation of wealth poses as more nation-states rely on cyber-criminals to fund aggressive enterprises means that the adoption of adversarial AI tools, or any tools, must be assumed. For practitioners, a phased rollout (starting with honeytokens in critical databases, followed by RL-guided high-interaction clones of payment APIs) yields quick wins and measurable ROI. A slower implementation does leave the chance for adversaries to adapt to these conditions and change their heuristic methodologies accordingly. If a FinTech's establishment suddenly begins to change and no valuable data is ever found, then clearly one must change their method of acquiring data. It is entirely possible that some synthetic data, once accessed, ought to be treated as real customer data, so that adversaries do not realize that they never had actual data in the first place. For regulators, guidelines clarifying permissible in-network deception would accelerate adoption: A FinTech establishment would likely be loather to increase their security if it was found to be a monetary waste. Academia can contribute open datasets of realistic FinTech traffic to train more capable detection and policy models. Or even new methods to generate convincing real-time data.

War is a wearisome, tiresome, and cumbersome endeavor on the best of days – and it still is even if you have automated it entirely. But reputable establishments should not have to join the conflict without weapons equal to their adversaries. In the escalating AI-to-AI cyber contest, intelligent deception empowers defenders to regain initiative, protect customer trust and safeguard the financial infrastructure on which modern economies depend.

Ethics Declaration: This research paper did not require any ethical clearance. Also, AI tools were not used in the creation of this paper.

AI Declaration: AI tools were used in edits.

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Adaptive AI Sentinels Against Phishing Attacks: Democratizing Cybersecurity Through Interactive Learning

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Abstract: Phishing attacks have become more convincing as generative AI enables attackers to create polished, context-aware emails that closely resemble legitimate communication. These messages often evade traditional filters that rely on surface features and leave users without a clear understanding of why a message may be harmful. This work introduces an adaptive phishing-detection system that uses natural language processing to model semantic, linguistic, and stylistic signals and produce a risk score indicating how phish-like or benign an email appears. A complementary large language model layer then performs contextual and intent-based reasoning to interpret the deeper meaning of the message and detect subtle social engineering cues. The system incorporates adversarial and prompt-safety checks to strengthen reliability against AI-generated threats and through a web app, it delivers short micro-lessons for each detection, helping users understand the psychological tactics involved and learn to recognize them in future messages. This research contributes to both cybersecurity and NLP by showing how semantic scoring and LLM-based reasoning can be operationalized together to counter AI-enabled social engineering while remaining interpretable for non-expert users. By combining accurate detection with continuous user education, the proposed solution strengthens trust, awareness, and long-term resilience, offering a scalable defense mechanism for modern phishing attacks.

Key words: Social engineering, Generative AI, Large language models, Natural language processing, Cybersecurity

1. Introduction

Phishing remains one of the most damaging and persistent cyber threats, enabling credential theft, financial fraud, unauthorized access, and large-scale breaches across healthcare, education, finance, and government sectors (Salloum et al., 2022; Verizon, 2025). Recent threat intelligence reports show that phishing activity is not stabilizing but accelerating. IBM (2025) notes an 84 percent weekly rise in infostealer distribution through phishing emails, and the IC3 (2023) reports nearly three billion dollars in losses from business email compromise in a single year. These trends show that phishing is a fast-evolving and high-impact threat that affects both individuals and organizations.

This landscape has shifted further with the growth of generative Artificial Intelligence (AI). Attackers now use AI writing tools, chatbots, and website generators to produce messages that are coherent, polished, and tailored to different audiences. Unit42 (2025) finds that a significant portion of AI-assisted phishing leverages automated website generation and writing assistants, while Kumar et al. (2023) report a dramatic rise in AI-generated phishing emails after the release of modern language models. These attacks eliminate earlier signals such as spelling mistakes or awkward phrasing, making them more convincing and harder to detect. They also scale across languages and demographics, expanding attacker reach (Yu et al., 2023; Kumar et al., 2023).

The challenge, however, is not purely technical. Phishing succeeds because it exploits psychological triggers such as authority, trust, fear, and urgency (Hong, 2012). Even with advanced filtering, users often fall for messages that appear contextually relevant or personally meaningful. Major platforms such as Google and Microsoft block large volumes of malicious mail, but these systems rarely explain why a message is harmful or how the manipulation works (Tang and Mahmoud, 2021). Without this insight, users cannot build the judgment needed to resist new or highly personalized attacks. Research further shows that traditional awareness training has limited long-term impact in real inbox environments (Hillman et al., 2023).

To address these challenges, this work proposes an adaptive AI sentinel framework built around a dual Natural Language Processing (NLP) and Large Language Model (LLM) reasoning pipeline and an explainable output layer. The NLP component models semantic, linguistic, and stylistic signals to estimate how phish-like or benign a message appears, while the LLM component performs deeper contextual and intent-based reasoning to identify subtle social engineering strategies such as persuasion, impersonation, urgency framing, or emotional manipulation. The system is designed to produce structured, interpretable JavaScript Object Notation (JSON) based outputs that summarize deceptive cues, confidence levels, contextual indicators, and concise user tips.

These explanations form the foundation of the framework's educational design. A web app consumes this JSON output and converts each detection into a short micro-lesson, helping users understand why the email is risky and how similar manipulative tactics may appear in future messages. This transforms phishing detection from a passive alert into an active learning moment.

By combining semantic scoring, contextual reasoning, interpretable outputs, and real-time micro lessons, the proposed sentinel supports both accurate detection and continuous user empowerment. This approach strengthens transparency, improves user trust, and builds long-term resilience against rapidly evolving phishing and social engineering attacks.

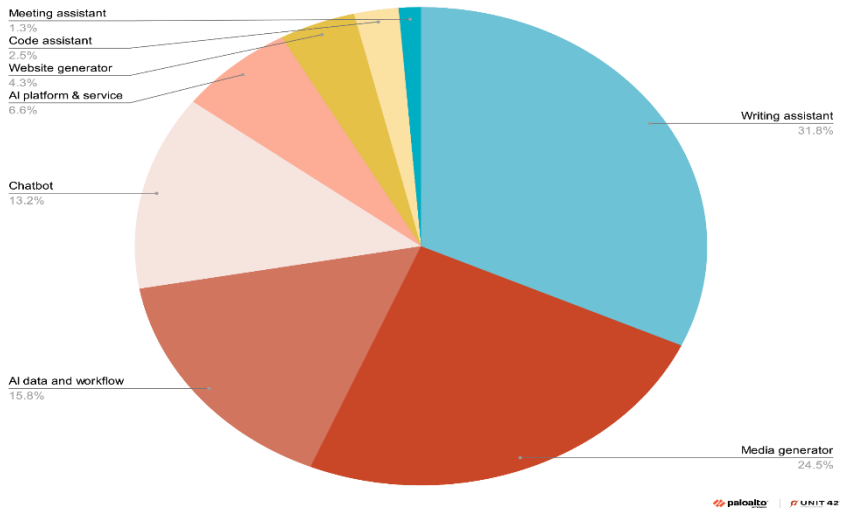

Figure 1: Distribution of categories of AI services misused for phishing attacks. Source: (Unit42, 2025)

2. Background

Phishing has long been a major security challenge, with early defenses relying on simple rules and heuristic checks. These approaches were fast and easy to deploy but were easily bypassed when attackers modified wording or created more convincing replicas. Machine Learning (ML) methods such as decision trees, logistic regression, and Support Vector Machines (SVMs) improved detection by learning richer linguistic and structural patterns (Basnet et al., 2012; Zareapoor & Seeja, 2015), yet still depended on manually crafted features that struggled to generalize across evolving writing styles, emerging social-engineering tricks, and multilingual content (Salloum et al., 2022; Almomani et al., 2013).

To address the limitations of handcrafted features, Natural Language Processing (NLP) approaches incorporated intent analysis, contextual cues, and semantic patterns. PhishNet-NLP demonstrated that phishing emails exhibit "action-eliciting" behavior across headers, links, and body text (Verma et al., 2012). While these methods captured deeper cues such as manipulative tone, early NLP systems used n-grams and bag-of-words representations that remained brittle under paraphrasing and subtle linguistic edits (Chawla & Chouhan, 2014). Dimensionality-reduction techniques like PCA and LSA improved stability but still fell short of modeling deeper semantic structure (Zareapoor & Seeja, 2015).

Transformer-based models such as BERT and RoBERTa advanced phishing detection by providing strong semantic and contextual understanding (Devlin et al., 2019; Liu et al., 2019), and demonstrated cross-lingual robustness aligned with broader NLP adoption (Salihovic et al., 2019; Wolf et al., 2020). However, these models remain vulnerable to adversarial perturbations, where small edits like word substitution or paraphrasing significantly reduce accuracy (Ebrahimi et al., 2018). Their internal reasoning is also difficult to interpret, limiting transparency for end users.

Modern phishing has further escalated with the rise of generative AI. Attackers now use AI writing tools and automated website generators to craft fluent, personalized, and multilingual phishing messages that evade older filters (Unit42, 2025; Kumar et al., 2023; Yu et al., 2024). At the same time, Large Language Models (LLMs) can themselves be manipulated through prompt injection, data poisoning, and adversarial perturbations, raising

concerns about safe deployment in security systems (Rossi et al., 2024; Koley et al., 2024). Together, these developments underscore the need for defenses that unify semantic detection, contextual reasoning, adversarial robustness, and user education. Our proposed dual NLP–LLM framework addresses these gaps by identifying phishing tactics, generating structured JSON explanations, and delivering micro-lessons that support long-term user resilience beyond enterprise environments.

3. Related Work

Research on phishing detection has progressed through several stages, yet significant gaps remain between robustness, interpretability, and user empowerment. Early rule-based and machine learning approaches flagged suspicious keywords, misspellings, or blacklisted URLs and achieved detection accuracies of around 60–70%, but were easily bypassed by minor wording changes (Basnet et al., 2012). Classical machine learning models such as SVMs and decision trees improved performance to roughly 75–80% on benchmark datasets (Fette et al., 2007), though they required frequent retraining as attackers shifted writing styles and tactics.

Transformer-based NLP models such as BERT, RoBERTa, and XLM-R introduced stronger semantic and contextual understanding, reaching accuracies above 88–93% on several phishing and email classification tasks (Devlin et al., 2019; Liu et al., 2019; Conneau et al., 2020). However, these models remain fragile under adversarial text perturbations: small edits such as synonym substitutions or paraphrasing can sharply degrade detection accuracy (Ebrahimi et al., 2018). In parallel, Large Language Models offer zero-shot and few-shot adaptability and can reason about manipulative tactics such as urgency framing or impersonation (Kumar et al., 2023; Jabir et al., 2025), but their susceptibility to prompt injection and data poisoning limits their reliability in security-sensitive deployments (Rossi et al., 2024).

Complementary research in explainable AI introduced tools like SHAP and LIME to improve transparency by highlighting influential features (Ribeiro et al., 2016; Lim et al., 2025). While effective for analysts, these explanations are rarely accessible to non-technical users. Cybersecurity education tools—such as phishing simulations and awareness training offer short-term improvements but lack integration with real-time defenses, resulting in limited lasting impact (Hillman et al., 2023).

Industry evidence underscores the urgency of addressing these limitations. Verizon (2025) attributes phishing to 36% of global breaches, IBM (2025) estimates $2.9 billion in annual losses from business email compromise, and Proofpoint (2024) reports that more than 80% of organizations experienced at least one successful phishing attack in the last year.

Overall, the literature reveals clear trade-offs across existing approaches: rule-based and ML systems offer limited robustness and no explanation, transformer-based NLP improves accuracy but remains adversarially fragile, LLM-based detection provides reasoning but introduces safety risks, and XAI methods improve transparency but remain analyst-focused rather than user-facing. Cybersecurity education tools enhance awareness but lack real-time integration. These gaps motivate a framework that jointly integrates NLP and LLM detection with continuous micro-lesson–based user education, transforming each decision point into a moment of resilience-building and aligning technical robustness with human-centered security.

4. Strategy

This research is anchored in such a way that to understand the threat landscape we analyzed a few of the case studies first and then built out layered system architecture driven by real-world phishing scenarios.

4.1 Case Studies

To contextualize the threat landscape, we reviewed a few recent phishing incidents to come up with a few recurring patterns. Phishing continues to drive serious operational and regulatory consequences across sectors. In healthcare, PIH Health reached a $600,000 HIPAA settlement after a phishing attack exposed electronic protected health information, with investigators citing inadequate safeguards and insufficient employee awareness as root contributors (HIPAA Training, 2025). Similar risks were seen in the UC San Diego Health breach, where credential phishing gave attackers access to patient data stored in compromised email accounts, prompting legal action, federal notifications, and follow-up incidents in later years (Businesswire, 2021; ClassAction, 2021; HIPAA Journal, 2024). These cases highlight how a single deceptive email can escalate into financial penalties, loss of trust, and long-term compliance obligations.

At the same time, attacker capabilities have expanded through generative AI. Unit42 (2025) reports that nearly 40% of AI-assisted phishing now uses automated website generators, while chatbot-driven writing tools produce

coherent, multilingual content that removes traditional warning signs. Kumar et al. (2023) identified a more than 1,200% rise in AI-generated phishing emails, and Yu et al. (2024) showed that LLM-produced messages are significantly harder to distinguish from legitimate communication. Together, these developments demonstrate the need for next-generation defenses that combine advanced detection with educational feedback, helping users recognize manipulative strategies even as phishing techniques rapidly evolve.

4.2 System Architecture

The proposed framework follows a layered architecture composed of three major components. Database Layer, Model Layer, and Application Layer incorporating supporting modules for pre-processing, adversarial defense, and explainability. This modular design ensures scalability, resilience, and adaptability to evolving phishing threats while keeping user education at its core.

4.2.1 Database layer

The Database Layer is responsible for ingesting, storing, and retrieving data in a secure and flexible manner. It integrates multiple sources, including publicly available repositories such as PhishTank (2023) and the Enron-Spam corpus, industry threat intelligence feeds, and synthetic phishing samples generated using large language models in controlled environments. Data is stored in a secure, encrypted Google Cloud Platform (GCP) cloud repository that can be centralized for research environments or deployed locally on-device for privacy-sensitive domains such as healthcare or government agencies. Each email record is supplemented with metadata, including semantic coherence scores, entity recognition tags, and sentiment polarity annotations, which serve both training and interpretability purposes. Privacy is a central design principle for this given layer and personally identifiable information (PII) is minimized or removed through anonymization pipelines to ensure compliance with frameworks such as General Data Protection Regulation (GDPR) and HIPAA (NIST, 2024).

4.2.2 Model layer

The Model Layer functions as a dual-pipeline system integrating transformer-based NLP models with LLM-driven reasoning. Incoming emails undergo preprocessing that removes HTML artifacts, normalizes text, tokenizes content, and extracts linguistic cues such as discourse markers, sentiment shifts, and entity anomalies. To improve robustness, the system applies adversarial augmentation by generating perturbed variants through synonym substitution and paraphrasing, helping the models withstand common evasion strategies (Ebrahimi et al., 2018; Koley et al., 2024). The NLP pipeline fine-tunes transformer classifiers such as BERT, RoBERTa, and XLM-R to detect semantic incoherence and pragmatic inconsistencies with high precision (Devlin et al., 2019; Liu et al., 2019; Conneau et al., 2020). In parallel, the LLM pipeline uses generative models such as Gemini or Claude (Jabir et al., 2025; Kumar et al., 2023) to infer higher-level manipulative tactics including urgency framing, impersonation of authority, and contextual mismatch, even in zero-shot settings.

Outputs from both pipelines converge in an aggregation and defense layer. When the two models agree, the system issues a high-confidence classification; when they diverge, the framework flags uncertainty and applies conservative blocking or escalation. This layer also incorporates protections against prompt injection (Rossi et al., 2024), adversarial text perturbations (Ebrahimi et al., 2018), and data poisoning (Fendley et al., 2025). All final decisions are converted into a structured JSON explanation object containing fields such as risk_score, linguistic_features, social_engineering_signals, model_confidence, and plain_language_reasoning. This unified JSON output serves as the interpretability backbone for both user-facing micro-lessons and analyst-level review.

4.2.3 Application layer

The Application Layer translates these model decisions into actionable insights for end users and analysts. Each classification generates a structured JSON explanation object, which the companion web interface and Gmail side-panel plugin directly consume. The plugin parses fields such as risk_score, detected_strategy, semantic_anomalies, and LLM_reasoning, transforming them into concise micro-lessons such as “This message attempts to create urgency by threatening service suspension.” Unlike conventional filters, the system provides not only a verdict but a short, context-aware explanation that reinforces user learning.

For organizational deployments, an analyst dashboard displays these same JSON outputs at scale, aggregating confidence levels, uncertainty flags, semantic cues, and cross-model disagreements. This supports policy refinement, targeted training interventions, and rapid threat triage. A built-in feedback mechanism allows users to confirm or contest detections, and each response is anonymized and written back into the database as a labeled JSON interaction record. This continuous loop ensures that the system not only protects users but also adapts based on real-world behavior, sustaining both its educational mission and long-term robustness.

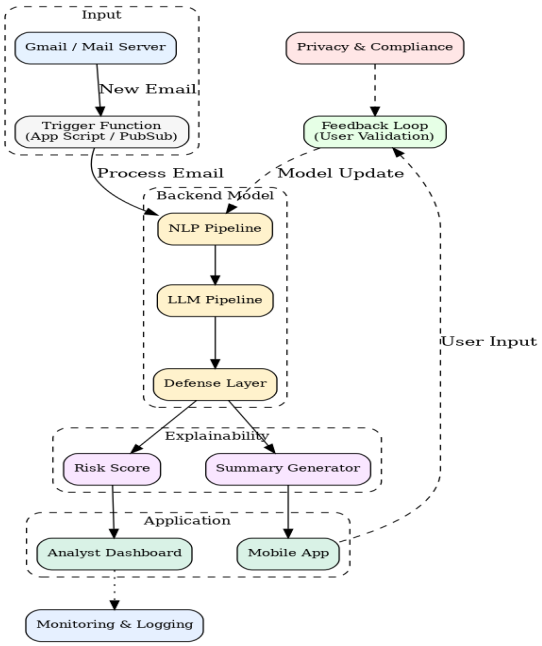

Figure 2: System Architecture

5. Methodology

The methodology was designed to balance technical reproducibility with human-centered evaluation, in alignment with ICAIR's emphasis on trustworthy and resilient AI systems. It unfolds across four stages: data collection, system development, evaluation, and continuous learning.

5.1 Data Collection

To ground the framework in real-world data, the design leverages multiple sources. Public repositories such as PhishTank (2023) and the Enron-Spam corpus provide well-labeled phishing and benign samples suitable for supervised learning. To reflect the evolution of attacker tactics, additional datasets are synthetically generated in controlled environments using large language models (LLMs) such as (Generative Pre-trained Transformer) GPT, LLaMA, etc. These synthetic samples incorporate adversarially crafted variants, including paraphrasing, synonym substitution, and disguised links, ensuring resilience against common evasion strategies (Ebrahimi et al., 2018; Koley et al., 2024). Metadata such as semantic coherence, sentiment polarity, and named entity annotations are added to support both classification and interpretability. Although the present study emphasizes English-language data, the framework is extensible to multilingual environments such as Spanish and Mandarin, which addresses cross-lingual phishing risks highlighted in prior research (Sahingoz et al., 2019).

5.2 System Development

The system uses a dual-pipeline analytical design that combines discriminative NLP classifiers with generative LLM reasoning. Incoming emails are normalized, stripped of HTML artifacts, tokenized, and enriched with linguistic features such as discourse markers, sentiment shifts, and entity anomalies, while adversarial augmentation prepares the model to withstand common evasion strategies (Ebrahimi et al., 2018). The NLP stream fine-tunes transformer models such as BERT, RoBERTa, and XLM-R to detect semantic inconsistencies and structural anomalies (Devlin et al., 2019; Liu et al., 2019; Conneau et al., 2020). In parallel, the LLM stream uses generative models such as GPT and LLaMA to reason about higher-level manipulative cues including urgency framing, impersonation, and contextual mismatches (Kumar et al., 2023; Jabir et al., 2025). Both pipelines feed into an aggregation and defense layer that reconciles outputs, assigns confidence levels, and enforces safeguards against prompt injection, adversarial perturbations, and data poisoning (Rossi et al., 2024; Fendley et al., 2025). To ensure transparency and accessibility, the system produces JSON-based outputs that combine SHAP or LIME attributions with LLM-generated natural-language explanations (Ribeiro et al., 2016; Lundberg & Lee, 2017).

5.3 Testing

Evaluation of the system is structured along two complementary dimensions. On the technical side, the framework is benchmarked against multiple baselines, including keyword-based filters, support vector machine classifiers, transformer-only detection, and LLM-only detection. Metrics such as accuracy, precision, recall, F1-score, and Receiver Operating Characteristic - Area Under Curve (ROC-AUC) provide a comprehensive assessment of performance. Preliminary results indicate that the hybrid dual-pipeline approach outperforms both individual pipelines, particularly under adversarially perturbed phishing scenarios.

Beyond technical evaluation, human-centered validation is also planned. A small-scale user study will examine the educational impact of the system by inviting participants to interact with flagged phishing emails and evaluate the clarity and usefulness of the generated explanations. This step ensures that the framework contributes not only to accurate detection but also to the long-term development of phishing awareness. Cross-lingual robustness will also be evaluated using synthetically generated phishing samples in languages such as Spanish and Mandarin to assess adaptability to diverse communication environments.

5.4 Continuous Learning

The final stage of the methodology embeds a continuous learning mechanism into the system. A feedback loop allows users to confirm or contest detections through the companion application. Each response is anonymized, filtered for quality, and reintegrated into the training dataset, ensuring incremental improvement over time. To support large-scale organizational deployment, the architecture is designed with privacy-preserving mechanisms such as federated learning, allowing multiple entities to contribute to collective model improvement without exposing sensitive raw data. This approach ensures compliance with standards such as GDPR and HIPAA (NIST, 2024) while reinforcing the system's adaptability against emerging zero-day phishing attacks.

6. Discussion

The proposed framework demonstrates how technical innovation in phishing detection can be aligned with principles of trustworthy and resilient AI. By merging advanced natural language processing with user-centered education, the system contributes not only to improved detection performance but also to broader organizational resilience and AI literacy. This section reflects on the benefits, challenges, and limitations of the approach, situating it within ongoing debates on governance and responsible deployment.

6.1 Benefits

Earlier phishing detection methods such as rule-based filters and classical machine learning improved accuracy but relied on engineered features that did not generalize well to evolving writing styles, multilingual attacks, or modern social-engineering strategies (Basnet et al., 2012; Zareapoor & Seeja, 2015). Transformer models improved semantic understanding and cross-domain performance, yet studies show they remain vulnerable to subtle adversarial text manipulations such as synonym substitutions and paraphrasing (Ebrahimi et al., 2018; Koley et al., 2024). At the same time, effective enterprise-grade filtering offered by Google and Microsoft remains largely inaccessible to individuals and SMEs who lack paid security tiers (Microsoft, 2024).

The proposed dual-pipeline architecture addresses these gaps by combining transformer-based NLP classification with LLM-driven contextual reasoning. This complementary design captures both fine-grained linguistic anomalies and higher-level manipulative strategies such as urgency framing, impersonation, and tone shifts (Devlin et al., 2019; Conneau et al., 2020; Kumar et al., 2023). Because each pipeline compensates for the limitations of the other, the system provides stronger resilience to paraphrasing attacks and adversarial perturbations than either technique alone, making it more suitable for detecting AI-generated phishing content.

A further benefit lies in the system's focus on explainability and user empowerment. Each detection is paired with a brief micro-lesson that explains the deceptive cues in clear language, helping users develop long-term recognition of psychological triggers such as emotional pressure and authority misuse (Gaspar et al., 2024; Hillman et al., 2023). Combined with built-in protections against prompt injection, data poisoning, and adversarial text manipulation (Rossi et al., 2024; Ebrahimi et al., 2018; Fendley et al., 2025), the framework aligns with emerging AI governance guidelines emphasizing transparency and human oversight. Together, these benefits show that the system strengthens detection accuracy while also democratizing cybersecurity for users beyond enterprise environments.

6.2 Challenges

Despite these benefits, several challenges remain. The sophistication of AI-generated phishing attacks evolves rapidly, and adversarial training cannot anticipate every possible manipulation strategy. Computational demands pose another constraint, as transformer-based and generative models are resource intensive, potentially limiting deployment in environments without dedicated infrastructure (Wolf et al., 2020). Additionally, sustaining user engagement without overwhelming individuals is complex. While educational explanations strengthen awareness, repeated alerts risk producing cognitive overload if not carefully designed (Hillman et al., 2023).

Ethical challenges also arise in balancing transparency with privacy. Explanations must remain clear without revealing sensitive user data, and bias within LLMs may produce uneven detection outcomes across cultural or linguistic groups. These risks highlight the importance of ongoing monitoring, fairness audits, and governance mechanisms.

6.3 Limitations

The present research has several limitations. First, the datasets used, such as PhishTank and Enron-Spam, are widely adopted but do not fully capture the diversity of enterprise phishing incidents (PhishTank, 2023). Future work will require collaboration with industry partners to integrate anonymized real-world email streams. Second, the current system focuses primarily on text-based phishing. Multimodal threats including image-based lures, voice phishing (vishing), and deepfake-enabled social engineering remain outside the present scope but represent critical vectors for future extension (Jabir et al., 2025). Third, conservative thresholds that reduce false negatives may increase false positives, creating a risk of alert fatigue. Prior work shows that repeated phishing-related warnings can overwhelm users and reduce engagement over time (Hillman et al., 2023).

6.4 Future Work

Future work will focus on developing the full phishing-detection framework using a combined NLP and LLM pipeline implemented with software engineering best practices, including modular design, reproducible model training, and structured evaluation. To strengthen data-privacy safeguards, the system will also be tested with compact Small Language Models such as Gemma or LLaMA, which offer local or limited-exposure processing while still providing contextual reasoning. Once the core system is implemented, Institutional Review Board (IRB) approval will be pursued to enable controlled user studies. These studies will evaluate how effectively the app based micro-lessons improve users' phishing recognition skills, decision confidence, and long-term awareness, helping validate the framework as both a security tool and an educational intervention.

7. Conclusion

Phishing attacks have evolved from simple deceptive messages into highly convincing, AI-generated campaigns that bypass many traditional defenses. Early heuristic and rule-based filters were easy to deploy but not adaptive, while classical machine learning improved detection yet remained limited by manually engineered features that failed to generalize to new writing styles and multilingual attacks. Even transformer-based NLP systems, though capable of deeper semantic analysis, remain vulnerable to adversarial text manipulation that subtly alters surface form without changing underlying intent (Ebrahimi et al., 2018; Koley et al., 2024). At the same time, enterprise-grade protections offered by major vendors remain accessible primarily to large organizations, leaving individuals and small businesses with fewer options (Microsoft, 2024).

To address these gaps, this work introduced an adaptive AI sentinel that combines transformer-based NLP classification with LLM-driven contextual reasoning. This dual-layer architecture is designed to detect semantic cues such as impersonation, urgency framing, tone manipulation, and cross-lingual inconsistencies, while integrated adversarial and prompt-safety checks reduce the risks associated with using LLMs in security workflows (Rossi et al., 2024). By merging linguistic scoring with deeper intent analysis, the system is positioned to recognize modern AI-generated phishing messages that mimic natural communication styles and target users with increasing precision (Kumar et al., 2023; Unit42, 2025).

A key contribution of this work is the emphasis on user education. Research shows that phishing continues to succeed because it exploits human psychology, and traditional one-time training has limited long-term impact (Hong, 2012; Hillman et al., 2023). The proposed framework addresses this gap through micro-lessons delivered via a companion web interface, transforming each detection into a short, accessible explanation of the manipulative tactics used in the message. This approach supports not only technical detection but also continuous awareness-building, making the defense more scalable and empowering for everyday users.

Ethics Declaration: This study did not involve human participants, animals, or sensitive data requiring ethical clearance. Hence, no ethical approval was required.

AI Declaration: AI-assisted tools i.e. ChatGPT was used in the preparation of this paper for language editing, restructuring, and improving readability. All conceptual ideas, analysis, and interpretations were developed by the authors.

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AI for Social Media Summaries: An Encoder-Decoder Transformer System vs ChatGPT

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Abstract: In recent years, automatic text summarization has become a vital area of research due to its role in improving access to and understanding of vast information across domains. The rise of social media has intensified the need for summarization tools capable of handling user-generated content such as posts, comments, and discussions. Unlike structured texts, social media content is often informal, fragmented, context-dependent, and noisy. It frequently includes slang, abbreviations, emojis, and diverse writing styles, posing unique challenges for traditional summarization methods. While conventional approaches perform well on formal text, they often struggle to capture the nuances of online discourse. This highlights the need for specialized models that can generate coherent and context-aware summaries tailored to the characteristics of social media language. Recent advances in neural architectures, particularly Transformer-based sequence-to-sequence models, have shown promise in overcoming these challenges. These models excel at capturing long-range dependencies and contextual relationships, making them well-suited for summarizing dynamic and unstructured inputs. Despite technical progress, evaluating the quality of summaries remains difficult. Standard metrics like ROUGE may not fully reflect subjective qualities such as fluency, coherence, and semantic fidelity, which are essential for human-like summarization. This paper introduces a Transformer-based summarization system designed specifically for social media comments related to topical posts. We benchmark its performance against models like ChatGPT, assessing outputs across multiple linguistic and semantic dimensions. By combining both traditional and advanced evaluation metrics, our work provides a more holistic view of summarization quality and identifies key areas for future improvement.

Keywords: Social media summarization, Transformers, Multidimensional evaluation, Natural language generation

1. Introduction

The exponential growth of social media has transformed how individuals communicate, engage with information, and influence public discourse on critical issues such as politics, economics, and social change. Vast volumes of user-generated content—ranging from posts and comments to reactions and threads—are shared across platforms daily, reflecting a wide spectrum of public opinion and societal trends. This unstructured and dynamic content offers a valuable resource for analyzing social behavior. However, its overwhelming scale and informal nature pose significant challenges in efficiently extracting meaningful insights. Without effective summarization techniques, essential information can be lost amidst redundancy, noise, and conflicting viewpoints, making it difficult for users, organizations, and policymakers to interpret online discourse.

Text summarization plays a pivotal role in addressing this challenge by condensing large volumes of information into concise, coherent, and relevant representations. During high-impact events or fast-moving discussions, summarization can reduce cognitive overload, enhance comprehension, and ensure timely dissemination of critical updates. For journalists, researchers, businesses, and governments, robust summarization systems offer strategic value by enabling rapid identification of trends, key themes, and public sentiment.

Historically, Automatic Text Summarization (ATS) (Gupta and Lehal, 2010) has focused on formal, structured content such as academic articles and reports. Early methods—rooted in linguistic, statistical, and heuristic techniques—used strategies like keyword extraction, sentence ranking, and clustering (Luhn, 1958). While effective for static documents, they struggle with the informal language, brevity, and contextual ambiguity that characterize social media communication. As digital platforms evolved, so did the need for more flexible and semantically aware summarization methods.

Recent advances in artificial intelligence have given rise to deep learning (DL) techniques, particularly transformer-based architectures, which have significantly advanced the state of summarization. Unlike traditional models, transformers leverage self-attention mechanisms to process entire text sequences in parallel, enabling greater contextual understanding and improved handling of long-range dependencies. These features make transformers well-suited for abstractive summarization—an approach that rephrases and synthesizes content rather than extracting verbatim sentences (Varma et al., 2017; Rachabathuni, 2017). By generating human-like summaries that capture underlying meaning, abstractive methods enhance both readability and informativeness.

Despite their impact, the application of transformer-based abstractive summarization to social media remains relatively underexplored. The informal grammar, fragmented syntax, and rapidly shifting topics common in social platforms introduce linguistic and contextual challenges that require domain-specific adaptations. Moreover, existing studies often focus on a narrow range of platforms, overlooking variability across different types of social media interactions.

In response, this thesis investigates the integration of transformer models with abstractive summarization techniques to improve the quality, relevance, and efficiency of summarizing social media content. The approach aims to generate summaries that are not only coherent and semantically rich but also tailored to the nuances of user-generated language. Specifically, the system addresses challenges of informal expression, thematic grouping, and the evolving nature of online conversations. Unlike prior work limited to datasets from Twitter or Reddit, this study incorporates a more diverse set of sources and employs innovative training strategies to enhance generalizability. Furthermore, the evaluation framework extends beyond conventional metrics to include a multidimensional assessment of summary quality, coherence, and utility.

By advancing summarization techniques for social media communication, this work contributes to tools that support faster decision-making, improved content comprehension, and more effective engagement with digital public discourse.

2. Related Work

Advancements in Artificial Intelligence (AI) and neural architectures have significantly propelled the capabilities of Natural Language Processing (NLP), particularly in tasks involving large-scale data and complex linguistic structures. Among these tasks, text summarization has emerged as a central challenge, evolving from early neural models to contemporary transformer-based systems.

Initial explorations in automatic text summarization employed Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNNs) (Gao et al., 2019). These architectures were among the first to show promise in abstractive summarization, especially within domains characterized by informal language such as social media. Notable contributions in this space include the Attentional Encoder-Decoder framework (Liang, 2020), as well as attention-augmented models (Wang and Ren, 2021), which improved the identification of salient information in noisy, user-generated text. The introduction of sequence-to-sequence models with integrated attention mechanisms (Bhandarkar and Thomas, 2023) marked a pivotal step, enabling more nuanced and context-aware summary generation through enhanced encoder-decoder coupling.

The emergence of Transformer architectures (Vaswani et al., 2017) revolutionized NLP by replacing recurrence with self-attention mechanisms, allowing more efficient modeling of long-range dependencies. Transformers rapidly achieved state-of-the-art performance across tasks (Gupta 2022), including summarization. For example, a multi-stage model for Chinese summarization (Su 2020) combined BERT encoders with bidirectional LSTMs and a document-level transformer, demonstrating the effectiveness of hybrid designs in long-form summarization.

Transformer models have also been adapted for dialogue summarization, capturing conversational dynamics with greater fidelity (Singhal et al., 2020). Comparative evaluations of leading transformer-based models—including BART, PEGASUS, and T5—have shown consistent superiority of T5 in ROUGE metrics (Blekanov 2022). Beyond traditional text corpora, summarization has expanded to include sources such as the WikiHow dataset (Pal 2022) and web content enhanced by social media signals (Nguyen et al., 2020), leveraging models like BERT and T5 for broader generalization across styles.

Despite these advances, the targeted summarization of user-generated comments remains underexplored. Prior work has focused predominantly on summarizing primary post content or event narratives, with less

emphasis on downstream user interactions. Studies drawing from Twitter and Reddit (Blekanov 2022; Li 2020; Kerui 2020)—and, in some cases, Sina Weibo—have used hybrid architectures pairing pre-trained BERT encoders with Transformer-based decoders (Li 2020; Kerui 2020) or alternative summarization modules (Tampe 2021). While these models yield promising outputs, research on comment-level summarization, particularly in informal and fragmented threads, remains nascent. The T5 model, though strong in general-purpose tasks, has only recently been applied to this domain (Blekanov 2022).

Parallel efforts have explored sentence-level summarization in review datasets (Rawat et al., 2021), using the Universal Sentence Encoder with statistical heuristics and graph-based reduction to extract informative sentence fragments. These methods enhance content density while addressing constraints of brief textual inputs.

In recent years, prompt engineering has emerged as a novel strategy for adapting large language models (LLMs) without full retraining. By designing task-specific input prompts, researchers can steer model behavior and improve performance across NLP tasks. Frameworks like OpenPrompt (Ding et al., 2022) support this process with modular tools for prompt-based learning, spanning architectures like masked language models (MLM), autoregressive language models (LM), and sequence-to-sequence (Seq2Seq) frameworks.

Further refinements include entity chain representations (Narayan et al., 2021), which improve coherence by structuring input, and prefix-tuning (Li 2021), a parameter-efficient fine-tuning method introducing task-specific vectors while keeping base parameters frozen. Prompt-tuning (Lester 2021) extends this by learning tunable prompts for frozen models, offering a cost-effective, reusable alternative to full fine-tuning. These lightweight methods are useful in resource-constrained settings or domains requiring rapid adaptation.

In specialized fields like clinical NLP, where conventional methods often miss domain-specific subtleties, prompt engineering has shown notable improvements in both flexibility and performance (Wang et al., 2024). These developments support a broader shift toward prompt-based methodologies as an efficient alternative to traditional training (Liu et al., 2021).

Taken together, this body of work highlights growing interest in adaptable, context-sensitive summarization—particularly those leveraging transformers' expressive power and prompt engineering's task-specific control.

3. Methodological Framework for Transformer-Based Summarization

The methodological foundation for the proposed abstractive summarization framework is grounded in the transformer architecture, selected for its proven ability to model complex linguistic dependencies and handle the semantic variability inherent in user-generated social media content. Transformers are especially well-suited for this domain, given their demonstrated efficacy in capturing subtle contextual cues across fragmented and noisy text on platforms like Twitter and Reddit.

Unlike traditional extractive techniques or earlier neural models such as RNNs—including LSTM and GRU—that suffer from sequential processing and limited memory, transformers use self-attention mechanisms to process entire sequences in parallel (Vaswani et al., 2017). This capability is critical for modeling the long-range dependencies prevalent in dispersed, context-sensitive online discourse.

Summarization is framed here as a multi-dimensional task defined by three core criteria: coherence, ensuring logical flow; informativeness, preserving core content; and conciseness, reducing redundancy while maintaining clarity. This principled approach underlies the system's design and supports the use of abstractive strategies over extractive ones. While extractive models select and combine source fragments, transformer-based abstractive models generate fluent, semantically rich summaries better aligned with the intent of the original material.

The system is structured into four modules:

- Preprocessing: Cleans informal input, normalizes abbreviations/emojis, and removes noise.
- Representation Learning: Encodes text using transformer embeddings like BERT (Devlin et al., 2019) or T5 (Raffel et al., 2019).
- Summarization Engine: Uses fine-tuned transformer models with reinforcement learning and attention refinement.
- Evaluation Framework: Combines automatic metrics with human benchmarks for comprehensive validation.

The choice of transformers reflects not only performance but conceptual fit, supported by their success across NLP tasks (Gupta 2022; Blekanov 2022; Nguyen et al. 2020). Ultimately, this framework treats transformers as foundational to addressing the unique linguistic challenges of modern social media summarization.

3.1 System Description

3.1.1 Motivation for transformer-based social media summarization

The exponential growth of content across digital and social media platforms has led to a deluge of information that users must parse to derive meaningful insights. Social media platforms, especially during unfolding events, are flooded with posts, comments, and reactions, often resulting in redundancy and thematic drift. This volume impedes comprehension and masks the core information users seek.

Abstractive summarization serves as a vital solution for distilling essential content from noisy data. Social media content holds value far beyond ephemeral communication—it contributes to digital journalism, informs policy debates, and enables the study of societal behavior at scale. Effective summarization of user-generated comments supports applications in crisis response, social analytics, and public opinion monitoring.

However, summarizing social media data poses distinctive challenges:

- Informality and Non-standard Language: Social texts often forgo grammatical norms, using slang, abbreviations, emojis, and emoticons (e.g., “<3”, “:P”), mirroring spoken language and emotional spontaneity.
- Contextual Fragmentation and Topic Drift: Threads diverge from the original topic, producing disjointed, non-linear conversations that hinder coherent summarization.
- Lexical Sparsity and Multimodality: Posts are concise, embedding meaning in short text, symbols, and images—limiting the context available to traditional models.

Transformer-based architectures offer a robust solution. With multi-head self-attention, they model long-range dependencies and complex, non-linear context. Pre-trained on diverse corpora (Gupta 2022), they generalize across registers, interpreting irregular syntax, emotive symbols, and fragmented structures.

Transformers preserve factual content, sentiment, and communicative intent—essential for representing social discourse. Their scalability enables real-time, high-volume social media summarization. Building on these strengths, we present a modular, transformer-based system for comment-level abstractive summarization across social platforms.

3.1.2 Overview of the proposed system

The proposed system focuses on generating abstractive summaries from clusters of user comments associated with individual social media posts. Unlike prior models that center on tweet threads (Blekanov 2022; Li 2020) or Reddit discussions (Kerui 2020), this system although trained exclusively on data from a single platform (Facebook), the system is designed to generalize across platforms, demonstrating adaptability to diverse speech structures and linguistic characteristics, thereby ensuring applicability in a variety of communicative environments.

The system architecture integrates the foundational transformer model with a four-stage processing pipeline (Figure 1):

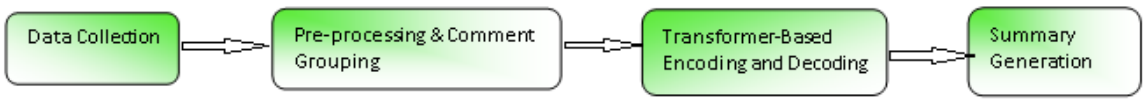

Figure 1: Social Media Summarization Pipeline

1. Data Collection: The dataset is sourced from Facebook1, a platform with short, unstructured, and variable comment threads. These threads often include repeated content, emojis, informal language, and user-specific references—making them ideal for testing robust summarization techniques. Unlike structured document collections, this dataset reflects the idiosyncrasies of organic online discourse.
2. Pre-processing and Comment Grouping: Pre-processing reduces linguistic noise and normalizes input through:

- Removing emojis, special characters, dashes, and punctuation
- Tokenizing text while preserving case-sensitive abbreviations
- Grouping comments by post ID or title to form semantically related clusters

Thematic grouping helps the model focus on coherent discourse units, reducing cross-topic interference. This strategy draws on dictionary-based clustering approaches used in prior pipelines (Bhandarkar 2023; Li 2020).

3. Transformer-Based Encoding and Decoding: Tokens are converted into IDs and passed through embeddings processed by a multi-head attention mechanism (eight heads). Following Vaswani et al. 2017, the encoder includes:

- Multi-head self-attention
- Feed-forward layers
- Residual connections and layer normalization

The decoder receives encoder outputs and a right-shifted target sequence. Masked self-attention prevents future token access. Cross-attention layers integrate contextual representations, and a softmax classifier outputs token distributions.

4. Summary Generation: The decoder auto-regressively generates one token at a time, conditioned on previous tokens and encoder context. This enables fluent, coherent, and human-like summaries with semantic integrity and pragmatic tone.

Unlike extractive or graph-based reductions (Rawat et al., 2021), our abstractive method captures paraphrasing, inferred meaning, and dialogic nuance—critical for informal, sentiment-rich environments like social media. This modular pipeline remains scalable and adaptable for evolving datasets and platform constraints.

4. Comparison With ChatGPT

To benchmark the performance of our summarization framework, we conducted a comparative evaluation against ChatGPT, a widely adopted large language model developed by OpenAI in 2022. Built on the GPT (Generative Pre-trained Transformer) architecture, ChatGPT leverages deep learning and natural language processing to generate human-like text. Its fine-tuning via Reinforcement Learning from Human Feedback (RLHF) enables alignment with user intent, making it highly effective in various language tasks, including summarization.

For this comparison, a random subset of user comment threads was selected. Each set of comments was prefixed with the prompt “summarize:” and input into ChatGPT to generate corresponding summaries. These outputs were evaluated using the same suite of metrics applied to our system—grouped into reference-based, reference-free, and human-aligned categories.

4.1 Comparison Using Reference-Based Metrics

Reference-based evaluation metrics quantify the quality of machine-generated text by comparing it against human-authored references. These metrics are widely adopted to assess dimensions such as lexical overlap, semantic similarity, and content coverage. This section provides a concise overview of the reference-based metrics employed in the current analysis, with emphasis on their roles in evaluating alignment between system-generated summaries and gold-standard outputs.

Evaluation was conducted using standard metrics from the ROUGE (Lin 2004) family, including ROUGE-1, ROUGE-L, ROUGE-Lsum, ROUGE-S, and ROUGE-WE. These metrics capture a range of textual similarities, from exact lexical matches to structurally and semantically informed correspondences.

[1] https://github.com/jbencina/facebook-news

As illustrated in Figure 2, the Proposed Model demonstrates superior performance across all ROUGE variants in comparison to ChatGPT. For instance, the ROUGE-1 F1-score achieved by the Proposed Model (0.3292) exceeds that of ChatGPT (0.2739), reflecting greater overlap with key content words in the reference summaries. While both models yield moderate recall, the higher precision and F1-scores associated with the Proposed Model indicate stronger alignment with salient information in the source texts.

Scores for ROUGE-L, ROUGE-Lsum, and ROUGE-S are comparatively lower, as expected given their more stringent criteria regarding sequence structure and skip-bigram matches. Nevertheless, the Proposed Model maintains a consistent advantage across these metrics, suggesting enhanced preservation of both lexical and structural aspects of the target summaries.

The ROUGE-WE metric, which incorporates semantic similarity through pre-trained word embeddings, further underscores this trend. The Proposed Model attains a ROUGE-WE score of 0.9568, slightly higher than ChatGPT's 0.9495. Although the numerical difference (Δ = 0.0073) is modest, it may reflect a meaningful improvement in semantic fidelity, particularly in contexts where conceptual accuracy is prioritized over surface-form similarity.

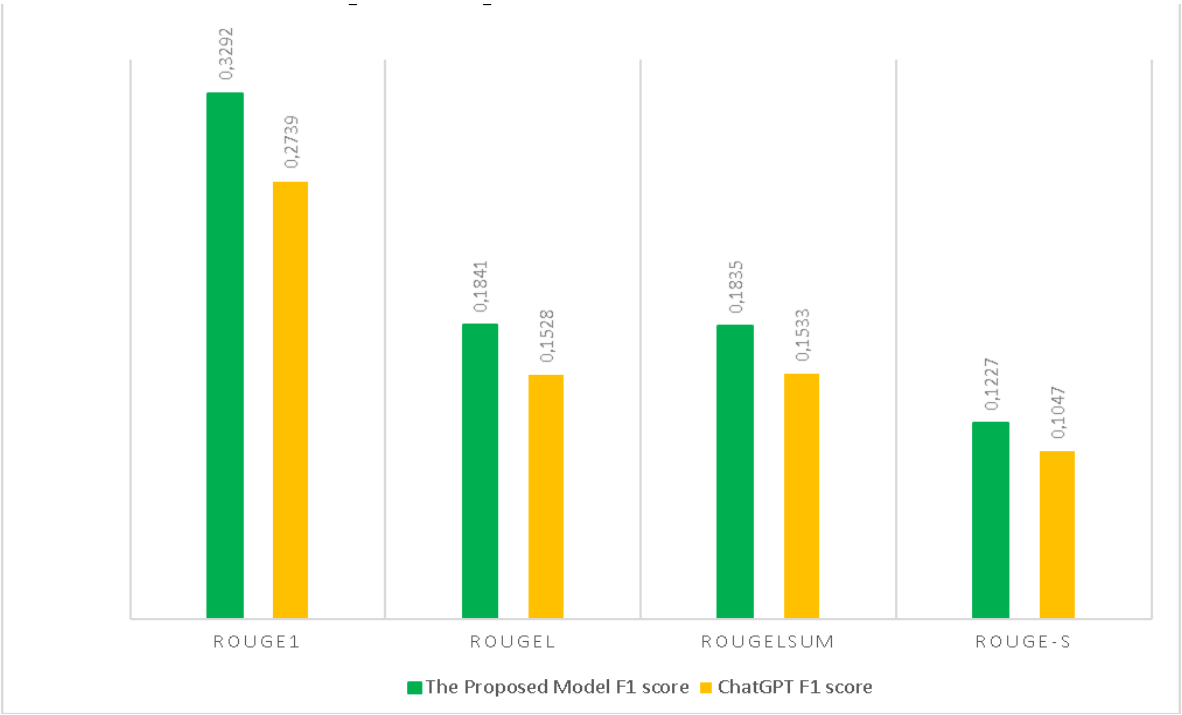

Figure 2: Comparison on reference-based metrics

4.2 Comparison Using Reference-Free Metrics

In contexts where human-authored reference summaries are unavailable, reference-free evaluation metrics provide an effective alternative for assessing the quality of automatically generated summaries. These metrics are particularly valuable in real-world applications where the construction of gold-standard references is infeasible due to resource constraints. Unlike reference-based methods, reference-free evaluation relies on intrinsic properties of the generated text—such as fluency, coherence, informativeness, and semantic consistency—enabling comprehensive quality assessment without dependence on external benchmarks.

This section presents a comparative analysis of generated summaries using a set of reference-free metrics, including Shannon Consistency, Shannon Coherency (Egan 2022), Semantic Distance-based Clustering (SDC) (Li 2022b), and SUPERT (Gao 2020). These metrics were selected to capture various dimensions of summary quality, particularly semantic fidelity and structural coherence. Figure 3 visualizes the average metric scores for the Proposed model and ChatGPT.

Across all evaluated dimensions, the Proposed model demonstrates superior performance. Higher scores in Shannon Consistency (0.9512 vs. 0.9447) and Shannon Coherency (0.9519 vs. 0.9471) suggest stronger logical structure and internal alignment within its outputs. These findings indicate that the Proposed model generates summaries with greater semantic stability across different input variations.

The most substantial performance gap is observed in the SDC metric, where the Proposed model achieves a score of 0.5746, substantially exceeding ChatGPT's 0.2646. This metric is designed to assess the preservation of semantic intent and minimize interpretive divergence. The lower score for ChatGPT implies greater variability and potential semantic drift, which may undermine reliability in applications requiring accurate content representation.

On the SUPERT metric, both models exhibit strong performance, with the Proposed model slightly outperforming ChatGPT (0.9990 vs. 0.9977). Although the margin is minimal, it further supports the Proposed model's ability to generate summaries that align closely with expected semantic clusters, even in the absence of reference summaries.

As a result, the Proposed model outperforms ChatGPT across all reference-free evaluation criteria, with particularly notable improvements in semantic consistency and coherence. These results underscore the effectiveness of reference-free metrics as a scalable and domain-agnostic evaluation framework, especially in settings where human-generated references are unavailable or impractical to obtain.

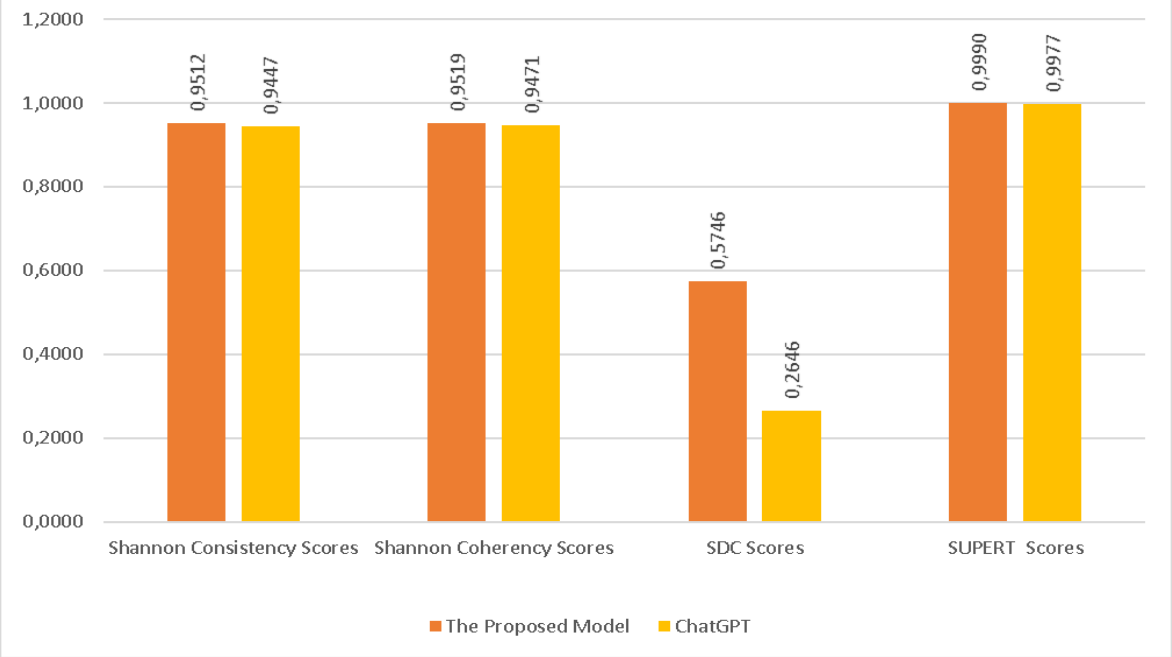

Figure 3: Comparison of reference free metrics

4.3 Comparison Using Human-Shaped Metrics

Evaluating abstractive summarization presents significant challenges, particularly within the domain of social media discourse, due to the subjective and multi-dimensional nature of the task. In contrast to extractive methods, effective abstractive summarization must accurately and succinctly convey the source text's essential meaning while employing novel and contextually appropriate phrasing, thereby emulating human summarization strategies (Ng, 2015). The presence of multiple valid summary interpretations for a given input further complicates the evaluation process, as no single reference summary can comprehensively capture all plausible variations.

These challenges are exacerbated in social media environments, where texts are often informal, grammatically inconsistent, and characterized by non-standard linguistic elements such as slang, emojis, and abbreviations. The dialogic and non-linear structure of discussions—frequently involving references to prior posts or thematic divergence—introduces additional contextual dependencies. Furthermore, the brevity and fragmented nature of social media content typically limit lexical richness and cohesion, complicating both the generation and evaluation of abstractive summaries. As such, a rigorous evaluation framework must account for linguistic variability, contextual coherence, and semantic fidelity across heterogeneous and dynamic textual inputs.

To address these concerns and evaluate qualitative aspects beyond traditional reference-based metrics, a comparative analysis was conducted using human-centered evaluation criteria across a Transformer-based summarization model (referred to here as the Proposed model) and ChatGPT. The assessment focused on six dimensions: consistency, lexical diversity, fluency, readability, semantic coherence, and overall coherence.

Results indicate complementary strengths across the models. The Proposed model demonstrated notable improvements in consistency, lexical diversity, readability, and semantic coherence. Specifically, consistency scores more than doubled those of ChatGPT (0.5627 vs. 0.2490), reflecting a stronger capacity to maintain internal logical structure and thematic stability across generated content. This attribute is especially pertinent in applications requiring structured outputs, such as automated reporting or multi-turn dialogue systems.

In terms of coherence, both models performed comparably, with a marginal advantage observed for the Proposed model (0.4054 vs. 0.3914). Lexical diversity was also higher in the Proposed model, indicating more varied vocabulary usage. While this may enhance richness, it introduces a potential trade-off with simplicity, which remains a key factor in user-facing applications.

Fluency was the one area in which ChatGPT outperformed the Proposed model (0.7925 vs. 0.7876), likely attributable to extensive pre-training on a broad and diverse corpus. Nevertheless, the Proposed model exhibited higher readability (0.4455 vs. 0.3626), suggesting it produces more accessible outputs, despite slightly lower fluency.

Semantic coherence scores were closely aligned, with a slight edge again favoring the Proposed model (0.4132 vs. 0.3948), indicating its greater aptitude for maintaining meaning across sentence boundaries. As illustrated in Figure 4, the Proposed model outperformed ChatGPT in five of the six human-shaped evaluation dimensions.

These findings highlight the differing strengths of the models under consideration. While ChatGPT maintains superior fluency, the Proposed model delivers a more balanced performance profile, excelling in dimensions critical for interpretive quality and structural consistency. These results underscore the Proposed model's suitability for applications requiring readability, consistency, and diversity, whereas ChatGPT may be more appropriate for tasks emphasizing conversational naturalness and fluid expression.

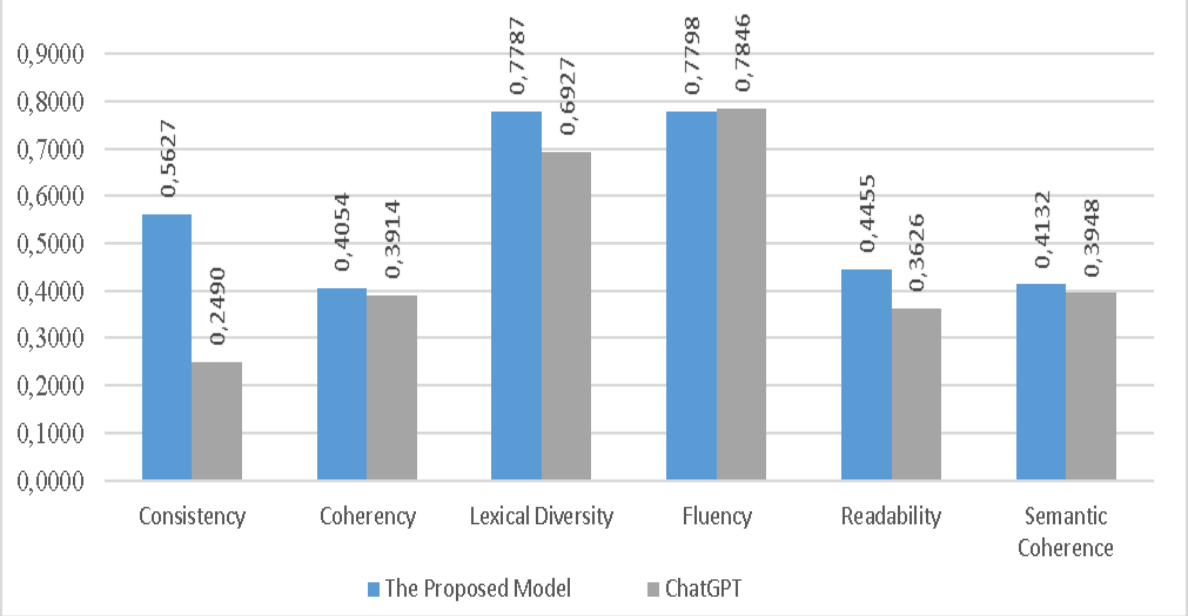

Figure 4: Comparison on human-shaped metrics

Future work will seek to enhance the fluency of the Proposed model without compromising its demonstrated strengths, aiming to achieve a more optimal integration of naturalness, consistency, and accessibility in abstractive summarization of social media content.

5. Conclusion and Future Work

In an era marked by the explosive growth of user-generated content, the ability to extract coherent, relevant, and timely insights from social media has never been more crucial. This research introduces a domain-adaptive abstractive summarization system that effectively addresses the inherent challenges of processing noisy, unstructured data typical of social networking platforms. By harnessing the power of transformer-based architectures and transfer learning, the system demonstrates significant advancements in fluency, contextual awareness, and semantic alignment, outperforming existing models—including ChatGPT 4.0—across a range of

both quantitative and qualitative evaluation metrics. Its robust preprocessing pipeline and attention-driven encoder-decoder design enable it to capture not only the factual essence but also the emotional and cultural nuances embedded in digital conversations.

Beyond its technical contributions, this work underscores the practical relevance of intelligent summarization in real-world applications such as sentiment tracking, trend analysis, public communication, and customer feedback synthesis. Importantly, the system's flexibility, scalability, and domain adaptability highlight its potential for both academic inquiry and industry deployment. However, the study also illuminates several critical avenues for future research. Enhancing computational efficiency through lightweight architectures, extending capabilities to multilingual and multimodal contexts, and enabling cross-platform and real-time summarization are all promising directions. These next steps are essential to addressing the dynamic, diverse, and increasingly global nature of social media discourse. Ultimately, this work lays a strong foundation for developing summarization technologies that do more than condense content—they interpret and contextualize it in ways that are meaningful to human understanding and decision-making.

Acknowledgements

The publication fees were totally covered by the University of West Attica.

Ethical Declaration: I confirm that ethical clearance was not required for this research.

AI Declaration: I have not used any AI tool to create this paper

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Adoption of Artificial Intelligence and Base Technologies of Industry 4.0: A Way to Improve Business Processes

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Abstract: Our article examines selected technologies associated with the Fourth Industrial Revolution (specifically the so-called base technologies) and their extent of utilization within business processes. The research was conducted on a sample of companies operating in the Slovak Republic. Based on data from 180 companies, we assessed the extent of implementation of these technologies. The results of our study show that some Industry 4.0 technologies have already been successfully implemented in most of the surveyed companies (in particular cloud computing for data storage, cloud networks for remote access to resources, and the Internet of Things). An especially positive finding is that cybersecurity measures have been implemented to the greatest extent, which is crucial for the successful and sustainable functioning of the entire Industry 4.0, with the importance of this area continuing to grow each year. On the other hand, artificial intelligence, machine learning, and deep learning are not widely used in most companies, nor do companies currently plan to adopt them. This field, however, provides significant potential for productivity growth and process optimization, and in recent years we have also observed a marked increase in the adoption of artificial intelligence within the general population. At present, only 14% of companies have successfully implemented these technologies. According to our findings, companies that do employ artificial intelligence and machine learning use them primarily in business processes to facilitate the analysis and evaluation of large datasets.

Keywords: Industry 4.0, Base technologies, Business processes, Artificial intelligence, Cybersecurity

1. Introduction

The Fourth Industrial Revolution is considered a socio-economic phenomenon that has the potential to influence and transform all sectors, offered products and services, corporate strategies (Prim, 2022), and fundamentally affect the way in which business processes are managed and performed. Within the Fourth Industrial Revolution, it is primarily the new technologies associated with it, such as artificial intelligence, machine learning, blockchain, cloud solutions, and other technologies, that directly influence these changes. As various researchers, such as Ross and Maynard (2021), point out, at present the fundamental changes are to a large extent associated with the technological progress brought about by the Fourth Industrial Revolution, also known as Industry 4.0. As Burritt and Christ (2016) states, Industry 4.0 is used as an umbrella term referring to a group of interconnected technological advances that form the basis for the increased digitization of the business environment. Technologies of Industry 4.0 combine cyber-physical structures, such as the Internet of Things and the Internet of Services, with other technologies, including artificial intelligence, big data, machine learning, and others. (Javaid, 2022) From this perspective, it is interesting to examine various types of technologies. Therefore, the aim of this article being to focus on a specific type of Industry 4.0 technologies, namely the so-called base technologies (Industry 4.0 Base Technologies). Another interesting aspect is the extent to which companies use Industry 4.0 technologies and how this influences their competitiveness. As Merlo (2020) states, the adoption of Industry 4.0 acts as a competitive differentiator – companies moving forward with Industry 4.0 initiatives gain advantages in the form of sophisticated new capabilities and new ways of strengthening competitiveness, while others are forced to catch up. Business processes can undergo significant changes with the incorporation of Industry 4.0 technologies. In particular, the use of artificial intelligence in business processes continues to attract significant interest, as artificial intelligence can be applied to the automation of business processes and the support of companies' decision-making processes. (Gomes et al., 2022) Despite the fact that Industry 4.0 has been discussed for several years, several studies point to problematic areas of its implementation (Ferkrisari, Kantola, 2024) and also propose maturity models to support this implementation. (Wagire et al., 2020) Maturity models are used, among other things, to evaluate the success of Industry 4.0 implementation. This article aims to examine whether companies pay attention to adapting business processes to the trends of the Fourth Industrial Revolution and to assess the extent to which they thereby use artificial intelligence and selected Industry 4.0 technologies, based on a chosen maturity model. In our research, we focused on a specific set of technologies called Industry 4.0 Base Technologies, as one of their features is that they enable companies to analyse and improve business processes. At the same time, our research focused only on a selected location, i.e. companies operating in the territory of the Slovak Republic, and we did not specialize in a single sector but

approached companies from various sectors and of different sizes in order to assess whether such characteristics also influence the adoption of artificial intelligence in business processes.

2. Theoretical Background

2.1 Industry 4.0 and Business Processes Improvement

The Fourth Industrial Revolution, also called Industry 4.0, brings new challenges for companies that directly affect how they operate, how they organize their business models, how they carry out business processes, how they produce and deliver their products and services, how they organize their relationships, and how they shape their competences. (Khider et al., 2025) Industry 4.0 is a term closely associated with technologies and technological progress. As with previous industrial revolutions, this revolution was not initiated by a single technology but is a synthesis of multiple technologies and technological advances. (Cabrita, 2019) Thanks to Industry 4.0, companies can use a range of digital technologies, systems, platforms, concepts, and architectures, such as artificial intelligence, augmented/virtual reality, (industrial) automation, big data, cloud computing/storage, cyber-physical systems, cybersecurity, enterprise resource planning (ERP) systems, the Industrial Internet, the Internet of Things, and intelligent/autonomous robotics. (Dos Santos et al., 2021) Whereas in the past, investments in new technologies and technological support for business processes were primarily aimed at reducing costs and increasing efficiency (Papulová et al., 2022), today this perspective shifts toward the implementation of technologies with the aim of achieving higher speed and flexibility, improving the quality of interaction with customers, and strengthening innovation. (Vaska et al., 2021) Technologies are dramatically transforming companies and entire industries, as they not only support existing processes but enable their modification and thereby directly foster not only process and organizational innovations but also innovations of business models (Papulová et al., 2022). Technology-based process improvement is shifting toward achieving new levels of competitiveness. (Javaid et al., 2022) Industry 4.0 directly affects a company's competitiveness by employing technologies that can improve business processes, for example in terms of their automation and digitization, through autonomous and intelligent systems. Industry 4.0 also enables automated, seamless, and connected networks of companies and other parties through the incorporation of the latest technologies, machinery, and infrastructure (Mahmood and Mubarik, 2020). From the perspective of process improvement in the context of Industry 4.0, the current trends in business process management include the following areas (Khider et al., 2025):

- process automation, enabled by technologies such as artificial intelligence, machine learning, and the Internet of Things (Nozari et al., 2024);
- Process digitization, which also enables the creation of new and innovative business models and organizational structures (Broccardo et al., 2024);
- process control and real-time monitoring (Ghobakhloo, 2020) contribute to information transparency and data analysis that enable higher-quality and faster decision-making (Elghaish et al., 2021);
- customer-centric processes that enable companies to deliver personalized and more efficient communication and interaction with customers (Ahmed & Shahzad, 2022).

2.2 Artificial Intelligence and Industry 4.0 Base Technologies

Industry 4.0 is often defined through technologies that are also referred to as "emerging and disruptive technologies" (Young, 2020), and attention is frequently directed to two groups of Industry 4.0 technologies: front-end technologies and base technologies (Ferrigno et al., 2023), which provide connectivity and intelligence for front-end technologies. (Frank et al., 2019) The focus on base technologies is particularly interesting in terms of opportunities to improve business processes. (Baden-Fuller and Haefliger, 2013) The front-end technologies (smart manufacturing, smart products, smart supply chain, smart working) address operational and market needs and have an end-application role in the companies' value chain, while the base technologies (Internet of Things, cloud, big data and analytics) provide connectivity and intelligence for front-end technologies. (Čater et al., 2021)

Wagire et al. (2020), within their proposed maturity model for Industry 4.0, distinguish three groups of Industry 4.0 technologies: Smart Manufacturing Technologies, Product- and Services-Oriented Technologies, and Industry 4.0 Base Technologies, and classify into the group of base technologies the following:

- Cloud computing networks for resource sharing – cloud services that enable companies to remotely access and use physical resources (e.g., devices and robots) and intangible resources (e.g., data, documents, software),

- Cloud computing networks for data storage – cloud services for the secure storage and retrieval of organizational data,
- Internet of Things – interconnected devices and sensors that communicate and interconnect machines, systems, and people,
- Internet of Services – web-based service platforms that enable the composition and delivery of digital services,
- Big data and real-time data processing – methods to collect, process, and analyze large, fast-moving datasets to support decision-making,
- Simulation tools – software for what-if scenario analysis (modeling configuration options) to develop predictive scenarios that support business decision-making,
- Artificial intelligence, machine learning, and deep learning – AI-based cognitive technologies (e.g., natural language processing, speech recognition, computer vision, object detection and recognition) that learn from data and enable personalization, automation, and process improvement,
- Industrial cybersecurity – organizational and technical measures that protect systems and data and ensure the confidentiality, integrity, and availability in industrial environments.

Although Wagire et al. (2020) refer to the items listed as "technologies," this label functions as an umbrella term that encompasses a broader range of digital technologies, systems, platforms, concepts, and architectures. For the sake of terminological consistency and brevity, we use the shortened label "technologies" throughout our paper, by which we explicitly mean this broader scope (i.e., not only specific technical solutions but also related systems, platforms, and conceptual or architectural approaches).

In particular, the use of artificial intelligence in the improvement of business processes continues to attract significant interest. Artificial intelligence can be characterized as the ability of computer systems to learn, process information, and make decisions, thereby replacing activities that would ordinarily require human intelligence. (Helm et al., 2020) Recently, with the increasing possibilities for acquiring large volumes of data (Big Data), artificial intelligence has been gaining increasing importance, as it can be used to process and analyse large amounts of data almost instantly, in real time (Gomes et al., 2022), while also identifying patterns, predicting outcomes, and proposing optimizations and decisions. In the context of artificial intelligence, machine learning and deep learning are often mentioned as its subfields: they can perform complex tasks such as speech recognition and natural language processing (Gomes et al., 2022) and, thanks to their ability to "learn" and use algorithms, also provide recommendations or make decisions (Helm et al., 2020). From the perspective of improving processes in companies, AI-based process analysis and optimization can use real-time data and employ machine-learning algorithms to uncover hidden patterns, predict failures and errors, and dynamically adjust decision-making based on insights from processed data (Bubenik et al., 2025). These possibilities for the adoption of artificial intelligence help improve the efficiency of existing business processes and enable business process automation. (Gomes et al., 2022)

3. Methodology

Although we first learned about Industry 4.0 in 2011 (Adolph et al., 2016), the topic continues to evolve, and the gradual implementation of Industry 4.0 technologies in companies creates room for further research. This article aims to examine whether companies pay attention to adapting business processes to the trends of the Fourth Industrial Revolution and to assess the extent to which they thereby use artificial intelligence and selected Industry 4.0 technologies, based on a chosen maturity model. In our research, we focused on a specific set of technologies known as Industry 4.0 Base Technologies, as one of their features is that they enable companies to analyse and improve business processes. To assess the degree of adoption of artificial intelligence and selected Industry 4.0 technologies, we used part of the maturity model by Wagire et al. (2020), which directly enables the evaluation of the extent to which artificial intelligence and other Industry 4.0 Base Technologies are used. For data collection, we used structured interviews with representatives of companies operating in Slovakia, and we did not focus on a single size category or on a single sector. The structured interview comprised 8 sections based on the 8 identified areas of Industry 4.0 Base Technologies. Data were collected in the years 2022–2024, during which we obtained 180 responses. To evaluate the individual levels of technologies, a 1–5 scale based on the Likert scale was used, with each level expressing the degree or extent of technology application in the given company.

4. Results and Discussion

4.1 Evaluation of Industry 4.0 Technologies Adoption

This section presents the main findings on the extent of use of Industry 4.0 Base Technologies in the analysed set of companies. We base our analysis on the selected maturity model and evaluate implementation levels for individual technologies. We focused on the following Industry 4.0 Base Technologies: Cloud computing networks for resource sharing; Cloud computing networks for data storage; Internet of Things; Internet of Services; Big data and real-time data processing; Simulation tools; Artificial intelligence, machine learning, and deep learning; Industrial cybersecurity. The results are presented in Table 1.

Table 1: Assessment of the implementation of Industry 4.0 Base Technologies

Industry 4.0 Base Technologies	1		2		3		4		5		Average
Cloud computing networks for resource sharing	20	11.11%	12	6.67%	13	7.22%	33	18.33%	102	56.67%	4.03
Cloud computing networks for data storage	17	9.44%	11	6.11%	12	6.67%	29	16.11%	111	61.67%	4.14
Internet of Things	40	22.22%	14	7.78%	6	3.33%	22	12.22%	98	54.44%	3.69
Internet of Services	71	39.44%	22	12.22%	22	12.22%	16	8.89%	49	27.22%	2.72
Big data and real-time data processing	45	25.00%	24	13.33%	15	8.33%	24	13.33%	72	40.00%	3.30
Simulation tools	73	40.56%	25	13.89%	17	9.44%	26	14.44%	39	21.67%	2.63
Artificial intelligence, machine learning, and deep learning	108	60.00%	18	10.00%	13	7.22%	15	8.33%	26	14.44%	2.07
Industrial cybersecurity	12	6.67%	12	6.67%	11	6.11%	29	16.11%	116	64.44%	4.25
Total: *Industry 4.0 Base Technologies*											*3.35*

Source: Own elaboration.

The implementation-level values for individual Industry 4.0 Base Technologies denote:

Level 1: Such technologies are not implemented and/or not planned.

Level 2: Requirements for introducing such technologies are being prepared and/or have not yet been officially approved as part of the organization's plan.

Level 3: Such technologies are being prepared for implementation and/or are part of the officially approved organizational plan.

Level 4: We are implementing such technologies.

Level 5: We have successfully implemented such technologies.

Based on the results in Table 1, we see that some Industry 4.0 Base Technologies are successfully implemented (level 5) in most companies, such as Cloud computing networks for data storage (62%), Cloud computing networks for resource sharing (57%), and the Internet of Things (54%). A very positive finding is that Industrial cybersecurity are the most successfully implemented (64%), since this area is critical to the successful implementation and the sustainable operation of Industry 4.0 as a whole; its importance is increasing year by year and, in the future, will pose a major challenge, not only from the perspective of Industry 4.0. On the other hand, Artificial intelligence, machine learning, and deep learning are not used, nor are they planned to be used (level 1) in most companies (60%), although this area offers substantial room to increase productivity and optimize processes; in recent periods, we also observe a significant increase in the use of artificial intelligence among the general population. (e.g., Deloitte, 2024)

4.2 The Level of Artificial Intelligence Adoption

According to our research, 14% of the companies in our sample have artificial intelligence technologies and the associated machine learning and deep learning successfully implemented (at level 5). In our study, we also examined whether certain company characteristics affect the adoption of artificial intelligence, for example company size, years in operation, whether it is a manufacturing or a services company, whether the sector in which the company operates matters, and also whether the company is domestic or foreign (i.e., whether a

majority stake in the company is held by foreign capital). We present the results of these more detailed assessments in Table 2.

Table 2: Level of artificial intelligence (AI) adoption across different types of companies

Company characteristics	1		2		3		4		5		Average
Size:											
Micro	18	78.26%	3	13.04%	0	0.00%	1	4.35%	1	4.35%	1.43
Small	31	68.89%	6	13.33%	2	4.44%	1	2.22%	5	11.11%	1.73
Medium	23	62.16%	1	2.70%	5	13.51%	4	10.81%	4	10.81%	2.05
Large	36	48.00%	8	10.67%	6	8.00%	9	12.00%	16	21.33%	2.48
Years in operation:											
Less than 5 years	5	100.00%	0	0.00%	0	0.00%	0	0.00%	0	0.00%	1.00
5 to 15 years	22	55.00%	7	17.50%	1	2.50%	3	7.50%	7	17.50%	2.15
More than 15 years	81	60.00%	11	8.15%	12	8.89%	12	8.89%	19	14.07%	2.09
Manufacturing:											
yes (manufacturing companies)	47	69.12%	6	8.82%	4	5.88%	4	5.88%	7	10.29%	1.79
no (non-manufacturing companies)	61	54.46%	12	10.71%	9	8.04%	11	9.82%	19	16.96%	2.24
Sector (NACE):											
Manufacturing; Mining and quarrying; Other industry;	43	69.35%	6	9.68%	3	4.84%	4	6.45%	6	9.68%	1.77
Construction	5	83.33%		0.00%	1	16.67%	0	0.00%	0	0.00%	1.33
Wholesale and retail trade; Transportation and storage; Accommodation and food service activities;	26	56.52%	9	19.57%	3	6.52%	2	4.35%	6	13.04%	1.98
Telecommunications; Computer programming, consultancy and related activities; Data processing, hosting and related activities; Information service activities;	3	20.00%	1	6.67%	4	26.67%	3	20.00%	4	26.67%	3.27
Financial and insurance activities;	10	50.00%	0	0.00%	0	0.00%	4	20.00%	6	30.00%	2.80
Real estate activities;	2	50.00%	1	25.00%	0	0.00%	0	0.00%	1	25.00%	2.25
Professional, scientific and technical activities; Administrative and support service activities;	11	64.71%	0	0.00%	2	11.76%	2	11.76%	2	11.76%	2.06
Public administration and defence; Education; Human health and social work activities;	8	80.00%	1	10.00%	0	0.00%	0	0.00%	1	10.00%	1.50

Company characteristics	1		2		3		4		5		Average
Foreign company:											
yes	34	47.22%	5	6.94%	9	12.50%	9	12.50%	15	20.83%	2.53
no	74	68.52%	13	12.04%	4	3.70%	6	5.56%	11	10.19%	1.77
Total: *Artificial Intelligence, Machine Learning and Deep Learning*											*2.07*

Source: Own elaboration.

From the standpoint of the average level of artificial intelligence implementation, companies on average reach level 2, which means that the requirements for introducing such technologies are being prepared and/or have not yet been officially approved as part of the organization's plan. When evaluating by company size, large companies reached a value of 2.48, only slightly above the average (2.07), which means that fewer than half of companies (41%) reach levels 3–5. By sector, we found that the highest average implementation value (3.27) was achieved by companies in Telecommunications; Computer programming, consultancy and related activities; Data processing, hosting and related activities; Information service activities, while another sector with above-average implementation was Financial and insurance activities.

If we look at other studies on the use of artificial intelligence in companies, based on a recently published Eurostat (2025) study, which examined 157,000 out of 1.54 million companies in the EU:

- In 2024, 13.48% of EU companies used AI technologies.
- In 2024, 41.17% of large EU companies used AI technologies.
- In 2024, AI was used most by companies in the information and communication sector.

These results are very similar to the findings of our study. We can concur with the conclusions of the Eurostat (2025) study that, according to our findings as well, artificial intelligence is used more in some sectors than in others, which likely suggests that AI may be more applicable to certain activities and processes. It is also noteworthy that non-manufacturing companies, on average, use this technology more than manufacturing companies (2.24 vs. 1.79). The Eurostat (2025) study indicated that, within non-manufacturing sectors, companies in Professional, scientific and technical activities exhibit a high level of AI use (30.53%). Since the Eurostat (2025) study did not separately identify Financial and insurance activities, we likewise observe a similarity here, as this is another sector with a higher rate of technology adoption. Similarly, Eurostat reports the lowest rate of technology adoption in construction, which we can confirm with our average value (1.33).

If we look at population trends (for example, Deloitte Digital Consumer Trends, UK, 2024), we can see that the use of artificial intelligence among ordinary consumers increased from 2023 to 2024. Similarly, the Eurostat (2025) study reports that from 2023 to 2024 the use of AI technologies increased by 5.45 percentage points. It can therefore be assumed that the use of artificial intelligence will continue to grow in the future. On the other hand, research by the National Bureau of Economic Research (NBER) in the US indicates that the pace of generative AI adoption is faster than for previous digital technologies (Conboye, 2025). Based on the interviews conducted, we found that the companies studied that use artificial intelligence and machine learning apply them mainly in business processes to facilitate the analysis and evaluation of large datasets, to support robotic process automation (RPA), and to automate standardized processes. Companies reported using artificial intelligence in production processes or in information and communication processes to support the processing and analysis of information, or to support communication with clients. Based on an international study by McKinsey (Singla et al., 2025), which in 2024 surveyed 1,491 respondents from 101 countries, we can see the specific business processes and areas in which AI is used in companies. The study states that 78% of companies use AI in at least one functional area (business functions), whereas in 2023 it was only 55%. The most frequently mentioned functional areas using AI are IT, marketing, sales, and service operations. Generative AI is used most in marketing; sales; product and service development; service operations; and software engineering. (Singla et al., 2025) Companies planning to introduce AI (level 3) reported that they primarily plan employee training, which is also confirmed by the Slack's Fall 2024 Workforce Index, according to which almost one-third of workers had no AI training (Melendez, 2024), which may explain why some companies do not yet use AI. As another study indicates, the non-use of AI may lie in the fact that its benefits are not sufficiently known or clear to companies (Conboye, 2025). On the other hand, the McKinsey (Singla et al., 2025) study shows how many companies already recognize the effects of using AI, for example in the form of time savings for employees, who can use

the saved time for new activities. Respondents (especially from larger companies) reported reductions in headcount and cost savings, which is one of the most notable effects of AI adoption. (Singla et al., 2025)

5. Conclusion

As with previous industrial revolutions, it was not tools, machines, or technologies, but the transformation of companies and society that constituted the real change. Even in the past, these processes were neither abrupt nor sudden. It took some time for companies to find the right use of new opportunities and align them at the level of product, process, and organizational changes. Across the industrial revolutions, it took decades to achieve the full utilization of the relevant tools, machines, or technologies. Although Industry 4.0 is no longer an entirely new topic and many companies have already implemented numerous Industry 4.0 technologies, our survey results still show differences. Some of the technologies have already been successfully implemented in most of the surveyed companies (in particular, cloud computing networks for data storage; cloud computing networks for resource sharing; and the Internet of Things), whereas artificial intelligence, machine learning, and deep learning are not widely used in most companies, nor did most companies, at the time of the data collection, plan to adopt them.

A limitation of our research is that we focused on a smaller sample of companies, and that the situation in the adoption of new technologies is constantly changing, with the degree of use increasing year by year. Future research could therefore focus on examining the causes of the low adoption of certain Industry 4.0 technologies (e.g., artificial intelligence or simulation tools) and on evaluating whether the rate of use (particularly of artificial intelligence) will continue to increase. It would also be advisable for further research to examine whether the use of artificial intelligence is more suitable for certain types of processes in terms of the division into core, support, and management processes, and possibly for specific processes such as customer communication, performance measurement analysis, and decision support. As other studies also show, the use of artificial intelligence is increasing and is creating potential for companies to achieve significant productivity gains and process optimization. In this context, future research should focus on the management aspects that ensure the successful implementation of these technologies.

Acknowledgements

This paper was supported by the National Research Agency of Slovakia [VEGA 1/0614/23 titled Preparedness of Companies for the Challenges Associated with Industry 4.0 in Terms of Business Processes and Business Process Management].

Ethics declaration: This study involved primary data collection through surveys of company representatives about selected managerial practices. The research was non-interventional, minimal-risk, and conducted with competent adult professionals (18+). The study did not involve animals or clinical data. At the time the study was initiated and conducted, the authors' institution did not require or recommended prior review/approval by an ethics committee. Accordingly, no formal ethics clearance or approval was sought or obtained.

Before participation, all respondents (company contact person) were informed about the purpose, scope, procedures, and expected benefits; the right to withdraw at any time without penalty (withdrawal possible until batch anonymization); the expected duration; foreseeable risks and discomforts (assessed as minimal) and mitigation measures; and the contact details of a designated research-team contact for any questions or concerns.

Company identities and data related to organizational practices and processes at the company level were kept confidential in reporting, data were collected and analyzed in aggregate, and any illustrative material was edited to remove identifying details.

No sensitive personal data were collected. Personal identifiers were not included in the analytical dataset. Survey data were anonymized (with any personal data processed only prior to anonymization), stored securely (encrypted, access-controlled), accessed only by the research team (two researchers), and handled in accordance with GDPR and institutional data-protection procedures. Anonymity and confidentiality of both individual participants and company-identifying records were maintained throughout.

The authors affirm that they carefully evaluated and ensured compliance with ethical standards for research involving human participants and that participants' rights and protections were upheld throughout the study.

The results were not commercially exploited.

AI declaration: The authors used an AI language model ChatGPT (model GPT-5 Thinking, OpenAI) solely to help with translation, stylistic revision, and grammar/spell-checking to improve clarity and consistency. AI tools were not used to draft entire sections of text, formulate arguments or conclusions, generate research ideas, collect/clean/analyze data, perform statistical tests, write code or produce figures/tables, or generate/verify references. All AI-assisted edits were treated as suggestions; the authors reviewed, revised, and approved all changes and take full responsibility for the final manuscript. No other AI systems were used.

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AGS-INTEL: Authentic and Granular Source for Data Breach Intelligence

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Abstract: As artificial intelligence reshapes the cybersecurity landscape, the demand for a trustworthy, real-time intelligence platform to track security incidents has become mission-critical. This paper proposes AGS-INTEL, an AI-driven platform designed to revolutionize data breach intelligence by providing a credible, real-time repository that consolidates, verifies, and contextualizes global security incidents. Unlike traditional databases, AGS-INTEL employs a validated scoring algorithm and enriched metadata to capture breach dimensions (legal, technical, sectoral, geopolitical), drawing from GDPR/HIPAA disclosures, threat intelligence, dark web forums, and academic reports, among other sources. Utilizing NLP and agentic AI, it extracts structured metadata from unstructured narratives while integrating ethical data scraping, regulatory compliance, and cross-jurisdictional filtering to ensure high fidelity. A visual analytics dashboard empowers stakeholders, including regulators, policymakers, cybersecurity professionals, and journalists, to analyze breach trends by industry, geography, and threat modality, enhancing transparency and risk governance. By delivering authenticated, actionable data, AGS-INTEL addresses critical gaps in existing tools, setting a new standard for ethical AI in breach intelligence and strengthening societal resilience against escalating cyber threats.

Keywords: Data breaches, Agentic AI, Cybersecurity, Threat intelligence, Web scraping, Ethical AI

1. Introduction

The exponential rise in data breaches has made the accurate tracking and analysis of these incidents a global imperative. From multinational corporations to critical infrastructure providers, no entity is immune to the consequences of data loss, credential theft, and system compromise. Kumar et al. highlight proactive defenses against cyber threats as vital to effective governance in the current age (Kumar 2025b). Yet despite the abundance of breach reporting platforms, the world lacks a single, universally trusted, and methodologically rigorous source of breach data. Current databases often suffer from limited verification, incomplete metadata, geographic bias, or inadequate context for regulatory and research use. This paper presents AGS-INTEL (the Authentic & Granular Source for Data Breach Intelligence), a framework designed to serve as an authentic and comprehensive source of data breach intelligence that leverages the power of LLMs. Devised to fill critical gaps in data breach reporting, AGS-INTEL consolidates breach events across industries, continents, and attack vectors with emphasis on authenticity, completeness, and usability. Throughout this paper, we outline the motivation behind the design of AGS-INTEL, addressing the limitations of existing platforms and highlighting the growing need for reliable breach reporting to inform policy, threat intelligence, insurance modeling, and academic research. By adopting a structured approach grounded in information forensics, machine learning, and legal data mining, the system is positioned to function as a globally authoritative breach intelligence repository. The remainder of the paper describes the system's architecture, data sources, verification methodology, and implications for cybersecurity governance and resilience.

2. Related Work

The landscape of data breach repositories has evolved significantly amid the rising frequency and impact of cybersecurity incidents. As new threats continue to emerge, assessing risk has become increasingly challenging, hindering initiatives such as the growth of cyber insurance (Kumar 2025a). In this context, breach repositories have become more critical than ever toward making sense of the current paradigm. This section reviews existing breach repositories, highlighting their methodologies, strengths, and limitations, as well as academic efforts that can help to improve breach intelligence. These insights inform the design of AGS-INTEL, which is structured to address critical gaps in authenticity, granularity, and global coverage.

2.1 Currently Existing Repositories

Several widely used platforms currently provide data breach intelligence, each with distinct approaches to data collection, verification, and user interaction. Below, we analyze a sample of key repositories to understand what makes them stand out.

Privacy Rights Clearinghouse (PRC)

The Privacy Rights Clearinghouse (PRC), established in 1992, aggregates breach notifications from 15 U.S. government agencies, including the U.S. Department of Health and Human Services and state Attorneys General. PRC employs AI to normalize scraped text and extract contextual metadata, such as organization type and breach details, with multiple automated validation checks to ensure accuracy. Its strengths include broad U.S. public breach coverage and user-backed accuracy validation. However, it is limited to publicly reported U.S. incidents, missing non-disclosed or international ones, with occasional duplicates persisting despite normalization. While PRC covers the major states that comprise most reported data breaches, it does not take into account every state, leaving potential for some breaches to fall through the cracks.

"Have I Been Pwned" (HIBP)

Launched in 2013, "Have I Been Pwned" (HIBP) aggregates data from public breach dumps and security agency feeds, such as the FBI, offering k-anonymity-based password and email checks. Its API supports integrations with tools like Firefox and 1Password, and its "Dump Monitor" bot detects new leaks in near real-time. HIBP's strengths lie in its broad sourcing and privacy-focused querying, but it is constrained by its reliance on public data, which excludes private breaches, and the potential for unverified dumps to include inaccurate information.

XposedOrNot

XposedOrNot, established in 2017, is a community-driven, open-source platform that aggregates public breach data and provides domain-level breach analysis. It offers a free API, risk scores for compromised emails, and industry-based breach classifications. Furthermore, it also has mechanisms in place to manually rate the credibility of breach reports. It boasts features to help ordinary people stay on top of breaches such as an alert system capable of notifying users of domain-specific breaches and a function where users can input an email to see its risk rating depending on how compromised it is. However, it lacks advanced predictive analytics, and its manual processing/verification slows operations and risks errors.

Leak-Lookup

Since 2016, Leak-Lookup has provided a user-friendly interface for searching against billions of breached records, with a pay-per-lookup model and a limited free API. It focuses on real-time breach updates but lacks transparency about its data sources. Furthermore, premium features also restrict accessibility for non-paying users.

Identity Theft Resource Center (ITRC)

The ITRC, founded in 1999, compiles credible data from "government agencies, news media outlets, company news releases, filings, and publications, industry and trade websites, and direct notices provided by consumers or companies" (ITRC n.d.). It offers an interactive dashboard and victim support services but lacks a public API. Its Breach Alert platform provides metadata like business sector, affected individuals, data types, and attack vector. Updates occur weekdays (or weekends for significant incidents). As a whole, ITRC emphasizes victim support and education over technical data aggregation. The ITRC is considered a credible source, but its lack of an API and gaps in coverage limit its effectiveness on a larger scale.

Verizon Data Breach Investigations Report (DBIR)

The DBIR, published annually since 2008 by Verizon Business, analyzes thousands of incidents (e.g., over 22,000 in 2025) from global contributors. Verizon's sources include international law enforcement agencies, forensic firms, law firms, cyber insurance agencies, cybersecurity industry sharing groups, and their own Verizon Threat Research Advisory Center. DBIR offers detailed attack vector and industry trend insights but lacks real-time updates and a public API. Its confirmed-breach focus and annual cycles limit timeliness and granularity. However, its worldwide focus, high credibility, and unique sourcing methods make it a vital resource for breach intelligence despite the limitations.

SpyCloud

SpyCloud specializes in account takeover prevention, aggregating breach data from the dark web and other closed sources in the criminal underground. Their team analyzes more than 25 billion data breach assets per month. SpyCloud niches in retrieving data from non-public, unsavory outlets (vs. official government sources), though credibility is a concern. One other factor that holds SpyCloud back is that it is a paid service, which limits its reach.

DLA Piper GDPR Fines and Data Breach Survey

DLA Piper's annual survey, started in 2019, aggregates GDPR breach notifications from 31 European jurisdictions. Its NOTIFY tool aids client compliance but lacks a public API. This survey appears to be a valuable resource due to its European focused intelligence, but it lacks important metadata for the breaches it reports, which limits applicability (Neto 2021).

ENISA Threat Landscape Reports

The European Union Agency for Cybersecurity (ENISA) publishes annual Threat Landscape Reports, aggregating breach and incident data across Europe. While not a searchable database, its European focus, similar to DLA Piper, could also provide a valuable alternative perspective compared to America focused breach repositories. However, it also comes up short in its non-real-time reporting which limits timeliness.

Trend Micro Zero Day Initiative (ZDI)

Established in 2005, ZDI focuses on vulnerability intelligence rather than breaches, purchasing and verifying zero-day vulnerabilities before public disclosure. It is currently considered "the world's largest vendor-agnostic bug bounty program" (Trend Micro n.d.). The program sources vulnerability intelligence and then in-house researchers will rigorously verify the credibility before reporting it to the affected company. Public reports will generally only be made once a vulnerability is patched, although in the meantime, Trend Micro will use the intelligence to update the protection filters on its products. While not a breach database, ZDI data could enhance breach repositories by helping to link vulnerabilities to incidents. This could allow for deeper, more informative, breach analysis.

MITRE CVE Feeds

The MITRE Common Vulnerabilities and Exposures (CVE) database, established in 1999, provides standardized identifiers and details for publicly disclosed vulnerabilities, including CVSS scores. Widely used across the cybersecurity industry, it supports vulnerability tracking and risk assessment. While not a breach repository, its integration with breach data enables linking incidents to exploited vulnerabilities, unlike most breach-focused platforms. Alongside ZDI, integrating MITRE vulnerability details could greatly improve the analysis of breach data.

2.2 Relevant Academic Work

Recent academic studies highlight challenges that AGS-INTEL is designed to address and novel techniques relevant to its implementation. Pursuing a similar mission to AGS-INTEL, Neto et al. discussed the development of a comprehensive global breach database. Their framework sourced breach details from government entities, security research groups, research entities, and media reports. The group constrained their sourcing to only these types of public sources to ascertain credibility. The result was a database engineered to chronicle incidents that took place between 2018 and 2019. Key difficulties faced included lack of standardization in reporting and the difficulty in sourcing intelligence from outside of the US and Europe (Neto 2021). Issues such as obstacles in determining credibility and lack of standardized reporting could be mitigated by recent advances in artificial intelligence. Ayuso et al. have discussed the emerging potential for AI integration into web scraping to greatly improve performance in data collection. Bots can be created to collect links from the web to establish sources, extract data from these sources, and then save that data to a database (Ayuso 2024). With AI, this process can be accomplished much more effectively by immediately adapting to the unique structure of dynamic websites. No matter the way the information is formatted, AI can effortlessly parse through it and return all the desired info in a standardized manner. This technique can be applied towards sourcing information concerning data breaches from a wide variety of reporting outlets. Meanwhile, Noor et. al have introduced a novel machine learning framework that takes the data presented in threat intelligence repositories to semantically analyze the root cause of the incident and predict future occurrences. This system is capable of pinpointing a threat incident classification with high reliability (Noor 2019). Such approaches strengthen breach databases by providing more relevant insights and can be leveraged to assess the credibility of cyber threat intelligence.

2.3 Gaps and Opportunities

Existing repositories excel in areas like PRC's regulatory depth, HIBP's accessibility, and SpyCloud's dark web insights, but face limitations: incomprehensive public data reliance, inconsistent coverage, lacking credibility appraisal, manual faults, and limited real-time/predictive capabilities. In the modern age, agentic AI enables novel advancements in metadata extraction and credibility scoring to boost the range and reliability of breach

databases. AGS-INTEL consolidates the strongest aspects of existing solutions, creating a comprehensive source of intelligence on known breaches. Furthermore, our solution integrates modern LLM-based enhancements designed to advance the worldwide understanding and analysis of breach intelligence.

3. Proposed Solution

Our proposed solution comprises a large-scale, comprehensive database that charts all known data breaches across the world with meaningful metadata and analysis. This design integrates data from all major pre-existing repositories to minimize gaps in coverage. The framework encompasses data from all major states, European jurisdictions under the GDPR, threat intelligence feeds, company disclosures, dark web forums, user submissions, and academic reports. A key issue that currently plagues data breach repositories is the non-standard reporting across the board. Such a monumental obstacle is overcome through the use of agentic AI powered data collection and parsing. Regardless of reporting format, LLM agents are designed to extract useful information and reformat it into standardized database entries.

To address credibility concerns that plague current repositories, AGS-INTEL incorporates AI-driven trust ratings. Each reported breach is assigned a credibility rating, and entries below a defined threshold are excluded from publication. The framework includes a transparent citation trail for each breach that reveals where the details were sourced from. These measures help ensure that large volumes of data can be ingested while maintaining authenticity and reliability.

To further strengthen the depth of breach analysis, AGS-INTEL integrates intelligence on known vulnerabilities and links them to breaches. By pulling from sources such as ZDI and MITRE CVE, the system accumulates vulnerability intelligence and then employs an algorithm to attach vulnerabilities to breaches where relevant matches exist. This information supports a deeper understanding of breaches and how they came about.

To enhance the user experience, the system incorporates several widely adopted features that other data breach services offer. This includes a clean, easy to use, front-end user interface with visual analytics to boost comprehension. The framework also provides a credential-based query service enabling users to verify if their data has been compromised. A notification system is integrated to help users stay up-to-date on breaches that may be relevant to them. Finally, AGS-INTEL is envisioned as a publicly accessible, free-to-use platform that promotes open data safety for all.

4. System Architecture

The architecture of AGS-INTEL encompasses a modular, scalable system engineered to collect, process, verify, and present global data breach intelligence in real time. Comprising four core layers: Data Ingestion, Verification and Normalization, Core Database, and User Interface, this framework ensures comprehensive coverage, high trustworthiness, and actionable insights. Each layer leverages modern artificial intelligence and data science techniques to address the limitations of existing breach repositories. The system is designed to handle the complexity of diverse data sources while maintaining regulatory compliance, ethical standards, and user accessibility.

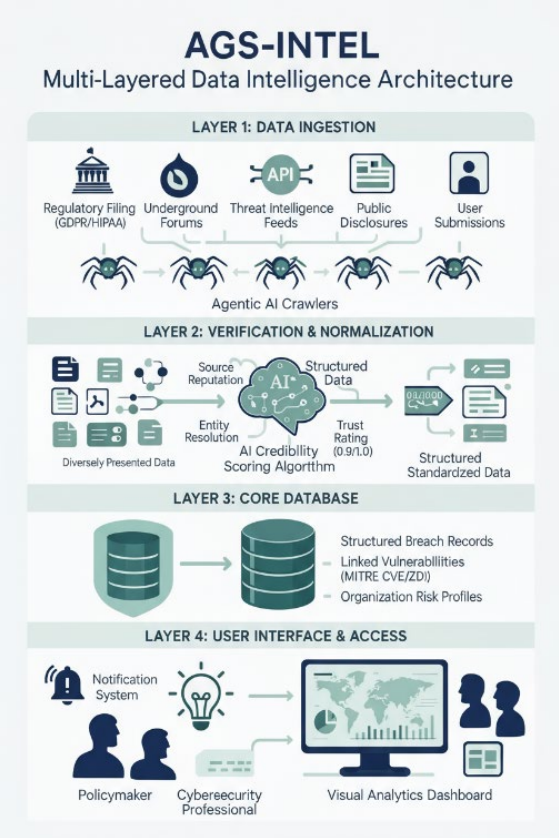

Figure 1: AGS-INTEL System Architecture Flow

4.1 Data Ingestion Layer

The Data Ingestion Layer is the foundational pillar of AGS-INTEL, designed to aggregate breach-related data from an exhaustive array of sources, including all major pre-existing repositories, regulatory bodies, and emerging channels. Building on insights from Related Work regarding global sourcing challenges, this layer addresses gaps like geographic biases and incomplete coverage by collecting raw data from diverse sources. The layer employs AI-driven ingestion pipelines, inspired by Ayuso et al. (2024), to efficiently capture high-volume, heterogeneous data.

AGS-INTEL ingests data from eight distinct source categories: (1) existing breach repositories (e.g. PRC, HIBP, etc.), (2) U.S. state and federal breach notification registries, (3) international regulatory filings (4) company press releases and investor disclosures (5) threat intelligence feeds and public breach dumps, (6) dark web and underground forums, (7) vulnerability intelligence reports (ZDI), and (8) user submissions. This combination enables comprehensive coverage by ensuring both depth through verified incidents and breadth through early-stage leaks and global occurrences.

The ingestion layer employs a hybrid pipeline to handle diverse data formats and high ingestion velocities, focusing on raw data collection without standardization (reserved for the next layer). Methods are optimized for adaptability, leveraging agentic AI systems capable of reasoning, planning multi-step actions, and adapting dynamically. These agents operate with minimal human intervention while maintaining oversight through automated audit logging and periodic human review. This design enables efficient coverage of all data source categories by orchestrating tools, handling anomalies, and ensuring resilience. Below, each method is detailed with a breakdown of its mechanisms.

- **AI-Powered Web Crawlers**: These autonomous crawlers, built on agentic AI models, scrape unstructured or semi-structured content from websites. Agents start with seed URLs, explore linked pages, and use NLP to identify breach-relevant sections. For dynamic sites, agents simulate user interactions (e.g., scrolling or form submissions) while respecting ethical boundaries. Agentic operations include decision-making on crawl depth and adaptive retrying if sites change layouts,

addressing the challenges in existing solutions regarding non-standard formats. Crawls run on schedules with fault tolerance via distributed agents.

- **API Integrations**: Direct, structured integrations pull data via RESTful or GraphQL APIs. This ensures low-latency, high-volume ingestion without web overhead.
- **Real-Time Monitoring and Feeds**: Agentic AI agents subscribe to streaming feeds and monitor channels using semantic search and anomaly detection, processing incoming data in real time. Agents filter noise and aggregate from multiple streams. For dark web sources, agents use Tor-enabled passive listeners to detect leaks without engagement (Xu 2021). Agentic features include autonomous escalation and integration with keyword-based filters, ensuring timeliness that exceeds current solutions.
- **User Submission Portal**: A secure, web-based interface allows manual uploads, with AI validating and enriching submissions in real time. Agents scan uploaded files for relevance using NLP, cross-reference against known incidents, and flag for human review if needed. This pipeline extends coverage to non-public or emerging breaches.

4.2 Verification and Normalization Layer

Given the heterogeneity and varying reliability of breach data sources, the Verification and Normalization Layer plays a crucial role in transforming raw ingested data into structured, trustworthy data for analytical and predictive tasks. This layer ensures the consistency, completeness, and authenticity of each breach record before it enters the core AGS-INTEL database.

- **Data Normalization**: Raw breach records often vary widely in structure and granularity, and observed datasets reflect detection/disclosure biases and uneven reporting across incident types and jurisdictions (Romanosky 2016). To enable downstream comparison and analysis, all records are normalized to a standardized schema that includes breach date, organization, industry sector, data types exposed (e.g., email, SSN), breach vector, affected geography, and source. LLMs adaptively handle variations in format, such as converting GDPR notifications from DLA Piper sources or U.S. state registries into standardized entries, ensuring global comparability.
- **Deduplication and Entity Resolution**: Multiple sources often report the same breach with slight variations. To prevent inflating statistics and introducing inconsistencies, AGS-INTEL applies probabilistic matching algorithms (e.g., based on Jaccard similarity for entity names, timelines, and impact metrics) to identify and merge overlapping reports. The system automatically updates existing records when secondary sources contribute additional details, preserving data integrity and avoiding duplication.
- **Credibility Scoring**: To mitigate reliability gaps in sources like dark web forums or unverified dumps, each breach receives an AI-generated trust rating on a scale of 0-1, based on factors including source reputation, cross-corroboration across multiple sources, metadata completeness, and ML confidence in extraction. Entries scoring below a 0.5 threshold are excluded from the core database but logged for potential future validation; included entries display the rating transparently, allowing users to gauge reliability.
- **Breach Classification and Enrichment**: Using a multi-label classification model fine-tuned on historical breach data, breaches are classified by type (e.g., ransomware, phishing) and mapped to the MITRE ATT&CK framework for threat actor tactics. Additionally, records are assigned CVSS scores for severity and linked to relevant vulnerabilities from integrated sources like ZDI and MITRE CVE feeds based on similarity matching. An algorithmic matching process correlates breach details (e.g., exploit patterns) with vulnerability intelligence to infer root causes and present them to users, enhancing analytical depth beyond current repositories.
- **Transparency and Oversight**: Each record maintains a transparent citation trail linking back to the original sources. When a breach entry is created or updated, the source is logged in the database for accountability. Furthermore, entries include AI-generated confidence levels, enabling expert users to distinguish between high-certainty and tentative classifications. Low-confidence records are flagged for manual review by analysts.

4.3 Core Database Layer

The Core Database Layer acts as the centralized repository for AGS-INTEL, storing normalized and verified breach intelligence in a scalable, query-optimized structure. It accommodates the vision of a comprehensive global database with standardized entries, vulnerability integrations, and organization trust ratings, while overcoming

limitations in current solutions like incomplete metadata or lack of real-time access. This layer supports advanced querying, trend analysis, and risk forecasting.

The database schema is designed to support multidimensional breach intelligence. Each entry includes fields such as breach date, affected organization, breach type, exposed data types, source citation, credibility score, geographic scope, and linked vulnerabilities. Records are cross-referenced with organization profiles, which contain metadata like industry, size, location, historical breach count, and trustworthiness score. Vulnerability data includes CVE IDs, CVSS scores, exploit status, and MITRE ATT&CK mappings.

The tech stack for the database layer involves development tools that are well suited to handling large collections of data. AGS-INTEL incorporates a hybrid storage architecture leveraging a relational database built with PostgreSQL. This environment houses structured breach and vulnerability data and supports operations such as JOINs, aggregations, and filtering. Elasticsearch powers full-text and fuzzy search capabilities. Redis serves as a caching layer to accelerate high-frequency lookups (e.g., email and domain breach checks). Finally, TimescaleDB extensions support time-series analytics on breach timelines and trend assessments.

AGS-INTEL supports the following advanced features in its database implementation:

- **Indexing and Optimization**: To support low-latency queries over a large volume of breach records, the system applies aggressive indexing on critical fields, including breach type, domain, industry, and CVE IDs. Materialized views are used to precompute aggregated statistics for dashboard reporting. Partitioning by breach date and geography enhances scalability for regional queries.
- **Data Integrity and Versioning**: Breach records are treated as immutable snapshots to preserve auditability. If updated or corrected, a new version is stored with a reference to the original, and changes are logged. Each field is citation-tracked, maintaining a transparent record of the sources used to populate it.
- **Security and Privacy**: To ensure data privacy and regulatory compliance, AGS-INTEL employs a multi-layered security framework. Sensitive personal information, such as full email-password pairs, is never stored in plaintext. Inspired by *Have I Been Pwned*, passwords are processed using a k-anonymity model, where only the first six characters of a hash are stored to prevent direct re-identification (Hunt 2022). All data transmissions between system components and external interfaces are encrypted using TLS. Internally, strict access control policies govern write operations, restricting modification privileges to authenticated analysts and automated system processes. These safeguards collectively ensure data confidentiality, integrity, and auditability in alignment with GDPR and CCPA standards.

4.4 User Interface and Access Layer

The User Interface and Access Layer of AGS-INTEL enables stakeholders, including cybersecurity analysts, researchers, policy makers, and the general public, to interact with breach intelligence through an intuitive and transparent platform that supports diverse access modes, such as real-time dashboard visualizations and programmatic API integration. Users can query breach records in real time using multiple input modalities, such as email address, domain, company name, breach vector, CVE ID, or geographic region, with the lookup interface emphasizing performance and privacy. The interactive front-end dashboard allows users to filter breaches using a variety of characteristics, offering easily understood visual analytics. A customizable alerting system allows real-time notifications for relevant breaches. These features align with AGS-INTEL's mission to expand public breach knowledge.

5. Limitations, Risks, and Evaluation

While AGS-INTEL aims to deliver a robust and comprehensive platform for global data breach intelligence, certain limitations must be acknowledged. These challenges stem from the complexity of aggregating diverse data sources, ensuring reliability, and maintaining usability while adhering to ethical and legal standards. Below, we outline these limitations and describe how our system’s architecture incorporates mitigation strategies. We then present a framework for evaluating these mitigations post development to ensure the system performs effectively and evolves with emerging needs.

5.1 Data Ingestion Challenges

Collecting data from volatile sources, such as dark web forums that frequently change or go offline, risks incomplete coverage. AI-driven crawlers may also introduce biases, such as favoring English-language content or struggling with anti-scraping measures. AGS-INTEL mitigates these by using multilingual NLP models

supporting over 20 languages and adaptive crawlers that retrain on failed attempts. Redundant ingestion pipelines, including API integrations and user submissions, provide fallback options, while a source health monitoring system dynamically adjusts to unreliable feeds, ensuring broad and resilient data collection. Finally, since generative AI is not entirely resistant to hallucination, AGS-INTEL's verification layer cross-validates reports during credibility scoring to ensure the authenticity of ingested data.

5.2 Database and System Performance

Real-time ingestion and large-scale storage create performance challenges. Immutable versioning of breach records increases storage overhead, and balancing low-latency querying with resource-intensive analytics may result in trade-offs between speed and depth. Ensuring fault tolerance and scalability under surging data volumes remains a nontrivial engineering task that AGS-INTEL must address.

5.3 Security and Privacy

AGS-INTEL processes highly sensitive breach intelligence, necessitating robust safeguards for confidentiality, integrity, and availability. Despite protections like k-anonymity lookups and TLS encryption, risks remain such as re-identification from partial hashes, insider misuse, and adversarial manipulation of AI components. To mitigate these, AGS-INTEL adopts a multilayered defense architecture incorporating secure hashing algorithms, strict role-based access control, web application firewalls, input sanitization, and rate-limiting to resist denial-of-service and injection attacks. These technical controls are designed to ensure compliance with GDPR and CCPA principles of data minimization and pseudonymization.

Inspired by established platforms like Have I Been Pwned, AGS-INTEL's credential lookup system avoids storing personally identifiable information. Only compromised emails and passwords are retained, stored separately in isolated databases with no linking mechanisms to prevent reconstruction of user profiles. Users cannot browse the entire catalog; instead, they must query specific credentials, and these queries are not logged to preserve privacy. For general breach reports, only non-sensitive aggregate statistics are collected, such as the quantity of affected records, data categories, and broad impact descriptors (e.g., employees, customers, third-party collaborators), without retaining any raw leaked data.

Given AGS-INTEL's reliance on agentic AI for ingestion, verification, and enrichment, AI-specific vulnerabilities such as data poisoning are paramount concerns. Adversaries may attempt to exploit model outputs or introduce malicious inputs, potentially resulting in false breach entries or inflated credibility scores. To counter these threats, AGS-INTEL utilizes multi-source cross-validation, ML-driven anomaly detection (such as isolation forests), and mandatory expert review of low-confidence AI classifications. Periodic retraining on sanitized datasets further limits the propagation of adversarial data.

Security risks for AGS-INTEL are systematically assessed using a hybrid threat model (Table 1) that integrates the STRIDE framework (Spoofing, Tampering, Repudiation, Information Disclosure, Denial of Service, Elevation of Privilege). Threats are analyzed across all system layers—Ingestion, Verification, Database, and User Interface—to identify vulnerabilities, estimate impact, and match mitigations.

Table 1: AGS-INTEL Threat Model

Category	Example Threats	Impact	Mitigations
Spoofing (Authenticity)	Impersonation of source feed providers to inject false data	Compromised data provenance, loss of trust	Signed API requests, mutual TLS authentication, source allow-lists, credibility verification algorithm
Tampering (Integrity)	Insertion of poisoned or adversarial data into ingestion or retraining datasets; manipulation of AI-generated metadata; tampering with in-transit database entries	Corrupted intelligence dataset, inaccurate public outputs	Data validation pipelines, anomaly detection (isolation forests), sanitized model retraining, manual review of anomalies, immutable versioning, input validation, WAF filtering
Repudiation (Accountability)	Insider actor hides activity or modifies logs	Reduced auditability and non-repudiation	Immutable, timestamped audit trails; cryptographic signing of logs

Category	Example Threats	Impact	Mitigations
Information Disclosure (Confidentiality)	Model inference or metadata leakage through analytical outputs	Privacy breach	Differential privacy in AI outputs, query rate-limiting, TLS 1.3 encryption
Denial of Service (Availability)	Overloading query APIs through automation	Disruption of alerts and data feeds	Redis caching, autoscaling clusters, CAPTCHA on interactive endpoints
Elevation of Privilege (Authorization)	Abuse of access token or privilege escalation by compromised analyst account	Full database exfiltration or alteration	RBAC with least privilege, zero-trust continuous authentication, token expiration policies

5.4 Ethical and Legal Considerations

Collecting and disseminating breach intelligence raises complex ethical and legal challenges. Scraping and dark web monitoring may conflict with national laws, while storing and analyzing leaked personal data, even in hashed form, poses compliance risks under the GDPR, CCPA, and other regulations. It is important to consider applicable laws and address how AGS-INTEL maintains compliance.

Sourcing breach intelligence from dark web forums and public breach dumps involves acquiring and possessing stolen data, which risks violating the CFAA if handled improperly. According to the U.S. Department of Justice (2020), access must be obtained using legitimate credentials while adhering to all forum policies. Furthermore, it is critical to avoid any exchange of information on these forums. AGS-INTEL will limit activities to passively scraping publicly available discourse without engaging in communication with forum users, thereby minimizing legal risks. Additionally, purchasing stolen data poses significant concerns; to ensure ethical and legal compliance, AGS-INTEL will refrain from any dark web data purchases, sourcing only free, publicly released information.

Under the GDPR, hashed personal data, even when salted, is generally categorized as pseudonymized personal data, not fully anonymized data (GDPR, Art. 4(5)). As a result, it is subject to specific compliance obligations such as the right to access and the right of erasure (GDPR, Art. 15, 17). To ensure full compliance with the GDPR, AGS-INTEL will adhere to its foundational principles by processing any such data under a lawful basis of legitimate interests (GDPR, Art. 6(1)(f)), specifically the pursuit of enhanced cybersecurity resilience and public awareness of breaches, which would outweigh potential risks to data subjects given the platform's protective safeguards. Data minimization (GDPR, Art. 5(1)(c)) will be strictly enforced by aggregating only non-sensitive metadata from public sources, such as breach statistics, affected sectors, and vulnerability links, while avoiding the collection or storage of directly identifiable personal information beyond what is necessary for verification. Transparency and accountability (GDPR, Art. 5(1)(a) and (2)) will be upheld through detailed documentation of data processing activities, including source citation trails and audit logs. The right to access and erasure will be upheld through AGS-INTEL's freely available credential lookup system alongside the ability to request removal of credentials. Integrity and confidentiality (GDPR, Art. 5(1)(f)) will be maintained via the robust security measures described in the previous section. These measures not only mitigate compliance obligations for pseudonymized data but also position AGS-INTEL as a responsible actor that works to prioritize safety and privacy above all.

5.5 Evaluation Framework

To validate these mitigations and ensure AGS-INTEL's effectiveness after development, we will implement an evaluation plan with iterative six-month cycles combining quantitative metrics, qualitative feedback, and real-world testing. For verification and normalization, we will measure deduplication and classification accuracy against benchmark datasets. Our target is 99% deduplication accuracy, ensuring that duplicate entries remain rare occurrences manageable through periodic manual review. For classification, we aim for at least 92% accuracy, following the benchmark established by Noor et al. (2019) for machine-learning–based cyber threat analysis. Data ingestion coverage will be evaluated relative to leading repositories (e.g., HIBP, ITRC, PRC), with a target of $\geq$ 20% more global incidents captured. System performance will be evaluated through latency tests (targeting under 500ms for queries) and scalability under simulated high loads. Security will be tested via vulnerability scans and adversarial simulations, with a goal of zero critical findings in annual audits. Usability will be gauged through user surveys aimed at assessing ease of understanding, perceived usefulness, and willingness to recommend to others. Ethical and legal compliance will be verified through independent third-party reviews

to ensure continued alignment with data-protection regulations. A staged beta with controlled users will monitor live metrics like alert accuracy and system uptime (targeting 99.9%), benchmarks aligned with commercial-grade reliability expectations for real-time CTI services. As iterative testing progresses, user feedback will guide continuous improvements, while transparent publication of evaluation outcomes will foster accountability and stakeholder trust.

6. Conclusion

The conception of AGS-INTEL represents not only a technical contribution but also a rethinking of how cybersecurity knowledge can be governed in the age of AI. Rather than accepting fragmented repositories and uneven reporting as inevitable, this work envisions breach intelligence as a shared global resource that is transparent, verifiable, and continuously improving. The real test for AGS-INTEL lies not in its algorithms alone but in how well it earns trust across stakeholders: regulators who depend on credible oversight, organizations that weigh disclosure against reputation, laypeople seeking clarity, and researchers who require reliable data to advance the field. Moving forward, AGS-INTEL's framework provides a foundation for practical implementation and benchmarking against leading repositories. Its evaluation methodology enables systematic assessment of credibility scoring, multilingual coverage, and enrichment accuracy at scale. By maintaining an iterative cycle of testing and refinement, the system is positioned to adapt alongside the evolving threat landscape. Through its emphasis on authenticity, accessibility, and analytical depth, AGS-INTEL exemplifies how AI-driven intelligence platforms can redefine the future of breach analysis and digital trust.

Ethics Declaration: This research did not involve any activity that required ethical clearance.

AI Declaration: Artificial intelligence assisted in drafting and editing this paper. All core ideas, research, and design originate solely from the authors. The content has been rigorously validated for accuracy and fully reflects the authors' intent.

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Prompt Engineering Language in The Agile Product Backlog Refinement Process

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Abstract: Contemporary advanced business services and products increasingly incorporate artificial intelligence components, such as chatbots and generative AI, across various domains. These are delivered through dedicated, complex, innovative software programs and projects initiated by virtually all industry sectors. Complex project management include challenges such as: the complexity of product backlogs with a number of requirements, highly dynamic changes in customer expectations impacting product backlog quality and requirements engineering, labour shortages, advanced tool adoption and automation, predictability of deliveries, insufficient transparency of processes applied to product backlog management, communication barriers between business and project teams. The primary objective of this paper is to address a key research gap related to the insufficient quality of product backlog management in complex agile software project environments. The paper addresses the research question regarding the potential application of chatbots and generative AI as a methodology to conduct reliable agile product backlog evaluation and subsequently enhance refinement processes through dedicated Prompt Engineering Language (PEL). This paper emphasizes the importance of a structured description of product backlog items and its impact on the overall quality of agile product backlog and delivered software products. Following the literature review, the author's empirical research presents a detailed analysis of the research gap and focuses on applying chatbot and generative AI solutions to evaluate agile product backlog items and to improve related agile refinement processes. Research results demonstrate that agile product backlog refinement processes can be supported by chatbots and generative AI utilizing dedicated Prompt Engineering Language (PEL). These tools are not designed to create business value directly but rather enhance the efficiency and automation of product backlog management processes to respond rapidly to stakeholder expectations within agile environments, ultimately achieving superior project outcomes. Nevertheless, numerous challenges must be addressed, particularly related to AI governance and compliance with numerous policies including data privacy, intellectual property, legal, security and internal ones.

Keywords: Product backlog quality, Product backlog refinement, Prompt engineering language (PEL), Agile software development, Agile project management, Requirement engineering

1. Introduction

Development of advanced products and services raises many challenges in software development projects related to the vast number of changing requirements and complexity of product backlog management (Lucassen et al., 2016; Trkman et al., 2019). Customer demands and competitive market pressures require rapid deliveries, often without extensive project planning, but focusing on modern agile project management approaches. Highly dynamic changes in customer specifications and expectations impact the quality of requirements engineering (Nistala et al., 2022; Lu et al., 2023).

Increasingly, complex projects seek advanced tools support and artificial intelligence, such as chatbots and generative AI (Marczak-Czajka and Cleland-Huang, 2023; Ronanki, Cabrero-Daniel and Berger, 2023). Reliable and high-quality AI chatbot results require prompt creation with sufficiently good structure (White et al., 2023) to support agile product backlog refinement in a predictable manner and therefore to offer a practical tool for software organisations facing delivery pressures, quality issues, and transparency problems. PEL can be understood as one of the methods to create reliable, deterministic and high-quality results important to practitioners seeking actionable AI implementation strategies.

Recent research studies have highlighted the importance of AI tools to address those challenges, but practical and scalable adoption will require addressing non-standard requirements engineering, domain-specific vocabulary, and scalability issues in complex projects with numerous dependencies (Nistala et al., 2022).

The primary goal of the empirical research in this paper is to respond to the research question about the potential application of chatbots and generative AI as a methodology to conduct reliable agile product backlog evaluation and subsequently enhance refinement processes through dedicated prompt (PEL). The aim of the paper is also to expose the importance of structured description of user stories and its impact on the overall quality of agile product backlogs and delivered software products.

The research results showed that agile product backlog refinement processes can be supported by chatbots and generative AI with dedicated and carefully structured prompts. These tools are not designed to create business

value directly or fully automate the process, but to enhance product backlog management to respond rapidly to stakeholder expectations.

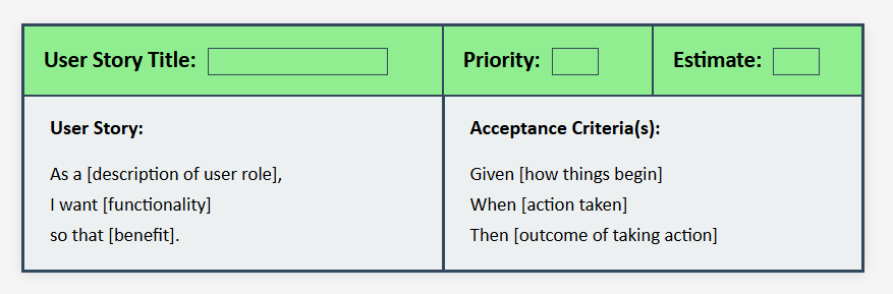
A literature review and prompt engineering using AI chatbots were applied to conduct this research study and to verify research hypotheses. The confusion matrix with a set of classification metrics was applied to evaluate the performance of the final system prompt. The basic limitation of the research study is the limited access to a larger number of production backlog samples. As a future research opportunity, it might be beneficial to repeat the similar analysis with different prompt patterns as well as with other AI chatbots to compare results.

The structure of the paper is as follows: section two presents theoretical underpinnings, section three presents the methodology approach, section four presents empirical research results, and finally section five contains a discussion of the results and conclusions.

2. Theoretical Underpinnings

2.1 The User Story as a Functional Requirement in Agile Software Development

User stories are one of the most commonly applied methods for describing the functional requirements of products in agile software development projects (Lucassen et al., 2016; Levy et al., 2022). The user story is described in natural business language to define end-user needs in the most concise way (Levy et al., 2022), to establish priorities for those needs and to facilitate communication and collaboration between end-users, business teams, and development teams (Hendriana, Raharjo and Fitriani, 2023). A user story should unambiguously reflect the needs of end-users in terms of the business value they expect in the final product or service functionality (Dimitrijevic, Jovanovic and Devedzic, 2015).



Source: Made by the author

Figure 1: User Story Template

A typical user story has a clearly defined template (Figure 1): *"As a <user role> I want to achieve <goal/functionality> so that I can <(receive) benefit>"*, which requires specification of the user role, action in the form of functionality or aim for it, and the expected benefit that this action is intended to deliver (Cohn, 2004). Furthermore, user stories are associated with one or more acceptance criteria, namely a list of activities that allow for verification of whether the user story delivered by the development team is ready from the business perspective, and take the form: *"Given – defines initial conditions, When – describes the action performed for the given functionality, Then – specifies the expected result"* (Cohn, 2004). The fundamental properties of a user story are: business value, priority, and effort estimate (Cohn, 2004).

The principal processes associated with the user story lifecycle are: identification and creation, refinement – continuous improvement as further details emerge, and management within agile planning activities (Dimitrijevic, Jovanovic and Devedzic, 2015; Dam et al., 2019). Enhancement of tools and processes for agile product backlog management is the key challenge in software development projects (Dam et al., 2019).

The quality of user stories is the primary focus of numerous research studies related to agile software development (Hendriana, Raharjo and Fitriani, 2023; Xu et al., 2023), as it relates to the nature of the agile approach applied in complex project domains, with frequent and informal face-to-face communication in highly dynamic environments. Ambiguity and differing interpretations amongst key stakeholders represent one of the principal issues related to user story quality (Dalpiaz et al., 2019; Amna and Poels, 2022), due to the challenge of selecting the appropriate approaches or proposing holistic solutions. User stories are not intended to be detailed requirements specifications, design, or architectural solutions, but rather concise and brief functionality goals (Cohn, 2004).

An important research finding related to user story quality is the implementation of high-quality processes for elicitation and refinement throughout the entire lifecycle, from creation, through iteration planning and execution, until final delivery (Levy et al., 2022; Xu et al., 2023). Although the quality of user stories has been investigated extensively, there remain opened future research areas, including insufficient research studies in practical industry applications, lack of domain industry context-awareness, inadequate quality of supporting tools, diverse specification formats, mutual dependencies, and the search for more effective requirements representation than user stories (Lucassen et al., 2016; Trkman et al., 2019).

2.2 AI Tools Support for User Story Creation and Refinement Process

There exist different approaches for the creation and elicitation of new user stories and their subsequent refinement. The most common approaches follow template-based methods to ensure valid syntax and semantics (Cohn, 2004; Dalpiaz et al., 2019), SMART (Specific, Measurable, Achievable, Relevant, Time-bound), INVEST (Independent, Negotiable, Valuable, Estimable, Small, Testable) criteria (Levy et al., 2022), user feedback incorporated by UX designers (Lu et al., 2023), and test-based approaches focused on acceptance criteria of delivered business value (Cohn, 2004). The primary challenges for this strategy are related to ambiguity and unstructured user stories, mixed functional and non-functional requirements, insufficient domain knowledge, subjective prioritisation, creation of atomic user stories with less complex dependencies, communication amongst different teams, and writing effective user stories (Dalpiaz et al., 2019; Lu et al., 2023).

Following recent research studies, AI tools support (such as Natural Language Processing) and generative AI solutions (such as AI chatbots) are highlighted to address those challenges; however, their adoption will require resolution of several obstacles including document diversity structures, domain-specific vocabulary, adaptation to practical industry applications, and scaling to complex projects with numerous dependencies (Nistala et al., 2022; Marczak-Czajka and Cleland-Huang, 2023; Ronanki, Cabrero-Daniel and Berger, 2023; Siahaan, Raharjana and Fatichah, 2023). Application of ChatGPT has demonstrated the ability to generate contextual human-valued user stories with well-defined product features, to inspire stakeholders to consider and discuss previously unconsidered features, and to generate user stories across all stakeholder roles and features in a systematic manner; however, it requires human oversight for analysis, prioritisation, and contextual adaptation and should not be intended to fully automate product backlog management processes (Marczak-Czajka and Cleland-Huang, 2023; Ronanki, Cabrero-Daniel and Berger, 2023). Major challenges identified in the application of ChatGPT were related to improving performance and quality metrics, complexity of created solutions (including trustworthiness, transparency and explainability), limited diversity and stakeholder perspectives, insufficient input data about the product itself, and difficulty in articulating benefits in user stories (Marczak-Czajka and Cleland-Huang, 2023). Future research in the area of generative AI application should focus on creating customised prompts to provide consistent results (with more deterministic approaches and fewer extrinsic hallucinations), automated pipeline integration for testing at scale with real-world industry products and domain-specific projects, comparison of different AI models and prompting strategies, and evaluation of effectiveness by exploring quality metrics (Ronanki, Cabrero-Daniel and Berger, 2023).

Logistic regression and discriminant analysis allow the use of numerous user story features (often dichotomous variables) to be classified into different improvement groups (Tillmanns and Krafft, 2017) to improve the user story quality during continuous refinement processes. Creating customised prompts to provide more deterministic results with fewer hallucinations may require precise fact-level validation mechanisms for ensuring the granular factual accuracy that customised prompts demand to achieve the fine-grained hallucination detection and correction capabilities essential for maintaining deterministic output consistency across diverse prompt configurations (Sawczyn et al., 2025). Deployment of automated pipelines with AI tool support and generative AI solutions for scalable industry products may require cloud frameworks for scalable and computational demands (i.e., multimodal analysis of speech and video in agentic solutions) and dynamic resource allocation that can be efficiently met through elastic cloud orchestration systems that provide on-demand access to distributed computing resources whilst maintaining cost-effectiveness and operational flexibility (Miroslaw et al., 2015).

IT democratisation enables business users (Citizen Developers) to create semi-professional solutions (such as numerous RPA, Low-Code or No-Code solutions) without IT department involvement, becoming essential due to high IT resource demands (Sobczak, 2018), which may partially cover needs for user story creation and refinement processes. IT democratisation is part of a broader cultural transformation where university research can facilitate knowledge transfer, similar to how entrepreneurial universities drive innovation by combining

resources and knowledge between science and business sectors to create cultural shifts (Sobczak, 2018; Dameri and Demartini, 2020).

The full functional verification of user stories may not be an achievable goal even with improved AI tools applied; however, following Blikle and Chrząstowski-Wachtel (2018, p. 11-15): "*not verification, but specification is the real bottleneck in functional verification*", therefore improving user stories to ensure the compatibility of product specification with the user expectations. A domain-specific language (DSL) as a specification language with concepts, rules, and vocabulary of a particular domain is more tailored to its unique needs and can be considered to solve the challenges related to the appropriate language for user stories.

The literature review demonstrates a significant impact of AI tool application support for user story elicitation and refinement in improving its quality. This important step revealed a high-level research gap related to the poor quality of agile product backlog, continuous processes of creation, management, and refinement, inherently embedded within the agile approach, as well as the application of AI tools for those processes. For this research gap, one can formulate the following research question:

Is the application of chatbots and generative AI as a methodology to conduct reliable product backlog evaluation and subsequently enhance agile product backlog refinement processes possible through dedicated Prompt Engineering Language (PEL)?

Based on the presented studies, we formulate the following hypotheses:

> ***H1:*** *The quality of written agile product backlog items is inadequate for complex software development projects and it can be evaluated using Prompt Engineering Language as a generative AI chatbot method.*
>
> ***H1.1:*** *User roles in user stories of agile product backlog items are missing in at least 20% of the evaluated product backlog.*
>
> ***H1.2:*** *Functionality goals in user stories of agile product backlog items are missing in at least 20% of the evaluated product backlog.*
>
> ***H1.3:*** *Business value goals in user stories of agile product backlog items are missing in at least 20% of the evaluated product backlog.*
>
> ***H1.4:*** *Product descriptions are provided instead of functionality goals in user stories of agile product backlog items in at least 20% of the evaluated product backlog.*
>
> ***H1.5:*** *Technical language is used instead of business language in user stories of agile product backlog items in at least 20% of the evaluated product backlog.*
>
> ***H2:*** *User story acceptance criteria for agile product backlog items can be generated based on high-quality user stories according to acceptance criteria templates using Prompt Engineering Language as a generative AI chatbot method.*

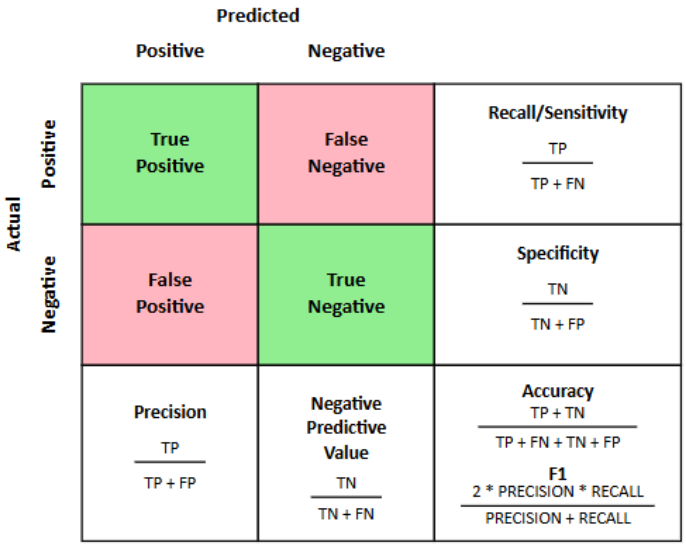
3. Methodology

A prompt is a set of natural language instructions given to a large language model (LLM) such as ChatGPT to guide its behaviour, customise its output, and program it to perform specific tasks. Prompt engineering is the systematic approach of designing and structuring these prompts to effectively communicate with LLMs and achieve desired outcomes (White et al., 2023; White et al., 2024).

Effective prompts should begin with conversational scoping statements such as "*from now on*" or "*act as X*" to establish clear context, followed by fundamental contextual statements that convey the core ideas and constraints. These should include conditional statements that specify when particular rules or behaviours should be applied (White et al., 2023). The most effective approach involves combining multiple patterns for enhanced results, starting with broad prompts and then incrementally narrowing them down with additional constraints as needed (White et al., 2024). The outcome depends on providing concrete examples when defining custom properties, using well-known terminology that the LLM was likely trained on, and iteratively refining prompts based on the quality of received outputs (White et al., 2023). Customised prompts can direct LLMs to perform requirements-related tasks such as analysing stakeholder needs, generating requirement specifications, or validating requirement completeness without requiring full model retraining, but with an LLM fine-tuning process on earlier pre-trained LLMs or with application of different mechanisms for reliable hallucination detection (Sawczyn et al., 2025).

There exist groups of patterns that fall into several major categories, addressing different aspects of LLM interaction. **Input Semantics** control group patterns are aimed at understanding input, **Output Customisation** group patterns focus on types, formats, structure of the generated output, **Error Identification** categories focus on identifying and resolving errors in the output, **Prompt Improvement** categories focus on improving the quality and accuracy of the input and output by requesting verifiable facts, explanations of reasoning, and better question formulations, **Interaction** group patterns change the conversation dynamics through interactions with users, letting the LLM ask questions, assigning specific roles, or breaking complex problems into manageable sub-questions, and **Context Control** groups focus on controlling the contextual information (White et al., 2023). For software development engineering specifically, one may be interested in pattern groups such as **Requirements Elicitation**, System Design and Simulation, Code Quality or Refactoring (White et al., 2024).

The confusion matrix is a methodology to evaluate the performance of logistic regression and classification machine learning models (Tillmanns and Krafft, 2017) as well as advanced neural networks such as those applied in AI chatbots. The confusion matrix indicates the classifier's success by providing a simple matrix table with four combinations of predicted and actual values that helps visualise whether the model is "confused" in distinguishing between two classes (Gusarova, 2023). The summary and formulas of key metrics based on the confusion matrix for classification machine learning models are presented in Figure 2. The precision metric is most appropriate when minimising false positives is critical, for example, in loan approvals where one wants to be confident about predicted positive cases, even if some true positives are missed (Gusarova, 2023). Recall is most appropriate when finding all positive cases is the priority and some false positives can be tolerated, such as medical diagnosis for serious diseases where missing a true positive case is more costly than having false alarms (Gusarova, 2023). F1 Score is used when there is a need to balance both precision and recall, especially in cases where the dataset is imbalanced or when both false positives and false negatives have significant costs that need to be optimised together (Gusarova, 2023).



Source: made by the author based on M. Gusarova (2023)

Figure 2: Confusion matrix with classification metrics

The following research study analysed business requirements originating from two datasets of user stories. The first dataset comprised 100 user stories derived from an actual IT project, representing a random sample from a larger product backlog managed in Atlassian JIRA software. The second dataset consisted of 100 user stories originating from workshops conducted with students during postgraduate studies classes, describing the functionality of fictional products devised for exercises in creating business requirements in the form of user stories. Anthropic Claude Sonnet 4 AI chat was used as a generative AI tool to conduct this research study with an example system prompt created by the author. Finally, results gathered with the chat were compared with manual assessment (Ground-Truth) by using a confusion matrix with classification metrics.

4. Results

4.1 User Story Analysis System Prompt

The iterative empirical research process combined with experiments on recommended prompt engineering language patterns (White et al., 2023; White et al., 2024) allowed for the creation of the system prompt executed in Anthropic Claude Sonnet 4 AI chat to conduct product backlog evaluation and refinement for two explored datasets of user stories. The system prompt applied for user story evaluation and refinement:

You are an experienced Agile Product Owner with 20 years of experience in Agile Project Management. A model user story should be a clear and concise sentence following the User Story Standard Format and should not be too technical a product description but rather an expected functionality to reach user goal/benefit and possibly understood with business language by both Development Team and Product Owner and Stakeholders.

Analyse each user story against the standard user story format and provide a summary table.

User Story Standard Format: "As a [persona], I [want to], [so that]."

Where:

- Persona: Who we're building this for (specific user type/role)
- Want to: User's intent/goal (implementation-free description)
- So that: Overall benefit/bigger picture they're trying to achieve

Examples:

- As Max, I want to invite my friends, so we can enjoy this service together.
- As a manager, I want to understand my colleagues' progress, so I can better report our success and failures.

Task: Review each user story and indicate (Y/N) if it contains each required component. Then refine each user story to follow the standard format while keeping the idea of task as close as possible to be compliant with user story standard template and using a business language focused on expected functionality and goal by users rather than product description. Create acceptance criteria using Given/When/Then format for each user story. Present results in a table format with columns: User Story | User Role | Functionality | Business Value | Product Description | Business Language | User Story Refined | Acceptance Criteria

Where:

- Product Description indicates: Y = too much product description, N = focused on functionality to achieve rather than product description.
- Business Language indicates: Y = uses business language as expected, N = uses more technical than business language.
- User Story Refined: Provide refined version following standard format. User stories requiring refinement are those with at least one N in columns 2, 3, 4, 6 or Y in column 5. Do not create artificial information - use placeholders like <user role> for missing information that Product Owner needs to complete.
- Acceptance Criteria: Create using Given/When/Then format following template: "Scenario: (explain scenario). Given (how things begin), when (action taken), then (outcome of taking action)." Focus on testable conditions and user experience rather than technical implementation.

The results of the user story analysis are presented in Table 1, which contains the percentage of requirements fulfilling the examined criterion related to our research hypotheses, separately for each dataset (IT Project and Workshops). The results are provided separately for manual human analysis (Ground-Truth) and for analysis using Anthropic Chat with our self-developed system prompt.

Table 1: Summary results of user stories analysis (CHT – Chat, GT – Ground-Truth)

Dataset	Method	Dataset Size	User Role [H1.1]	Functionality [H1.2]	Business Value [H1.3]	Product Description [H1.4]	Business Language [H1.5]
IT Project	GT	100	73%	82%	32%	49%	70%
IT Project	CHT	100	73%	69%	13%	11%	20%
Workshop	GT	100	100%	100%	65%	0%	100%
Workshop	CHT	100	89%	100%	61%	4%	100%

Source: Made by the author

In order to verify the research hypotheses, the focus was placed on real IT project results (refer to rows 1 and 2 in Table 1), whilst the workshop results serve more to confirm the possibility of improving user story quality once appropriate training is established within on-the-job processes. User roles were missing in 27% of user stories (**confirmed H1.1**) and this is relatively easy to improve based on workshop results. Functionality was missing in 18% (**H1.2 was rejected**); however, it was close to the 20% threshold and, based on workshop results, also exposed room for easy improvement. Business value was missing in 68% of the IT project and in 35% of the workshops, which definitely **confirmed H1.3** and exposed the challenge of formulating it. In addition to the three mandatory template items of user stories, excessive product description compared to expected functional requirements was identified in more than half the user stories (51%) – **confirmed H1.4** – and overly technical language instead of business language was identified in 30% of user stories – **confirmed H1.5**; however, both appear easy to refine with proper training or tool support based on workshop results. In summary, although H1.2 is rejected, the overall quality of user stories can be improved, either with human review or dedicated tool support (**confirmed H1**).

Table 2 provides two selected examples of original user stories, one from each dataset, together with the chat output results with refined text of the user story and proposed generated acceptance criteria that allow verification of the second hypothesis. It is important to note that the chat was asked directly in the prompt not to imagine those missing parts, but to highlight them with placeholders such as <user role> or <take action> that the one responsible for product backlog management needs to complete.

Table 2: Examples of refined user stories and generated acceptance criteria

Dataset	Original User Story	Refined User Story	Acceptance Criteria [H2]
IT Project	As a PO need to Validate status change for tickets to be able to resolve the tickets	As a PO, I want to Validate status change for tickets to be able to resolve the tickets, so that **<business value>**	Scenario: ***User achieves the desired functionality***. Given PO needs to **<perform action>**, when they **<take action>**, then **<expected outcome>**
Workshop	As a user of an online bookstore I want to have the possibility to browse titles from a given category	As a user I want to browse titles from a given category so that **<business value>**	Scenario: User browses category titles. Given the user is on the bookstore, when they select a category, then they can view all titles in that category

Source: Made by the author

Examples of refined user stories and generated acceptance criteria (Table 2) allow hypothesis **H2 to be confirmed**, as even a simple AI chat prompt with human language (PEL) can be used to trigger at least the review of those items for potential improvement within the product backlog refinement process.

4.2 User Story Analysis Evaluation Metrics

The summary of classification metrics evaluation is presented in Table 3. All five classification metrics (Accuracy, Precision, Recall, Specificity and F1) for both datasets (IT Project and Workshop) were calculated using the exact formulas as shown in Figure 2, for each of the five evaluated user story properties (User Role, Functionality, Business Value, Product Description and Business Language). Confusion Matrix elements (TP – True Positives, FP – False Positives, TN – True Negatives and FN – False Negatives) used in the classification metrics formulas were calculated based on Predicted Values from Chat (CHT) and Actual Values from Ground-Truth (GT).

Table 3: Summary results of evaluation metrics

Dataset	Metric	User Role [H1.1]	Functionality [H1.2]	Business Value [H1.3]	Product Description [H1.4]	Business Language [H1.5]
IT Project	TP	73	65	12	8	17
IT Project	FP	0	4	1	3	3
IT Project	TN	27	14	67	48	27
IT Project	FN	0	17	20	41	53
IT Project	Accuracy	1.000	0.790	0.790	0.560	0.440
IT Project	Precision	1.000 (+)	0.942 (+)	0.923 (+)	0.727 (+)	0.850 (+)
IT Project	Recall	1.000 (+)	0.793 (+)	0.375 (-)	0.163 (-)	0.243 (-)
IT Project	Specificity	1.000	0.778	0.985	0.941	0.900
IT Project	F1	1.000 (+)	0.861 (+)	0.533 (-)	0.267 (-)	0.378 (-)
Workshop	TP	89	100	61	0	100
Workshop	FP	0	0	0	4	0
Workshop	TN	0	0	35	96	0
Workshop	FN	11	0	4	0	0
Workshop	Accuracy	0.890	1.000	0.960	0.960	1.000
Workshop	Precision	1.000 (+)	1.000 (+)	1.000 (+)	0.000	1.000 (+)
Workshop	Recall	0.890 (+)	1.000 (+)	0.938 (+)	N/A	1.000 (+)
Workshop	Specificity	N/A	N/A	1.000	0.960	N/A
Workshop	F1	0.942 (+)	1.000 (+)	0.968 (+)	N/A	1.000 (+)

Source: Made by the author

Values above 0.7 were taken as reasonably fair and acceptable for this type of research study example, aimed for further improvements in practical implementation. For our imbalanced datasets, accuracy can be misleading and evaluation focus was placed more on precision, recall, and F1. Although most results are good or excellent (0.8-0.9 or higher), the key is to establish benchmarks based on specific use cases, business requirements, and domain standards rather than relying solely on general value thresholds. In the case of this research study, the most important conclusion is that **one can assess in a predictable, measurable and reliable way and compare the different prompts (PEL) and chatbot results**.

Similarly to the previous section, the focus is on real IT project results (refer to Precision – row 6, Recall – row 7 and F1 – row 8 in Table 3), whilst the workshop results serve more to confirm the possibility of improving user story quality with additional training. Very good precision results (above 0.9) provide confidence that it is feasible to identify exact elements from the user story template (User Role, Functionality or Business Value) that require improvement – **confirmed verification of hypotheses H1.1 – H1.5**. Recall and F1 metrics revealed that evaluation of Business Value, Product Description and Business Language of user stories might be more challenging, resulting in more false negatives – this means the production solution should be fine-tuned with a more precise prompt (PEL) to specify how to detect those elements and finally achieve better confidence levels.

5. Discussion and Conclusions

The empirical research results as well as the literature research review confirmed the possibility of AI tool application support for user story elicitation and refinement to improve its quality. The quality of agile product backlogs, as well as continuous processes of creation, management, and refinement within the agile approach, can be enhanced with the application of AI tools, chatbots and generative AI with dedicated Prompt Engineering Language (PEL) allowing reliable results to be received as confirmed by measurable metrics in the presented research results, therefore filling the identified research gap (Marczak-Czajka and Cleland-Huang, 2023; Ronanki, Cabrero-Daniel and Berger, 2023). Both user stories and acceptance criteria can be generated with a high level of quality; however, the final version of PEL should be tuned to the production purpose of a given industry, domain context and scalability requirements (Nistala et al., 2022). Taking these into consideration, it requires

human attention to results review and adaptation as it is not intended to blindly or fully automate product backlog management processes (Siahaan, Raharjana and Fatichah, 2023).

The research findings indicate a noticeable lack of accuracy in user stories derived from the real IT project. This discrepancy is acknowledged with both Ground-Truth data results as well as AI Chat results, exposing two major items that drive good quality user stories with AI tool support – tuning the PEL prompt itself, as mentioned, and what is equally important, user input at a sufficient level of information. In agile software development, the common underlying root causes of missing or insufficient input may be related to the agile approach itself, as it is primarily applied in complex project domains with frequent and informal face-to-face communication, where changes are provided iteratively throughout its lifecycle. Thus, user story creation and refinement are also based on input fed from the product owner and stakeholders in a frequently updated feedback loop (Cohn, 2004; Hendriana, Raharjo and Fitriani, 2023; Xu et al., 2023). This confirms that strong support is required for incorporating AI tools as well as human review within the agile feedback loop process.

Good quality of user stories and engineering requirements is crucial in the entire SDLC (Software Development Life Cycle) process as an input to AI-supported software code generation and AI-supported software code testing, verification and validation (possible future research), because ultimately incorrect stakeholder specifications and requirements will result in a working product or service that is mismatched with expected business value. Here, another future research may evaluate creating domain specification languages with concepts, rules, and vocabulary to fit particular domains and unique contexts of given industry domains to ensure a priori correctness before undertaking subsequent and costly SDLC steps (Miroslaw et al., 2015; Blikle and Chrząstowski-Wachtel, 2018). Once the input is proven, it can be further supported with advanced AI solutions such as machine learning, multimodal generative AI with agentic solutions, as well as IT democratisation approaches with low-code or no-code solutions such as RPA or agentic approaches to allow higher automation levels of software development processes (Tillmanns and Krafft, 2017; Sobczak, 2018). An important future research gap is related to enhancing the customised language prompts (PEL) to provide more deterministic and replicable results with fewer hallucinations (Sawczyn et al., 2025); however, at the same time being simple enough to be understood and developed by domain industry experts, without necessarily being software engineering professionals, IT experts or scientific researchers.

Ethics declaration: Ethical clearance was not required for the research.

AI declaration: Anthropic Claude Sonnet 4 AI chat was used as an AI Generative tool aimed to conduct the research study with the system prompt created by an author (see Appendix). Additionally the same chat was used for initial English proof reading and to create images. AI chat was not used to create the research concept or text of this paper.

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Use of GenAI to Obtain Public Information on Plastic and Reconstructive Surgery Procedures: A Focus on Migraine Surgery

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Abstract: Background: In recent years, Generative Artificial Intelligence (GenAI) technologies have seen rapid development and widespread public release. These tools are now accessible to both professional researchers and the general public, offering new ways to obtain information across a wide range of disciplines, including medicine. Given their growing presence in clinical and academic environments, it is important to understand the reliability and scientific rigor of the information these platforms provide. The aim of this study was to evaluate the quality, accuracy, depth and readability of responses generated by nine widely available GenAI tools when asked to describe the indications, outcomes, potential complications of migraine surgery and the available alternatives. **Methods:** Nine most prominent and widely used GenAI platforms—ChatGPT, Gemini, Perplexity, Elicit, Scispace, Consensus, PaperPal, Julius, and Mistral AI—were prompted with the same standardized questions: *"Detail the outcomes and complications of migraine surgery."*, "*What are the indications for migraine surgery?" and "What are the alternatives to migraine surgery?*". The responses were then assessed in terms of scientific credibility, clarity, readability, depth of information, and the presence of references to peer-reviewed literature or established medical knowledge. **Results:** Overall, the responses received were highly satisfactory. All tools delivered prompt replies that were logical and scientifically credible. However, the level of detail, specificity, and accuracy varied across platforms. The most comprehensive and detailed answers were provided, in order, by Mistral, Julius, Scispace and Consensus, while the most readable ones were given by Mistral, ChatGPT and Elicit. Readability analysis indicated that content generally required a college-level education. **Conclusions:** Across all platforms, the core principles of migraine surgery were accurately outlined, including the indications, the expected outcomes, the incidence and severity of possible complications and the possible alternatives. In terms of results, the consistently high success rate of the procedure was clearly emphasized and conveyed an accurate overview of its clinical relevance.

Keywords: Migraine surgery, Artificial intelligence, Headache surgery, Generative AI tools

1. Introduction

Generative Artificial Intelligence (GenAI) is a branch of artificial intelligence that utilizes generative models to produce text, images, videos, and other types of data. These models are trained to recognize and learn patterns and structures from large datasets, allowing them to generate new content based on user input—usually in the form of natural language prompts. In simple terms, these tools process specific user questions (prompts) and respond using a combination of freely accessible online information (e.g., from Wikipedia or open-source texts).

In recent years, many GenAI tools have become publicly accessible, serving both research purposes and public use. These tools are increasingly employed by healthcare professionals for research and institutional tasks, as well as by non-experts seeking information on the diagnosis and treatment of medical conditions. The rise of GenAI technology has significantly improved the efficiency and accessibility of medical knowledge acquisition, processing, and dissemination.

The use of GenAI in surgical and healthcare settings covers the following areas:

1. Enhancing Medical Knowledge and Education

- GenAI can condense vast amounts of medical literature, guidelines, and research into concise, digestible summaries.
- It supports medical training by generating case studies, describing surgical techniques, and simulating patient interactions.
- Through virtual tutor functions, GenAI helps medical students and surgeons stay updated on the latest advancements in the field.

2. Supporting Clinical Decision-Making

- Virtual assistants provide personalized medical guidance to patients and healthcare providers by analyzing medical databases.• Surgeons can leverage AI for best-practice reviews, complication risk assessments, and postoperative checklist evaluations to aid in sound decision-making.

3. Patient Education and Engagement

- GenAI helps translate complex surgical information into understandable language for patients.
- Chatbots and virtual assistants can answer frequently asked questions about preoperative preparation, recovery, and follow-up care.
- Multimedia content generated by AI, such as videos and interactive diagrams, improves patient understanding, informed consent, and treatment compliance.

4. Research and Systematic Reviews

- GenAI facilitates faster literature searches, assists in conducting meta-analyses, and identifies relevant studies efficiently.
- Global studies are analyzed using generative artificial intelligence (GenAI), with a focus on the evolution over time of surgical outcomes, complication rates, and innovative techniques.

5. Surgical Planning and Simulation

- AI-powered tools support preoperative planning by converting imaging data (e.g., MRI and CT scans) into 3D models, helping design optimal surgical strategies.
- Surgeons can use virtual simulations to practice and refine techniques before performing actual procedures.

Since Guyuron first proposed surgical treatment for migraines in 2000, this approach has gained growing scientific validation and clinical support. Despite its development over the years, the procedure remains relatively unknown both in academic circles and among the public. Consequently, the use of GenAI tools to obtain more detailed and accessible information on the topic is becoming increasingly relevant—for both medical professionals and laypeople.

We aimed to assess what type of information could be retrieved from publicly accessible GenAI tools when asked about the expected outcomes and potential complications of migraine surgery.

2. Materials and Methods

It was consulted nine of the most well-known and widely used GenAI tools: ChatGPT (OpenAI, San Francisco, CA, USA), Gemini (Google DeepMind, London, UK), Perplexity (Perplexity AI Inc, San Francisco, CA, USA), Elicit

(Elicit Research PBT, Oakland, CA, USA), Scispace (Polydora Technologies Private Ltd, Bangalore, India), Consensus (American Fork, UT, USA), PaperPal (Cactus Communications Services Pte Ltd, Singapore), Julius (Triller, New York, NY, USA), and Mistral AI (Paris, France). The software tools were selected based on three criteria: relevance to the field of biomedical research (excluding those primarily designed for other purposes such as music, image or video generation, or programming), their popularity (at the end of July 2024) and free accessibility. Each tool was posed the same questions: "Detail the outcomes and complications of migraine surgery.", “What are the indications for migraine surgery?” and “What are the alternatives to migraine surgery?”. The research was carried out during the month of August 2025. The responses, along with the bibliographic references (when available) on which the answers were based, were collected and analyzed. The accuracy and specificity of the responses have been assessed by the senior author (ER - who has specific clinical and scientific expertise in the field for over 20 years) in accordance with the guidelines provided by the American Society of Plastic Surgeons (https://www.plasticsurgery.org/reconstructive-procedures/migraine-surgery), with a score from 0 to 30 where 0 is insufficient and 30 is high.

3. Results

All the software provided logically valid answers, with response times consistently short and comparable (under 4 seconds) except for Elicit and Spispace, which took about 3 minutes.

The full responses from each tool are available in Additional Material I.

Our initial evaluation and comparison of the responses were conducted based on the quantity and quality of the bibliographic references cited (Table I-II-III).

Table 1: Degree of detail of the answers

SOFTWARE	References	Degree of detail of the answers	Flesch-Kincaid Score
ChatGPT	3	30	11.80
Gemini	0	25	12.35
Perplexity	4	28	16.62
Elicit	4	27	15.55
SciSpace	5	28	15.14
Consensus	10	26	17.06
PaperPal	8	25	15.62
Julius	4	27	17.17
Mistral AI	0	30	11.84

Summary data of the analyses conducted on the first prompt "Detail the outcomes and complications of migraine surgery", using the various softwares covered by the study.

Degree of detail of the answers from 0 to 30 where 0 is insufficient and 30 is high.

Table 2: Completeness and appropriateness of the answers

SOFTWARE	References	Completeness and appropriateness of the answers	Flesch-Kincaid Score
ChatGPT	2	24	14.35
Gemini	7	30	15.22
Perplexity	8	27	17.63
Elicit	9	26	11.70
SciSpace	15	26	23.37
Consensus	19	30	22.03
PaperPal	9	25	17.90
Julius	0	27	21.60
Mistral AI	0	30	13.65

Summary data of the analyses conducted on the second prompt: "What are the indications for migraine surgery?"

Degree of detail of the answers from 0 to 30 where 0 is insufficient and 30 is high.

Table 3: Completeness and appropriateness of the answers

SOFTWARE	References	Completeness and appropriateness of the answers	Flesch-Kincaid Score
ChatGPT	0	28	15.50
Gemini	8	28	18.28
Perplexity	7	26	17.43
Elicit	5	0	14.74
SciSpace	17	30	25.60

SOFTWARE	References	Completeness and appropriateness of the answers	Flesch-Kincaid Score
Consensus	6	28	19.37
PaperPal	7	26	22.64
Julius	0	30	27.95
Mistral AI	0	28	15.80

Summary data of the analyses conducted on the third prompt: “What are alternatives to migraine surgery?”

Degree of detail of the answers from 0 to 30 where 0 is insufficient and 30 is high.

Of all the tools, only Mistral AI failed to provide any references.

Based on the average, the AI tools are ranked by the number of references provided as follows: Spispace (12.3), Consensus (11.6), PaperAI (8), Perplexity (6.3), Elicit (6), Gemini (5), ChatGPT (1.3), and Julius (1.3).

The average scores for all systems are presented in Table IV.

Table 4: Completeness and appropriateness of the answers

SOFTWARE	References	Completeness and appropriateness of the answers	Flesch-Kincaid Score
ChatGPT	1.6	27.3	13.88
Gemini	5	27.6	15.26
Perplexity	6.3	27	17.22
Elicit	6	17.6	13.99
SciSpace	12.3	28	21.37
Consensus	11.6	28	19.48
PaperPal	8	25.3	18.72
Julius	1.3	28	22.23
Mistral AI	0	29.3	13.76

Mean scores for each AI software, based on the combined results of the three administered questions.

For the sake of completeness, it's worth mentioning that ChatGPT provided some inaccurate references.

Most of the references provided by Gemini and Perplexity were from websites rather than scientific publications.

In addition, Elicit provided an irrelevant answer (hallucination) to the third question.

The tools that delivered the most comprehensive and detailed responses were, in order: Mistral, Julius, Scispace and Consensus, while the most readable ones were given by Mistral, ChatGPT and Elicit.

All the software tools accurately presented the universally accepted principles of migraine surgery, covering the appropriate indications for the surgical treatment, the expected outcomes, the frequency and severity of potential complications, and the available alternatives to surgery. The high success rate of the procedure was consistently emphasized, while complications were uniformly described as minor, infrequent, and typically temporary.

Some platforms went further by including additional, potentially overly technical, details for a general audience. For example, Consensus discussed binary outcomes and distinctions between endoscopic and non-endoscopic techniques. Scispace provided success rates for different trigger sites. Perplexity organized outcomes by migraine intensity, frequency, and resolution rates. ChatGPT offered insights into various aspects, such as postoperative quality of life, types of complications, trigger site differences, and criteria for patient selection.

Specific percentages related to success rates or complication rates were rarely mentioned. Nevertheless, even in these cases, the answers remained sensible, accurate, and appropriate in tone.

To evaluate the clarity and comprehensibility of the responses, we used the reference software Text Inspector (WebLingua Ltd, UK). Developed by Professor Stephen Bax, an expert in Applied Linguistics, Text Inspector received the British Council ELTons Digital Innovation Award in 2017 and is academically supported by the Centre for Research in English Language Learning and Assessment (CRELLA) at the University of Bedfordshire. The tool assesses the educational level required to fully understand a given text, generating a score aligned with various educational benchmarks (Flesch-Kincaid Score, see Table V). The results showed consistently high scores across all responses, ranging from 11.70 to 27.95 (see Table I-II-III). While these high scores reflect the credibility and sophistication of the sources, they may also represent a barrier to understanding for individuals with lower levels of education.

Table 5: Flesch-Kincaid Score

Flesch-Kincaid Score	Corresponding US Educational Level	Approximate UK Equivalent	Typical Usage
1.0 – 3.0	Early Elementary School	Primary School (KS1-2)	Children's books, beginner reading materials
4.0 – 6.0	Upper Elementary/Middle School	Primary School (KS2) / Lower Secondary (KS3)	Standard classroom texts, general fiction
7.0 – 9.0	Middle School/Early High School	Lower Secondary (KS3)	Most adult fiction, general non-fiction, newspapers
10.0 – 12.0	High School	Upper Secondary (KS4-5)	Academic texts, some technical writing
13.0+	College/University	Higher Education(University or degree-level studies)	Advanced academic papers, complex technical manuals

Flesch-Kincaid Score

4. Discussion

To the best of our knowledge, only one other recent study—conducted by Chartier et al. —has explored the application of Generative AI in the context of migraine surgery. However, that research specifically examined the use of patient drawings as predictors of surgical outcomes. To date, no studies have investigated the information provided by various GenAI tools regarding headache surgery, particularly in relation to procedural success rates and potential complications.

Overall, the results of our analysis were highly satisfactory. All the tools evaluated delivered responses that were not only impressively fast but also generally sensible and scientifically credible, though with varying levels of accuracy.

The language used across all responses was consistently appropriate and correct. While the content was always comprehensible, it generally required a higher level of education—typically at the college or university level—for full understanding (see Table V).

The performance of a generative Artificial Intelligence system largely depends on the modality and nature of its training dataset. Most of the tools evaluated in this study generated responses based on information drawn from accredited scientific literature.

This is a particularly significant finding, as it reinforces the reliability and scientific validity of the information provided. In contrast, sourcing data from general websites—as opposed to peer-reviewed scientific publications—may increase the risk of inaccuracies or misinformation.

In our analysis three GenAI tools appeared to incorporate information from websites: ChatGPT, Perplexity and Gemini, and not exclusively from established and reputable scientific institutions.

It is important to highlight that—even in the absence of citations—the responses from the tools that did not reference scientific literature were still logical, coherent, and reasonable.

This aspect is particularly significant given the current absence of regulations or legal standards governing the accuracy of content generated by GenAI tools. In this context, the internal consistency and plausibility of the responses take on added importance.

It is crucial to clarify that our intention was not to establish a "ranking" of the tools evaluated. The applications of Generative AI are vast, spanning text generation, video creation, sound design, and image production. Each of the tools used in this study offers unique strengths and specialized use cases. Our objective was solely to assess the overall reliability of the responses provided, particularly in relation to a niche topic within the field of plastic surgery—migraine surgery—which continues to evolve.

This study focused on assessing the plausibility and factual accuracy of responses to a specific question, especially in the context of non-professional users seeking medical information. In our view, future research could explore the utility and precision of GenAI tools for medical professionals with a specific interest in migraine surgery—for example, as a resource in preparing reviews or conducting systematic research on the topic.

The use of GenAI in healthcare is growing rapidly, but it raises ethical concerns of equal importance, including:

- Protection of Data and Security: GenAI systems often rely on large datasets, some of which may contain sensitive patient information. Strict adherence to data privacy regulations such as HIPAA and GDPR is essential to protect patient confidentiality. Unregulated access to personal health data highlights the urgent need for robust AI security measures in most medical applications.
- Biased Algorithms and Lack of Transparency: Many AI systems function as "black boxes," where the decision-making process is not clear to users. In medicine, understanding how AI reaches certain conclusions is crucial. Poorly trained AI algorithms can introduce bias, potentially leading to unequal treatment of patients and adversely impacting marginalized groups. Researchers and developers must take active steps to identify and mitigate such biases.
- Likelihood of Misinformation: GenAI can generate authoritative-sounding but inaccurate or misleading content, which may negatively influence medical decisions. Ensuring that AI-generated medical information follows established guidelines and is evidence-based is vital.
- Lack of Benchmarking Against Expert Responses: This study did not compare GenAI responses with those from migraine surgery experts. A comparison with answers from board-certified neurologists or headache surgeons would provide a valuable reference to evaluate how closely AI-generated responses align with expert consensus.

The use of GenAI in medical and surgical fields brings to mind the classic computer science adage: "garbage in, garbage out." Most surgical and medical journals are behind paywalls, limiting access to high-quality medical information. This challenge is especially notable in plastic surgery, where physicians must adhere to strict ethical standards to protect patient confidentiality, particularly regarding clinical photographs. While GenAI can retrieve article abstracts from databases such as PubMed, the information it accesses tends to be limited to freely available content. Open-access materials often present information in a predominantly positive light and lack the critical evaluation provided by expert reviewers. Consequently, GenAI is unable to deliver the detailed, nuanced, and critical analysis necessary for informed clinical decision-making. Furthermore, dissenting or minority viewpoints are often overlooked in AI-generated content.

Funding: The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Conflict of Interests: The authors have no relevant financial or non-financial interests to disclose. None of the authors has a financial interest in any of the products, devices, or drugs mentioned in this manuscript.

Author Contributions: ER developed the concept, checked the results and wrote the manuscript. EB checked the results and wrote the manuscript.

Ethics approval: Not required.

AI declaration: AI tools were not used.

Availability of data and materials: The data analyzed in this study are available from the corresponding author upon request.

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A Literature Review on AI for Lifelong Learning: Tools, Benefits, and Opportunities

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Abstract: Lifelong learning plays a crucial role in both personal development and societal advancement. By continually enhancing their skills, individuals can better adapt to change and contribute to progress. In this regard, artificial intelligence (AI) supports lifelong learning by enabling personalised learning experiences, increasing accessibility, and fostering continuous education. This study examines existing research on AI's role in supporting lifelong learning, with a focus on personalised education, skill development, and the reduction of learning gaps across educational stages. A systematic literature review was carried out following the guidelines established to examine the evolving contributions of AI to the development and support of lifelong learning practices. This study follows the standards outlined in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA). Articles relevant to the study's objectives were identified through a systematic search of the Scopus database, limited to English-language publications in the field of social sciences over the past ten years. The search strategy employed the following string: ("Artificial Intelligence" OR "AI") AND ("Lifelong learning" OR "continu* education") AND ("personali* learning" OR "skill* development"). This process yielded a total of 14 selected studies, from which three themes were identified through thematic analysis: 1) perspectives shaping AI in lifelong learning, 2) benefits of AI tools in education, and 3) AI's potential for optimising and transforming learning. Findings show that diverse perspectives, along with social and cultural factors, shape the design and effectiveness of AI in lifelong learning. Various AI tools, such as adaptive learning platforms, provide personalised content and immediate feedback, enabling learners to progress at their own pace and promote skill acquisition. These tools offer clear benefits: they foster personalised learning experiences that go beyond mere productivity gains to truly enhance learners' capabilities. Personalised education models also optimise resource allocation by tailoring content to individual needs, improving outcomes in higher education settings. Looking forward, AI presents significant opportunities to transform education through tailored learning and teacher support. AI must balance technology with human interaction to foster critical thinking, creativity, and problem-solving essential to lifelong learning.

Keywords: Artificial intelligence (AI), Lifelong learning, Personalised learning, Skill development

1. Introduction

The rapid advancement of digital technologies is transforming both education and the labour market, with breakthroughs in artificial intelligence (AI), accelerated digital transitions, and shifting skill demands reshaping how individuals learn, work, and adapt. These developments have intensified the need to understand how digitalisation influences lifelong learning and the continuous development of competencies. In a world marked by constant societal change, the acquisition of new knowledge has become essential. Learning is an ongoing process that takes place not only through formal schooling or university education but also through a variety of other experiences and forms of instruction. Learning, whether formal or informal, should be seen in a long perspective. Even the globalisation we are living in now requires a long-term perspective on learning. Today, a lifelong learning perspective is a necessity, not only a choice (Laal & Salamati, 2012).

Lifelong learning is essential to meeting these challenges through enhanced competitiveness, increased innovation, and reinforcing social inclusion (Rial-Gonzalez et al., 2024). The scholars explain that the fourth industrial revolution, driven in part by advances in artificial intelligence, presents profound challenges for employment. The widespread integration of AI into the modern workplace carries systemic implications, with estimates indicating that up to 30 percent of work activities could be automated by 2030, which could influence the livelihoods of up to 375 million workers across the globe (Frey & Osborne, 2017).

Artificial intelligence creates many opportunities and challenges in society (Cummins et al., 2022; Seo et al., 2025), and its integration into education has gained increasing attention in recent years, as digital technologies continue to reshape both learning processes and labour market demands. AI is no longer limited to technical applications but is now influencing how individuals acquire knowledge, develop competencies, and participate in lifelong learning. Understanding these dynamics is essential, as AI not only personalises learning pathways but also has the potential to strengthen digital competence and empower key educational actors, including learners, educators, and institutions.

In light of this, the present study systematically reviews existing research on AI in the context of lifelong learning. Specifically, it seeks to address two central questions:

- In what ways does AI contribute to personalised and lifelong learning?
- How does the literature address empowerment of learners, educators and institutions in AI-supported education?

2. Background

The connection between work and education has long been characterised by complexity and continual change. In this context, lifelong learning emerges as a critical framework for navigating the shifting demands of the labour market and ensuring the continued relevance of education throughout an individual's career in today's rapidly changing world. According to Laal and Salamati (2012), the ability to learn throughout life is essential for everyone. Frey and Osborne (2017) note that in the United States, for example, approximately 50 % of all jobs could be automated within the next 10 to 20 years.

Lifelong learning encompasses the wide range of opportunities provided by social institutions as well as the diverse processes through which individuals acquire knowledge, skills, attitudes, values, emotions, beliefs, and a sense of identity (Jarvis, 2007). It is a continuous process that extends across the entire lifespan and takes place in many different contexts, both formal and informal (Jaldemark, 2021). In this way, lifelong learning is not only a personal activity but also a collective responsibility, linking individuals to broader cultural, social, and institutional systems (Jaldemark et al., 2021). More specifically, lifelong learning includes organised and unorganised learning throughout life, such as formal education, informal learning through work and other activities, and structured higher education opportunities for working professionals throughout their careers (Kristiansen et al., 2025). Continuing professional development, as scholars emphasise, represents a commitment to ongoing lifelong learning. This ongoing development of knowledge and competencies not only supports individual growth but also contributes to societal progress. By equipping people to adapt to changing circumstances and to participate meaningfully in collective advancement, lifelong learning has become a vital element of modern life (Reis-Andersson, 2024).

Within this context, artificial intelligence (AI) plays an increasingly important role by enhancing lifelong learning processes. AI technologies contribute by delivering customised educational experiences, broadening access to learning opportunities, and fostering sustained engagement in continuous education (Escotet, 2024; Fahimirad & Kotamjani, 2018). In doing so, AI strengthens the potential of lifelong learning to empower both individuals and societies in an era of rapid change.

2.1 The Role of AI in Lifelong Learning

AI has become an increasingly important driver of change in education, with significant implications for lifelong learning. By offering new possibilities for personalisation, accessibility, and flexibility, AI enables learning processes that align with the evolving demands of individuals and societies in the digital age (Bankins et al., 2024). One of the central benefits of AI is its capacity to provide personalised learning experiences. By adapting content to learners' individual progress, preferences, and learning styles, AI enables students to advance at their own pace (Hwang, 2014; Hwang et al., 2020). These adaptive and personalised approaches represent a significant shift from traditional, standardised education and align closely with the principles of lifelong learning. Beyond personalisation, AI also improves accessibility by helping to overcome barriers related to geography, time, and resources. Through intelligent tutoring systems, adaptive platforms, and predictive analytics, educational tools can be extended to a much wider audience, ensuring that high-quality learning opportunities are available regardless of learners' circumstances (Espinoza, 2025). In this way, AI contributes to more inclusive and equitable lifelong learning settings.

Another key contribution of AI is its support for continuous learning. By enabling flexible access to resources at any time and place, AI empowers individuals to pursue skill development alongside personal and professional responsibilities (Hamal et al., 2022). This flexibility is particularly important in a rapidly changing world, where upskilling and reskilling are essential to remain competitive and adaptable in evolving labour markets. Taken together, these affordances highlight AI's potential to strengthen lifelong learning through enhanced personalisation, accessibility, and flexibility (Block, 2024; Mariyono & Nur Alif Hd, 2025). By integrating these dimensions, AI contributes not only to individual growth but also to broader societal development, reinforcing the role of lifelong learning as a cornerstone of adaptation and progress in the digital age. Against this background, the following section outlines the methodological approach used in this study.

3. Method

Following the guidelines of Page et al. (2021), a systematic literature review was conducted to explore the evolving role of AI in fostering and supporting lifelong learning practices. The review adheres to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses standards (PRISMA, February 21, 2024). Relevant articles were identified through a systematic search in the Scopus database.

3.1 Search and Selection Process

About 117 studies used the query string: ("Artificial Intelligence" OR "AI") AND ("Lifelong learning" OR "continu* education") AND ("personali* learning" OR "skill* development") have been identified in Scopus database. No duplicates have been found. Of these, 46 studies were excluded at the initial stage because they were not in English (English-only studies were included), were published outside 2016-2025, or did not fall within the subject area of social sciences (e.g., studies focusing solely on technical aspects of AI without application to education were excluded). This resulted in 71 studies eligible for screening.

During the title and abstract screening, a further 21 studies were excluded for not meeting the inclusion criteria, most commonly due to a lack of focus on AI in lifelong or continuing education, absence of explicit links to personalised learning or skill development, or being primarily conceptual or theoretical discussions without addressing practical applications in lifelong learning contexts. These exclusions helped ensure that only studies directly relevant to the intersection of AI, lifelong learning, and personalisation were retained for the review. From the 50 studies that remained after initial screening, 19 were accessible in full text. During full-text review, five publications were excluded because they did not meet the inclusion criteria, specifically lacking relevance to the study's aim and research questions. This left 14 publications for the final analysis.

To ensure a transparent and systematic selection process, predefined inclusion and exclusion criteria were applied at each stage of the review. These criteria were guided by the study's aim and research questions, and they also reflected practical considerations such as language, publication year, and subject area. Table 1 presents the criteria, while Figure 1 (PRISMA flow diagram) visually illustrates the number of studies identified, screened, excluded, and included.

Table 1: Inclusion and exclusion criteria

Criterion	Inclusion	Exclusion
Topic relevance	Focus on AI in the context of lifelong learning, continuing education, personalised learning, or skills development	Publications that do not address AI in relation to lifelong learning, personalisation, or skills development
Type of study	Peer-reviewed journal articles and conference papers	Non-peer-reviewed sources
Research scope	Studies that contribute to the aim and research questions	Studies outside the scope of the research aim and questions
Publication year	2016-2025	Published before 2016 or after 2025
Subject area	Social sciences	Studies outside the social sciences domain
Language	Published in English	Published in other languages, not accessible for analysis
Accessiblity	Full text available	Full text not accessible

By combining these predefined criteria with a staged screening and review process, the study ensured both transparency and rigor in selecting the most relevant publications for analysis.

The overall selection process is illustrated in the PRISMA flow diagram (Figure 1), which shows the number of studies identified, screened, and excluded at each stage, as well as the final number of studies included in the review.

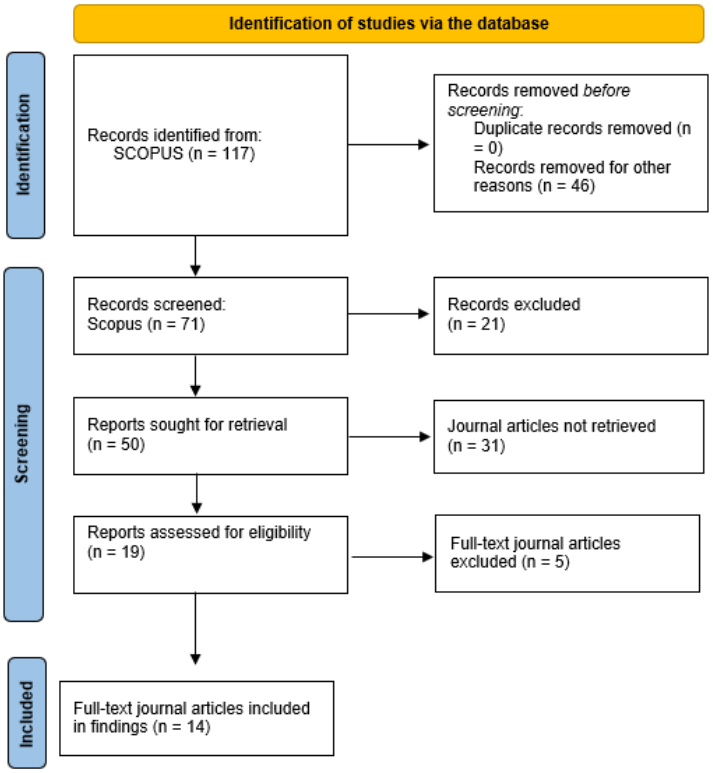

Figure 1: PRISMA flow diagram of the study selection process

3.2 Thematic Analysis

The thematic analysis followed Braun and Clarke's (2021) six-phase framework, which consists of familiarisation with the data, generating initial codes, searching for themes, reviewing themes, defining and naming themes, and producing the report. The analysis was conducted solely by the author, who carefully reviewed coding decisions to ensure consistency. In the first phase, I familiarised myself with the 14 studies by repeated reading and note-taking. In the second and third phases, the studies were coded and grouped into potential themes, with the understanding that, as Braun and Clarke (2006) highlight, themes must capture something significant in relation to the research questions rather than follow fixed rules. In phases four and five, these themes were refined and combined, resulting in three overarching themes related to lifelong learning, AI, education, and personalised learning. In the final phase, the report was produced, with each theme linked to the corresponding studies (A1-A14).

4. Findings

This section presents the findings of this study. To provide an overview of the material forming the basis for the analysis, the 14 included studies are presented in Table 2. The table summarises author(s), year, title, aim, and key findings.

Table 2: Studies included in the review

	Author(s), Year	Article's title	Aim of Study	Key Findings
A1	Adankon, G., & Houngue, P., 2024	How Can Intelligent Educational Technologies Address the Challenges of Professional Retraining in Africa: From Current State to Future Perspectives?	To explore the evolution and potential of intelligent educational technologies for professional retraining in web development.	IETs support personalisation, engagement, accessibility, and flexibility in retraining. Challenges remain in meeting learner needs and developing transversal skills.
A2	Al-Zahrani et al., 2024	Exploring the impact of artificial intelligence on higher education: The dynamics of ethical, social, and educational implications	To investigate the impact of AI on higher education, focusing on attitudes, ethics, and future expectations.	Positive attitudes toward AI; enhances teaching/ learning and administration; ethical concerns (privacy, bias, security) must be addressed.

	Author(s), Year	Article's title	Aim of Study	Key Findings
A3	Anghel, G. A. et al., 2025	The Integration of Artificial Intelligence in Academic Learning Practices: A Comprehensive Approach	To examine how students perceive and use AI tools in academic learning and identify factors influencing AI's integration into education.	AI use was linked to better academic performance, motivation, and personalised learning, supporting the development of lifelong learning skills.
A4	Boesl, D. B. et al., 2023	Foundations of an AI-based, cross-platform companion app for lifelong learning optimisation	To present the Apollo project framework for AI-based lifelong learning optimisation	AI-based app aims to support lifelong learning and continuing education by offering personalised, cross-platform learning pathways.
A5	El Bachari, E. et al., 2022	Personalised Learning Paths for Smart Education: Case Studies from Cadi Ayyad University	To explore AI and learning style models for improving digital and distance learning through personalised frameworks.	AI can effectively adapt learning paths, personalise online learning, and improve performance and outcomes.
A6	Ghnemat, R. et al., 2022	Higher Education Transformation for Artificial Intelligence Revolution: Transformation Framework.	To present an AI-based learning framework for transforming higher education and aligning outcomes with industry needs.	AI competency-based learning enhances engagement, accelerates outcomes, bridges the academia-industry gap, and fosters lifelong learning.
A7	Gulyamov, S. S. et al., 2024	Creating Self-Updating Digital Platforms Using Artificial Intelligence Technologies for Continuous Education and Professional Development	To propose AI-driven self-updating education platforms for adaptive and lifelong learning.	AI-enabled platforms can refresh content automatically, provide personalised learning, and support workforce resilience.
A8	Kallonas, C. et al., 2024	Empowering professionals: a generative AI approach to personalized cybersecurity learning.	To explore how generative AI can support personalised study plans in cybersecurity education to close the skills gap.	Generic training hinders effective upskilling; generative AI can enable tailored learning, motivation, and lifelong learning in cybersecurity.
A9	Puttajanyawong, N. et al., 2025	Utilizing Generative AI to Develop Programming Skill Through Self-Directed and Interactive Learning	Explore how generative AI can support programming skill development through self-directed and interactive lifelong learning.	Students without prior programming or AI experience gained motivation, skills, and positive attitudes toward self-directed learning; process supports lifelong learning across ages and genders.
A10	Ray, P. P. (2024)	A deep introspection into the role of ChatGPT for transforming hospitality, leisure, sport, and tourism education	Explore the role of ChatGPT and AI in transforming HLST education, including opportunities and challenges	AI personalises learning and streamlines tasks but raises privacy, quality, and equity concerns. Future directions include adaptive learning, intelligent assessment, collaboration, and lifelong learning.
A11	Sun, W. et al., 2024	Exploring educational transformation and innovation pathways in the era of artificial intelligence.	To examine AI's impact on education through reform, innovation, and equity theories.	AI promotes personalisation, equity, and lifelong learning, but raises privacy and ethical concerns.
A12	Xiao, Y., & Zhi, Y., 2023	An exploratory study of EFL learners' use of ChatGPT for language learning tasks: Experience and perceptions	To explore students' experiences and perceptions of ChatGPT in language learning.	ChatGPT supports language tasks and personalised learning; students used critical judgment to evaluate and adapt outputs, balancing integrity concerns.
A13	Yang, C. et al., 2025	Intersections between cognitive-emotion regulation, critical thinking and academic resilience with academic motivation and autonomy in EFL learners: Contributions of	To examine how cognitive-emotion regulation, critical thinking, and resilience influence motivation and autonomy in AI-mediated learning.	Emotion regulation, critical thinking, and resilience significantly enhance motivation and autonomy in AI learning, supporting lifelong learning skills.

	Author(s), Year	Article's title	Aim of Study	Key Findings
		AI-mediated learning environments.		
A14	Nedungadi, P. et al., 2024	The transformative power of generative artificial intelligence for achieving the sustainable development goal of quality education	To examine how generative artificial intelligence contributes to sustainable development goals on quality education, proposing policy/ practice directions.	Generative artificial intelligence can enhance equity, quality personalisation, and lifelong learning but raises ethical/ privacy concerns and risks widening the digital divide.

The thematic analysis of these 14 studies resulted in three overarching themes that capture how AI relates to lifelong learning, benefits of AI tools in education, and AI's potential for optimising and transforming learning. Many studies contributed to more than one theme. The included research employed diverse methods, such as surveys (A2, A3, A13), interviews (A12), case studies (A5, A9), and conceptual or framework proposals (A1, A4, A6, A7, A8, A10, A11, A14), thereby reflecting both empirical and conceptual perspectives. Table 3 presents an overview of these themes and their distribution across the reviewed studies.

Table 3: Themes identified in the thematic analysis

Theme	Description	Study
Perspectives shaping AI in lifelong learning	AI adoption and application are shaped by social, cultural, and contextual factors that influence design and use across diverse learning environments.	A1, A2, A3, A4, A7, A14
Benefits of AI tools in education	Adaptive platforms and other AI technologies enhance learning by personalising content, providing instant feedback, and supporting skill development.	A2, A3, A4, A8, A9, A11, A12, A13
AI's potential for optimising and transforming learning	AI enhances efficiency and outcomes through personalised learning resources, while its future promise lies in combining technology with human interaction to cultivate creativity, critical thinking, and problem-solving skills.	A2, A3, A4, A5, A6, A7, A10, A11, A12, A13, A14

The following sections elaborate on each theme in detail, highlighting key insights and patterns identified in the reviewed literature.

4.1 Perspectives Shaping AI in Lifelong Learning

The findings reveal that the design and effectiveness of AI in lifelong learning are influenced by diverse perspectives, as well as social and cultural factors. A1 illustrates how contextual challenges in Africa, such as limited financial support, reliance on mobile solutions, and work-family balance, affect AI adoption (A1). Similarly, A4 points to adaptability, as well as legal and economic barriers, as key influences on integrating AI into lifelong learning. A2 shows how attitudes and perceptions of students, faculty, and administrators shape AI adoption in higher education. While many expressed optimism, they also emphasised ethical concerns such as privacy, transparency, and bias, highlighting how social and ethical contexts influence the implementation (A2). A3 shows that factors such as age and digital competence shape how students use AI in education. Older learners face challenges in adapting to AI tools, while younger students integrate them more easily. These contextual differences highlight the importance of training and support to ensure equitable use of AI in lifelong learning contexts (A3). A7 underscores that successful adoption depends on ethical principles, collective responsibility, and national-level collaboration, ensuring AI platforms empower learners rather than constrain them (A7). Finally, A14 situates AI adoption within broader social and cultural perspectives, linking it to sustainability, equity, and inclusivity goals, while warning against the risk of deepening existing divides (A14).

4.2 Benefits of AI Tools in Education

A range of AI tools, such as adaptive learning platforms, were found to provide personalised content and immediate feedback, enabling learners to progress at their own pace while promoting skill acquisition. A1 highlights that adaptive platforms support flexible, personalised learning with feedback and practical projects. This helps adults in career transitions stay engaged while managing other responsibilities (A1). A2 shows strong benefits of AI tools, including personalised pathways, adaptive tutoring, real-time feedback, broader resource access, and streamlined administration, reinforcing AI's role in enhancing both teaching and learning outcomes (A2). A3 highlights several concrete benefits of AI, particularly tools like ChatGPT and recommendation systems. Students reported that AI supports personalised learning, improves access to resources, fosters motivation, enhances academic performance, and strengthens self-regulation (A3). Similarly, A4 notes that AI-enabled

platforms can provide flexible opportunities, interactive resources, and community engagement, supporting individuals from diverse backgrounds in maintaining professional development and continuous skill growth (A4). A8 demonstrates that generative AI, such as ChatGPT, can help learners build personalised study plans, organise resources, and develop specialised skills more effectively, especially in complex fields like cybersecurity (A8). A9 demonstrates how generative AI can enhance self-directed and interactive learning in vocational training through the MAR model (Motivation, Activity, Reflection, and Progression). Students developed programming, critical thinking, and teamwork skills, showing AI's value in guiding personalised learning. However, instructor support and ethical awareness remain essential to avoid over-reliance (A9). A11 highlights how tools like intelligent teaching robots, image and speech recognition, and deep learning enhance assessments, personalise learning, and improve classroom efficiency (A11). A12 shows that ChatGPT can act as a personal tutor by giving adaptive feedback, supporting language learning, and helping students improve essays and generate ideas. Students reported better autonomy and competence when using it as a learning partner (A12). Finally, A13 indicates that AI platforms offering personalised feedback and adaptive pathways can significantly boost motivation and autonomy in language learning (A13).

4.3 AI's Potential for Optimising and Transforming Learning

Personalised education models supported by AI also contribute to more efficient resource allocation. A1 points to future possibilities such as deep learning for finer personalisation and highlights AI's role in fostering creativity, critical thinking, and identity development in retraining (A1). A2 stresses AI's transformative potential in higher education. Participants envisioned AI reshaping teaching and learning, supporting collaboration, developing lifelong learning skills, and driving innovation, provided that ethical guidelines and implementation frameworks are in place (A2). A3 shows that AI can contribute to long-term transformation by fostering autonomy, critical thinking, and reflective practices. However, it also raises a debate about creativity: while AI can generate new ideas, it may risk limiting originality. These insights stress that AI's potential must be combined with careful pedagogical strategies to ensure balanced outcomes (A3). A4 presents AI as a lifelong learning companion, envisioning its role in transforming education beyond classrooms by integrating coaching, counselling, and industry certification opportunities. This positions AI as central to reshaping lifelong and continuing education for the digital era (A4). A5 shows how predictive models and personalised strategies enhance efficiency and accuracy in learning. It reinforces AI's potential to reduce barriers, adapt teaching to learner needs, and optimise outcomes without replacing traditional practices (A5). A6 envisions higher education transformed by AI, shifting from traditional coursework to problem-based learning tied to real-world and industrial challenges. Its proposed framework connects infrastructure, experts, and industry partners, underscoring AI's role in reshaping teaching, assessment, and institutional relevance (A6). A7 shows how AI-powered platforms that update themselves can give continuous, real-time personalised learning. These systems could turn lifelong learning into an ongoing journey for personal and professional growth, making AI an important part of future education (A7). A10 highlights ChatGPT's transformative role in education, offering personalised learning and research support, while stressing the need to address ethics, equity, and human-AI balance (A10). A11 positions AI as a key driver of educational reform, reshaping classrooms, teaching methods, and learning goals, while fostering innovation and future-ready competencies (A11). A12 highlights that ChatGPT promotes critical thinking, as students evaluated its outputs rather than relying blindly. This suggests AI tools can transform learning by fostering reflection, autonomy, and more responsible use of technology (A12). A13 demonstrates AI's transformative role in fostering critical thinking, emotional regulation, and resilience, thereby strengthening autonomy and engagement in lifelong learning (A13). Finally, A14 shows generative AI's transformative potential for optimising learning, from literacy and skill development to resilient, inclusive education systems, while warning that impact depends on responsible use, privacy safeguards, and strong human-AI collaboration (A14).

In summary, the reviewed studies show that AI in lifelong learning is shaped by social, cultural, and ethical contexts (Theme 1), offers clear benefits such as personalised feedback and flexible learning (Theme 2), and holds strong potential to transform education by fostering autonomy, critical thinking, and innovation (Theme 3). At the same time, its successful integration depends on responsible implementation, sensitivity to learner and contextual differences, and active collaboration between educators, institutions, and policymakers.

5. Discussion

Lifelong learning has long been seen as essential for adapting to changing labour markets and societal needs (Frey & Osborne, 2017; Laal & Salamati, 2012). In this review, three themes emerged that reveal how AI shapes lifelong learning through adoption perspectives, the benefits it brings, and its transformative potential. These

themes build directly on the view of lifelong learning as both an individual and collective responsibility (Jaldemark et al., 2021; Jarvis, 2007), where technology can either widen or reduce learning opportunities depending on its design and use.

First, the findings on perspectives shaping AI in lifelong learning showed how contextual elements, financial support, digital competence, cultural attitudes, and ethical concerns strongly influence AI adoption. For instance, A1 illustrated how financial and infrastructural challenges affect AI uptake in African contexts, while A3 pointed to differences in adoption depending on learners' age and digital competence. A2 highlighted how perceptions of students, faculty, and administrators shape the uptake of AI in higher education, where optimism is balanced with concerns about ethics, transparency, and bias. Similarly, A7 emphasised the importance of ethical principles and collective responsibility, and A14 underscored the broader societal context, linking AI adoption to inclusivity and sustainability. This connects back to Jaldemark (2021), who stresses that lifelong learning is embedded in broader social and institutional systems. Without supportive policies and inclusive design, AI risks reinforcing rather than reducing inequality.

Second, the findings on the benefits of AI tools in education revealed strong evidence that adaptive platforms, tutoring systems, and generative AI can personalise learning, boost motivation, and support self-regulation. A1 and A2 highlighted how adaptive systems provide flexible learning pathways, while A3, A8, and A9 demonstrated how tools like ChatGPT and similar systems can support motivation, collaboration, and skill development. A12 and A13 showed ChatGPT's role as a tutor and feedback provider, fostering competence and autonomy, and A11 pointed to the value of robots and recognition technologies improving assessment and efficiency. These findings align with Hwang (2014) and Hwang et al. (2020) on personalisation and Kristiansen et al. (2025) on professional development. At the same time, several studies stressed risks, including bias, privacy, inequality, and overreliance on AI (A2, A3, A10, A11, A12, A14). These cautionary findings underline the need for teacher guidance and ethical safeguards, echoing Escotet (2024) and Fahimirad and Kotamjani (2018), who view AI as a support, not a substitute, for human educators.

Finally, the theme on AI's potential for optimising and transforming learning highlighted its capacity to foster creativity, reflection, and autonomy, and to reshape education as a lifelong journey rather than a one-time stage. A1 suggested the role of deep learning for finer personalisation and creativity, A4 envisioned AI as a lifelong learning companion integrating coaching and industry certification, and A6 proposed frameworks linking higher education to real-world and industrial challenges. A7 described AI-powered platforms that update in real time, supporting continuous lifelong learning, while A10, A11, A12, and A13 all pointed to AI's transformative potential in reshaping classrooms, promoting critical reflection, and strengthening resilience and autonomy. A14 further extended this view by linking AI directly to the global agenda for sustainability and inclusivity, but also warning against risks such as inequity, bias, and over-reliance. This extends Jarvis's (2007) view of lifelong learning as identity development and resonates with Reis-Andersson (2024), who stresses lifelong learning as key to societal progress. Yet, as the findings and the background both point out, realising this transformative potential requires responsible governance, attention to ethics, and safeguards to ensure that AI fosters equity rather than exclusion.

In relation to the first research question, this review shows that AI contributes to lifelong learning by enabling personalised and adaptive pathways, providing flexible access to resources across contexts, and supporting continuous competence development. Regarding the second research question, the findings indicate that AI can empower learners by fostering autonomy, critical thinking, and resilience; empower educators by reducing routine tasks and enhancing pedagogical practices; and empower institutions by supporting innovation and wider access, while also raising important ethical and equity considerations.

In summary, this discussion shows that AI is reshaping lifelong learning in three interconnected ways: by being shaped through social and cultural contexts, by offering concrete benefits for learners and educators, and by holding potential for long-term transformation. These themes underline AI's dual role as both a practical tool for personalisation and access, and as a broader driver of change in how education is understood and practiced in a lifelong perspective.

5.1 Implications

One implication of this review is that much of the existing scholarship on AI in lifelong and personalised learning consists of secondary literature, such as reviews, bibliometric analyses, opinion pieces, and trend reflections, rather than empirical studies involving participants, interventions, or observed practices. While these secondary contributions help to map the field and signal areas of interest, they do not provide robust evidence about how

AI is actually integrated into lifelong learning in practice or how learners, educators, and institutions experience empowerment through AI. This imbalance suggests a pressing need for empirical, data-driven research, for example, case studies, experimental designs, or longitudinal investigations, that can validate claims made in conceptual and review papers. Without such work, the field risks being shaped primarily by theoretical or market-oriented narratives rather than by grounded evidence of impact.

6. Conclusion

Lifelong learning is increasingly recognised as essential in a rapidly changing society, where individuals are required to continuously update their knowledge and skills. AI plays a significant role in this context by enabling new forms of educational support. A core objective of AI in education is to provide personalised learning pathways through adaptive guidance and feedback that take into account learners' progress, preferences, and individual characteristics. In doing so, AI contributes to the broader goals of lifelong learning by facilitating continuous competence development and enhancing learners' ability to participate actively in society.

6.1 Future Research

Building on the limitations identified, future research should move beyond conceptual discussions and focus on empirical investigations of how AI is actually used in lifelong and personalised learning. Such research would generate the kind of grounded evidence currently missing in the field and provide a stronger foundation for policy and practice.

Ethical declaration: An ethical declaration was not required.

Generative AI statement: Artificial intelligence tools, specifically ChatGPT, were used during the writing process of this paper to support language editing and improve clarity. All content and ideas remain the sole responsibility of the author(s).

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Does AI Help (or Hinder?) Sustainability Marketing

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Abstract: This research study builds on the longitudinal research (Robertson, Deaville 23, 24) which highlighted factors relating to how the marketing industry are using Artificial Intelligence (AI). Content generation was the biggest area of use (and concern) within the sector. However, the research highlighted some major concerns, limitations and worries about "fake", "untruthful" and "unreliable" content and the "legal" implications from this, which has been used for the inspiration and starting point for this study. This research paper aims to further develop and reflect on the implications and issues of human led content versus AI generated content in the copywriting of sustainable / environmental marketing materials. It is hoped that this research will inform future development for practitioners developing environmental messaging for organisations.

Keywords: Human versus AI content, AI-Enabled environmental marketing, AI-Generated content, Content authenticity, Legal implications of AI, Sustainability communication, Green marketing ethics

1. Background

Building on a two-year mixed-methods study and the findings presented at the ICAIR 4th International Conference on AI research in Lisbon, this paper offers evidence-based insights into the evolving role of AI in sustainability marketing—highlighting both opportunities and ethical tensions that are critical for practitioners and scholars alike.

1.1 Research Questions and Approach for Proposed Model

RQ1: The difference between AI and human authored content for sustainable marketing messages

RQ2: A guide to help future sustainable content generation for business

1.2 Methodology of Previous Mixed-Method Research

In our previous mixed-method research we used qualitative surveys (Robertson, Deaville, 2024) in collaboration with digital marketing leaders. This developed our thinking from the previous mixed-method research conducted the year before in 2023 with over a hundred respondents. Survey responses from the 2023 and 2024 studies are included in Appendices 1 and 2 of this report.

We used Qualtrics as our survey platform for both phases. We collaborated with a networked group *Agency Hackers* who have 11,000 UK members, largely senior leaders in digital marketing. We shared the survey with potential respondents via social media, concentrating on LinkedIn through the networked group and digital agency partner's pages. The Data Marketing Association Digital (DMA) Task Force also inputted in the process with a workshop held between the phases.

Gaining responses became more challenging in the follow-up phase in 2024. We hypothesised that this may be due to the increase in content about Artificial Intelligence and general "noise" around AI in the media potentially reaching peak content; meaning our research survey had to cut through the noise, which was less easy to do. However, we gained over 129 individual responses (up 29 from the previous study) in 2024 but noted the increased efforts to gain this response rate.

Our respondents were broadly spread across senior level roles; in-house marketers (26%) and working in agencies (40%). Our respondents were 61% male and 36% female and the largest group were aged 35-54 (58%); 74% were educated to undergraduate degree / master's degree level. Five percent of respondents identified as Black, Asian, or belonging to other racially or ethnically minoritised groups.

As perhaps you would expect from the marketing sector, 93% stated that they were "extensively/to some extent" using AI in their marketing activities (Robertson, Deaville, 2024). And 91% stated that they were using AI-powered content creation tools (eg, ChatGPT, Copy.ai).

When asked in the 2024 study which areas of marketing AI would have the greatest potential impact, 46% stated creative process, 62% content creation, 40% research, and the largest group at 61%; data analysis and insights.

We also explored how respondents rated the quality of content produced by AI tools compared to human-created content and 43% felt it was "slightly / significantly" below human-created content.

Related to the quality of content produced by AI tools, we asked how much human intervention was typically required to make AI-generated content usable for their marketing purposes; 69% stated "moderate, extensive, substantial" editing was needed of this AI content.

We looked to the future and asked which areas of marketing AI would have the most impact in the next 3-5 years and 37% chose "content creation and search optimisation".

We used the barriers and challenges identified in the previous research as the foundation for the 2024 study. We explored the levels of human input on AI generated content in the second phase of research.

In our previous study (Robertson, Deaville, 2024), a third of the marketers (32%) stated they faced "ethical concerns" when implementing AI in their marketing. The free text box comments revealed a range of concerns and their approach to tackling these concerns, shown in table 1.

Table 1: (Robertson, Deaville, 2024)

Ethical concerns raised by respondents through the free-text responses in the survey	**Respondents approach to maintaining the ethical use of AI in marketing through the free-text responses in the survey**
"Sustainability, privacy, security, economic impact"	"Ensure the tools we choose are ethical and ensure there is no data collection involved with genAI"
"Lack of robust governance framework; both externally and internally"	"By setting limitations and ensuring there are clear boundaries. Effective prompt engineering will be vital also"
"Erosion of the critical thinking required to appraise quality output, whether created using AI or not"	"We will always say when something is AI generated"
"Environmental impact needs to be quantified and countered"	"I always ensure that I'm using reliable websites, AI Tools, and following the right type of people to learn AI through verified resources and reliable people in marketing industry"
	"It needs to comply with existing guardrails"

2. Developing Study Focus - AI and Human Centred Sustainable Marketing

2.1 Literature Review

This current research aims to develop the concept of AI and human centred sustainable marketing content. There is growing evidence that digital marketing plays a crucial role in engaging environmentally conscious consumers. Recent studies show that eco-friendly consumer behaviour is reshaping brand strategies, highlighting the importance of using accurate and relevant content to connect effectively with these audiences (Rana, Kumar, & Kapoor, 2021). However, there does not appear to be one single large-scale study that directly compares AI-generated versus human-generated sustainability messaging for public trust (i.e., sustainability campaigns, ESG/SDG content).

The aim of this study is to use the various studies that have been conducted in related areas as foundation / evidence that authorship (AI versus human) and source disclosure effect trust, credibility and message reception.

The area of sustainability messaging is an under explored area of research, which could be a unique case for further study, based on these findings.

The issue of trust has been central to several studies relating to AI usage. A recent global survey of 48,340 respondents across 47 countries found that only 46% of people are willing to trust AI systems (Gillespie et al., 2025).

Other research has examined the impact of using AI-generated images (vs. real photographs) in social media posts of green influencers; three experimental studies showed that compared to posts using real photographs, posts that use AI-generated images are less likely to receive favourable consumer responses (Narayanan, 2025).

According to the International Telecommunication Union's *AI for Good Impact Report* (2025), "AI systems increasingly shape the way sustainability narratives are created and consumed," highlighting the importance of transparency and ethical storytelling to sustain audience trust. This aligns with current concerns over whether AI-generated sustainability messages appear less credible or authentic than human-written ones.

Another study analysed the ethical/social/environmental risks of AI systems (e.g., energy consumption, resource-use, rare earth dependence), which is increasingly raised as an issue of AI usage. As AI reshapes industries its environmental and social impacts are under increasing scrutiny (SGS white paper) The latest white paper offers practical insights into how public and private sector organisations can embed sustainability ethics into every stage of the AI lifecycle – from development to deployment and beyond. (SGS white paper). Although this is not directly related to communications, we do see another level of trust and credibility erosion with the mention of AI usage and its environmental impact.

Recent experiments demonstrate that even when identical content is attributed to an AI author, audiences rate it as less credible and less trustworthy than when it is attributed to a human author (Zhu et al., 2024). Again showing the trust issues with AI.

In a study of 43 participants, readers were unable to reliably distinguish between AI-generated and human-written social media posts, underscoring how blurred the line has become in content attribution. The authors also propose guidelines for transparent disclosure of AI authorship to preserve trust in public content (Smith, (J., Doe, A. & Lee, C., 2024). Developing this thinking, another recent study finds that revealing AI authorship can significantly lower the perceived credibility of a message, showing that disclosure itself may undermine trust in AI-generated content (Schilke, 2025).

Although not specific to sustainability, another framework distinguished AI-generated from human-written content based on syntax, semantics, and pragmatics, highlighted that AI content, while fluent, often lacked depth and contained subtle factual inaccuracies (Ma, Liu, Yi et al, 2023).

Perhaps more importantly for marketers, engagement rates increase with human written content - not specific to environmental / sustainable content in this study;

2.2 Human-Written Articles Received 5 Times More Organic Traffic

Time on page and engagement metrics were significantly higher for human-authored pieces (Ross, 2025).

Another study showed 3,200 participants sustainability messages generated by:

Real humans

Simulated humans (AI trained on human data)

Fully synthetic AI personas

The study concluded human-authored messages were more persuasive in emotionally charged sustainability topics. Although AI-generated content was more effective when framed with data and logic, especially for audiences already inclined toward environmentalism (Doudkin, Pataranutaporn, Maes, 2025).

Other studies have explored how AI and human content performs across various marketing channels and also concluded that human content excels in emotional resonance and trust-building, whereas AI content is useful for scaling and consistency, but may struggle with nuanced ethical messaging (Wolf, 2024).

This relates to the speed and scale at which AI can act. Although AI was faster and more scalable, ideal for data-heavy sustainability reports, the human content was more trusted, especially when discussing ethical or controversial environmental issues (Wolf, S, 2024).

The theme of trust was developed by Xu, Huam, and Sade, 2024 in *Is AI better than humans?* and influencers endorsing sustainable products. The human influencers were more effective in emotionally framed, low-involvement sustainability messaging. And virtual influencers outperformed humans in rational, high-involvement product scenarios (e.g., eco-tech, sustainable finance).

Although Xu Yan et al. (2024) demonstrate that virtual influencers (VIs) outperform human influencers (HIs) in high-involvement, rational-appeal sustainable product scenarios, the authors do **not** present concrete examples of such product categories, which limits direct applicability for copywriting strategy.

The credibility concerns were higher for AI influencers, but cost-effectiveness and scalability made them attractive for certain campaigns.

The current literature review provides some evidence of different types of content and trust levels, relating to greenwashing (and greenwashing practices, delivered for different reasons). There are challenges around the best way of measuring content types and making this useful for businesses. It has been stated that greenwashing

is often on a "grotesque scale"; deliberate strategies which may be beneficial for firms but detrimental to society (Dorfleitner, Utz, 2024).

Edelman's yearly Trust Barometer (2024) also showed a decline in consumer trust towards AI-generated content. According to the 2024 Edelman Trust Barometer, only 30% of global respondents embrace AI, while 35% reject it, reflecting growing scepticism toward AI-generated content in marketing (Edelman, 2024).

The report also emphasises that innovation without trust risks societal instability, especially in areas like sustainability marketing where authenticity is paramount (Edelman, 2024).

Channel 4's use of an AI presenter in Will AI Take My Job? illustrates the growing role of artificial intelligence in public-facing media, raising questions about realism and trust (Channel 4, 2025).

This aligns with the 2024 Edelman Trust Barometer, which found declining consumer trust in AI-generated content, especially in contexts like sustainability marketing (Edelman, 2024).

Future developments could focus on addressing these gaps with more sophisticated, scalable AI and real-time detection. Related to this, the UCD Institute of Discovery in Ireland have built a climate change mitigation greenwashing detection tool which analyses the claims of companies (Cojoianu, Hoepner, Ifrim, et al, 2020). We also have seen companies such as EY develop a prototype known as the "Greenwashing Compass" (Quanta Intelligence, 2024).

However, being accused of greenwashing has never been a good for companies of any size, but the consequences for organisations may have just became far more serious. A new legislation makes greenwashing a criminal liability.

As of 1 September, '25, the UK's Failure to Prevent Fraud (FTPF) offence came into force under the Economic Crime and Corporate Transparency Act 2023. What was once primarily a regulatory or reputational issue (misleading sustainability claims flagged by watchdogs) can now lead to criminal liability (Economic Crime and Corporate Transparency Act, 2023).

Companies meeting two of three criteria (more than 250 employees, more than £36 million turnover, or more than £18 million in total assets), can be held liable if an "associated person" (which could be an employee or **agency acting on the company's behalf**) commits fraud that aims to benefit the company, unless the company can show it had reasonable fraud prevention procedures in place. The definition of fraud in the Act covers false representation, failure to disclose, and misleading statements by directors, all areas directly relevant to sustainability claims.

For businesses, this could be a turning point as greenwashing is now no longer just a matter for the CMA, ASA, but can carry unlimited fines and/or criminal consequences.

The legislation should help put sustainability at the heart of governance. In a world where trust is increasingly everything, proving your honesty may soon matter just as much as proving your impact.

2.3 Summary of Research Findings From Peer Papers

Study	AI generated	Human generated	Implications for practice
Gillespie et al., 2025	46% of people are willing to trust AI systems		**Trust issues with AI as source generator**
Narayanan, 2025	**AI-generated images** by green influencers in **social media posts gain less favourable consumer responses**	Real photographs by green influencers in social media posts gain more favourable consumer responses	**Trust issues with AI generated images**
Zhu et al., 2024	Identical content is attributed to an AI author audiences rate it as less credible and less trustworthy	Identical content attributed to human author more credible and trustworthy	**Trust issues with AI as source generator**
Schilke, 2025	AI authorship can significantly lower the perceived credibility of a message, disclosure itself may undermine trust in AI-generated content		**Trust issues with AI as source generator**

Study	AI generated	Human generated	Implications for practice
Ma, Liu, Yi et al, 2023	AI-generated content based on syntax, semantics, and pragmatics, highlighted that AI content, while fluent, lacked depth and contained subtle factual inaccuracies	Human generated content more accurate and with depth	**Human more accurate / depth** **AI introduces inaccuracies**
Ross, 2025		**Human-written articles received 5 times more organic traffic.** Time on page and engagement significantly higher	**Human content more engaging**
Doudkin, Pataranutaporn, Maes, 2025	AI-generated content more effective when framed with data and logic, especially for audiences already inclined toward environmentalism	Human-authored messages more persuasive in emotionally charged sustainability topics	**Human content persuasive / emotional** **AI role in data and logic**
Wolf, 2024	AI content useful for scaling and consistency, but may struggle with nuanced ethical messaging	Human content excels in emotional resonance and trust-building	**Human content more emotional and builds trust** **AI good for scale**
Xu, Huam, and Sade, 2024	Virtual influencers endorsing sustainable products outperformed humans in rational, high-involvement product scenarios (e.g., eco-tech, sustainable finance).	The human influencers endorsing sustainable products were more effective in emotionally framed, low-involvement sustainability messaging.	**Human influence emotionally framing is good** **AI influence worked well for rational high involvement products**
Edelman, 2024	Decline in consumer trust towards AI-generated content, only 30% of global respondents embrace AI, while 35% reject it, reflecting growing scepticism toward AI-generated content in marketing		**AI content rejection**

2.4 Findings Contextualised in Analytical Model

Using the data and insights from previous studies, an analytical model has been created to interpret messaging and the appropriate application of AI to human content in sustainable marketing communication.

This framework potentially allows researchers and practitioners to evaluate the appropriate balance between AI-generated, human-generated, or hybrid content across various communication contexts.

Each category is scored from 1 to 5, where 1 represents minimal application and 5 represents high application or effectiveness. The resulting scores guide decisions on content strategy in sustainable marketing communication.

The model follows the theory that organisations which are well resourced might introduce elements of internal and external comms that are AI / hybrid generated. If organisations are less well-resourced and focused (a "laggard"), they may well be wise to focus much of their activity in the hands of humans until they have built credibility to the next stage and created the all important trust. Therefore, the theory suggests a resource maturity curve where organisations move from human-led operations to hybrid and AI-driven communications as they gain capacity and trust.

3. Defining Organisational Archetypes

These user categories and personas helps stakeholders self-identify and see where they fit.

Category	Org typology	Resources	Comms Style	AI Application	Strategic Focus
High	**Org1**: High-performing, innovation-driven	Abundant	Integrated, proactive	Internal AI	Optimise, innovate, scale

	Org2: Operationally sound, cautious adopter	Stable	Structured, consistent	Internal AI	Improve efficiency, pilot external AI
Medium	**Org3**: Transitional, seeking efficiency	Limited	Reactive, basic	Hybrid AI/Human	Build trust, test AI in low-risk areas
Lower	**Org4:** Resource-constrained, trust-building	Scarce	Manual, fragmented	Human-led	Stabilise, build foundations
	Org5: Vulnerable, reactive	Minimal	Ad hoc	Human-led	Survival, trust-building

3.1 Strengths of Model

Trust acts as a prerequisite: emphasis that trust in AI systems must be earned, especially in lower-resourced environments.

Gradual AI integration: hybrid phase allows for experimentation without full reliance, which is smart risk management.

Internal vs. external comms distinction: Crucial—internal AI can be piloted with less reputational risk than external-facing systems.

3.2 Map AI Readiness Indicators

For each category would need to define:

Data maturity

Staff digital literacy

Leadership openness to automation

Appetite for risk

3.3 Create a Maturity Roadmap

To Show how an Org5 can become Org1:

Phase 1: Human-led stabilisation ➡	Phase 2: Hybrid pilots (internal) ➡	Phase 3: Internal AI scaling ➡	Phase 4: External AI integration ➡	Phase 5: AI optimisation and innovation

Included would be trust-building milestones like transparency, feedback loops, and ethical safeguards.

3.4 Develop use Case Libraries

For each phase, list practical AI applications:

Internal AI: Meeting summaries, workflow automation, sentiment analysis

External AI: Chatbots, personalised outreach, predictive engagement

This would help organisations visualise benefits and risks.

3.5 Embed Governance and Ethics

Especially for lower-resourced orgs, emphasize:

Human-in-the-loop systems

Clear escalation paths

Bias monitoring

Consent and transparency in external comms

3.6 How This Could Work in Practice

Imagine a nonprofit (Org4) with limited staff and budget

⬇

They start with human-led comms and manual reporting.

⬇

Introduce AI summarisation tools for internal meetings (low risk).

⬇

Build trust through consistent results and staff training.

⬇

Gradually pilot chatbot for donor FAQs (external hybrid).

⬇

Eventually scale to predictive donor engagement (Org2/Org1 territory).

⬇

The model gives them a safe, strategic path to AI adoption.

3.7 Organisation Spread

Category	How sustainable delivery	Resource levels	Internal comms	External comms	Total org score	5 (AI application – internal)	5 (AI application External)
High	5 (Org1)	5 (Org1)	5 (Org1)	5 (Org1)	20		
	4 (Org2)	4 (Org2)	4 (Org2)	2 (Org2)	16		
Medium	3 (Org3)	3 (Org3)	3 (Org3)	3 (Org3)	12	3 (Hybrid AI / Human)	3 (Hybrid AI / Human)
	2 Org4)	2 (Org3)	2 (Org3)	2 (Org3)	8		
Lower	1 (Org5)	1 (Org5)	1 (Org5)	1 (Org5)	4		
						1 (Human application– internal)	1 (Human application– external)

3.8 Strategic Planning

Use scores to guide investment:

Low scores → invest in training, trust-building, and pilot programmes.

Mid scores → scale hybrid systems.

High scores → optimise and innovate.

4. In Conclusion

This study aims to deepen our understanding of the fast-changing interplay between AI-generated and human-authored content in sustainable marketing. While we know AI offers efficiency and scalability, there are concerns around authenticity, trust, and legal accountability—especially in the context of greenwashing. By comparing content types and exploring trust dynamics, this research highlight the urgent need for clearer standards and ethical frameworks. The proposed guide aims to support practitioners in crafting credible, impactful environmental messaging that balances innovation with integrity. Ultimately, sustainable marketing must be both trustworthy and factual—whether powered by algorithms or authored by humans.

Ethics declaration: Ethical clearance was not required for the initial phases of the research conducted in 2023 and 2024, as the work was undertaken in collaboration with an external agency partner. However, appropriate ethical approval was subsequently obtained for later stages of the study.

AI declaration: AI tools (specifically Microsoft Copilot) were used to support various aspects of this research, including literature review exploration, reference formatting, conclusion framing based on original analysis, refinement of search terminology, and rephrasing of selected written content. No direct copying or pasting from AI-generated outputs was used, in accordance with the copyright declaration submitted.

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A Hybrid Model for Stock Market Forecasting: Integrating News Sentiment and Time Series Data with Graph Neural Networks

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Abstract: Stock market prediction has long been a challenging problem in the field of finance and investment. Accurately predicting the movements of stock prices is crucial for making informed decisions and maximizing investment returns. Traditional models mainly use historical prices. We found that there is a gap in research in integrating financial news into the model, which has emerged as a promising direction in enhancing predictive accuracy. This research aims to address this problem by exploring a multimodal approach by combining companies' news articles and their historical stock data to predict future stock movements. The objective was to compare the performance of a Graph Neural Network (GNN) model with an LSTM model. The methodology employed in this research involves an LSTM model that embeds the historical data for each company and a language model to embed news articles. These embeddings will represent nodes that have relationships presented by edges within a graph. Using a GNN message aggregation technique known as GraphSAGE, the model should be able to capture interactions and dependencies between news articles, companies, and industries and use this information to predict future stock movements. Two target variable approaches are explored: one focusing on the binary classification of whether the stock price will increase or decrease, and the other considering the significance of the increase. This methodology was evaluated on two datasets, the US equities dataset and the Bloomberg dataset. The results showed that the GNN model was able to achieve better performance than the baseline LSTM model on both datasets. The GNN model achieved an accuracy of 53% on the first target, a statistically significant 1% improvement over the baseline, and a 4% precision gain on the second target, which confirms the effectiveness of exploiting financial news using graph-based models. Furthermore, we observed that increasing the number of news samples led to improved accuracy. We also find that headlines contain stronger predictive signal than full articles which is consistent with evidence that headlines disproportionately shape readers' judgments and market reactions.

Keywords: Deep learning, Graph neural networks, Finance, Knowledge graph

1. Introduction

The stock market continues to play a crucial role in the global economy, providing a platform for individuals to invest their savings and potentially earn returns. Despite recent fluctuations, the stock market remains a key indicator of the overall health and stability of a nation's economy, and it continues to shape the economic landscape and investment decisions of both individuals and organizations. Therefore, financial analysts use various types of analysis for stock evaluation and decision-making; however, our focus is on both "Technical Analysis" (Fama & French, 1992) and "News-based Analysis". By definition, technical analysis uses charts and other statistical analysis to identify patterns in a stock's price and volume data to predict future price movements while news-based analysis involves evaluating the potential impact of news events, such as earnings reports, product launches, regulatory changes, and other relevant events, on a company's stock price and overall financial performance. AI has the potential to revolutionize the stock market prediction process, in which a lot of methods that use technical analysis or news-based analysis have been evaluated, whereas combining both approaches and representing them in a knowledge graph has not yet been extensively explored. Consequently, we have chosen GNNs that can mimic human behaviour and are particularly well-suited to tasks that involve modeling relationships and interactions between entities in a graph, such as those found in financial markets. But the stock market is a complex system, and making predictions about it is a challenging task. Hence, we will investigate whether using the graph representation helps the model learn how external information influences individual companies by considering their industry context and news impact.

2. Background and Related Work

In this section, we will provide an overview of the key components and techniques utilized in our model. And would also provide an overview of previous studies or works that have used similar techniques to predict the stock market. Our objective is to contextualize the research by highlighting the gap in the literature that the current study aims to fill and to provide evidence of the novelty of the current research. The following papers

will review studies that have used GNNs for stock market prediction, critically evaluate their methodologies and results, and explain how they differ from the current study.

2.1 Background

2.1.1 Graph neural networks

Let a graph be defined as $G = (V, E)$ where:

- V is the set of nodes, with $|V| = n$.
- $E \subseteq V \times V$ is the set of edges, with $|E| = m$.

The graph can be represented by an adjacency matrix $A \in \{0,1\}^{n \times n}$, where:

$$Aij = \begin{cases} 1 \; if \; (i,j) \in E \\ 0 \; otherwise \end{cases}$$

Each node $i \in V$ has a feature vector $\boldsymbol{x}i \in R^d$, and all node features are collected in a matrix $X \in R^{n \times d}$

The task is to predict a label $yi \in \{0,1\}$ for each node i.

The GNN follows a message-passing framework where, at each layer k, messages from neighboring nodes are aggregated and then combined with the current node's embedding. The message passing update rules at layer k are given by:

$$m_i^{(k)} = AGG^{(k)}\left(\left\{\left(x_j^{(k-1)}, x_i^{(k-1)}\right) : (i,j) \in E\right\}\right) \qquad (1)$$

Next, the embedding of node i is updated as follows:

$$x_i^{(k)} = COM^{(k)}\left(x_i^{(k-1)}, m_i^{(k)}\right) \qquad (2)$$

- $m_i^{(k)}$: The aggregated message for node i at layer k, which is a function of the neighboring nodes j and their respective embeddings $x_j^{(k-1)}$ from the previous layer.
- $AGG^{(k)}(\cdot)$: The aggregation function at layer k, which aggregates the messages from the neighbors of node i.
- $x_i^{(k)}$: The new embedding for node i at layer k, obtained by combining the current embedding
- $x_i^{(k-1)}$ with the aggregated message $m_i^{(k)}$.
- $COM^{(k)}(\cdot)$: The combination function at layer k, which combines the current node embedding $x_i^{(k-1)}$ with the aggregated message $m_i^{(k)}$.

2.1.2 Financial text analysis

FinBERT (Yang, et al., 2020) is a pre-trained language model that is specifically designed for financial text analysis. It is built by further training the popular Bidirectional Encoder Representations from Transformers (BERT) (Devlin, et al., 2018) architecture on a large corpus of financial documents, including SEC filings, earnings call transcripts, and news articles. Then it was fine-tuned for financial sentiment classification. It prepends a special token to the sentence [CLS]. In our context, the mentioned model was used to extract the news embedding.

2.1.3 Time series analysis

Time series analysis is a statistical method used to analyze data collected over time. In our context, time series analysis is used to analyze historical stock price data to identify patterns and trends, to make predictions about future stock prices, and to extract company embeddings using LSTM and Transformer models (Vaswani, et al., 2017).

2.2 Literature Review

In this section, we provide an overview of previous studies that have employed similar techniques for stock market prediction to contextualize our research and demonstrate its novelty. The existing body of work can be grouped into several key approaches based on the data used to construct the graph relationships.

One cluster of research focuses primarily on graphs derived from textual news data. For example, the *Heterogeneous graph knowledge enhanced stock market prediction* paper (Xiong, et al., 2021) which focused on predicting stock price fluctuations based on financial text using a Multi-grained Heterogeneous Graph (HGM-GIF) framework. A key limitation, unlike our approach, is that they solely relied on news data and did not

incorporate time series data. Similarly, the *Modeling the Stock Relation with Graph Network for Overnight Stock Movement Prediction* paper (Li, et al., 2020) introduced an LSTM Relational Graph Convolutional Network (LSTM-RGCN) model to predict overnight stock movements based on news titles. While these methods are adept at capturing event-driven relationships, they overlook the quantitative patterns found in historical stock prices.

A second approach involves constructing graphs from market data or pre-defined external knowledge, without incorporating news. The paper *Exploring Graph Neural Networks for Stock Market Predictions with Rolling Window Analysis* (Matsunaga, et al., 2019) employed Temporal Graph Convolution (TGC) to predict long-term stock values using supplier interaction data but did not utilize news information. Additionally, the *Using External Knowledge for Financial Event Prediction Based on Graph Neural Networks* paper (Yang, et al., 2019) focused on event prediction rather than stock movements, using graph neural networks to forecast future corporate events based on structured knowledge graphs. Along these lines, a recent paper builds a dynamic graph based on the similarity of stock features every day; however, it also doesn't consider information outside stock parameters and makes connections between companies based only on stock prices, which means it doesn't use news. These models effectively capture market structure but miss the crucial context provided by external news events. Taking this concept further, the paper Stock market price forecasting using evolving graph neural network (Korablyov, et al., 2025) propose an "evolving graph neural network" that uses a dendritic artificial immune network (DaiNet) to dynamically cluster stocks and update the graph structure daily based on price movements. While these dynamic methods are sophisticated, their relational graphs are still derived internally from price correlations, and they miss the crucial external context provided by financial news events.

Finally, some studies attempt to fuse multiple data sources. The paper A graph neural network-based stock forecasting method utilizing multi-source heterogeneous data fusion (Li, et al., 2022) developed a comprehensive model that fused transaction data, news text, and graphical indicators. In *Combining Financial Data and News Articles for Stock Price Movement Prediction Using Large Language Model* (Elahi & Taghvaei, 2024) used news articles with few-shot learning on large language models to predict stock movement, but they did not use graph structures and evaluated only 20 companies. While these approaches show promise, the integration of both news-based relationships and historical time-series data within a single GNN framework remains underexplored, which is the primary gap our research addresses. More recently, several survey and review papers have examined the broader use of Graph Neural Networks in financial prediction tasks. For instance, *Graph Neural Networks for Financial Market Prediction: Challenges, Opportunities, and Future Directions* (Zhou, et al., 2024) provides a comprehensive overview of existing architectures, datasets, and methodological challenges. This work further supports the relevance of integrating multimodal signals, such as market structure and textual sentiment, which aligns closely with our hybrid modeling approach. Our approach is distinct in its focus on using news to define the relationships between companies while using their historical stock data as the core features for prediction. This review highlights the unique contributions of our research in integrating news sentiment analysis and time series data for stock market prediction.

3. Task Formulation and Dataset

3.1 Task

Our goal is to predict the future stock price reaction based on the given news articles and stock history related to each company. We formulate the prediction as a classification problem in which the target class will be "1" for the stock price increase and "0" for the stock price decrease.

In our model, we explored two different approaches during the training process. The first approach involved extracting a single target variable, which focused on whether the stock increased. This binary classification task aimed to predict whether the stock price would go up or down without considering the magnitude of the change.

The target variable y_t is defined as follows:

$$y_t = \begin{cases} 1, & if(\text{close}_t - \text{close}_{t-1}) > 0) \\ 0, & \text{otherwise} \end{cases}$$

Where:

- $close_t$ represents the stock's closing price at time t.
- $close_{t-1}$ represents the previous closing price.
- $y_t = 1$ if the stock price has increased, and $y_t = 0$ if it has decreased or remained the same.

This approach focuses on predicting the direction of stock price movement, without considering the magnitude of the change.

However, inspired by the relevant research paper Modeling the Stock Relation with Graph Network for Overnight Stock Movement Prediction [Li et al., 2020], and considering real-world investment scenarios in which investors prefer significant returns rather than marginal ones. Therefore, we decided to adopt a second approach. In this approach, we introduced an additional target variable that accounted for the significance of the stock increase. By incorporating this variable, our model aimed to predict not only if the stock would increase but also whether the increase would be significant or not. Yet, we observed that [Li et al., 2020] used this significance-based target and only used accuracy as its evaluation metric, which seems to ignore the fact that using a shifted threshold with such data can alter the reported accuracy and potentially obscure the model's performance. as it can constantly predict one class and result in a deceptively higher accuracy. We avoided such problem by incorporating other metrics like F1, Precision, and Recall alongside accuracy.

$$y_t = \begin{cases} 1, & if(\text{close}_t - \text{close}_{t-1}) > 0.04 \times \text{std}(\text{close}_{t-N:t}) \\ 0, & \text{otherwise} \end{cases}$$

Where:

- $\text{std}(\text{close}_{t-N:t})$ is the standard deviation of the previous N closing prices *(the look back window)*.
- The factor 0.04 scales the threshold to represent a 4 % volatility-adjusted change.
- In our experiments, $N = 100$, i.e., we used the last 100 closing prices to compute this rolling standard deviation.

3.2 Dataset

We conducted experiments on two news datasets covering different time intervals and different sets of stocks to provide stronger evidence in favor of GNNs and LSTM models and compare their efficacy.

The US equities dataset includes 82k articles written between 2015 and 2020 related to 325 companies that trade on NASDAQ (Nasdaq, n.d.). We split it into 1100 training days and 175 testing days.

The Bloomberg dataset includes 450k articles from 2006 to 2013 on 625 companies that trade on NASDAQ and NYSE. Here, we drop the first 2 years as they include very few articles. And we split it into 748 training days and 117 testing days.

4. Methodology

4.1 Data Preprocessing

In this section, we outline the steps taken to preprocess our default dataset "US equities" before training the predictive model.

4.1.1 Companies extraction from news

To ensure that the news articles were relevant to the Nasdaq market, we extracted company names from the Nasdaq screener dataset using a customized named entity recognition (NER) approach. We then filtered both the news and historical data to exclude any data points that were not associated with the Nasdaq market.

4.1.2 Datasets alignment

The extracted company names were used to create a generic version of companies' names by mapping them to their corresponding symbols. This step was taken to ensure consistency in the representation of company names across different data sources and to facilitate the integration of different types of financial data. We also aligned the dates presented in the news dataset and historical dataset.

4.1.3 News encodings

To obtain news embeddings for the news article titles, we utilized a financial embedding model known as Sigma (Sigma AI, 2022), then we saved the news vector extracted to be used in graph creation later.

The Sigma model is a financial sentiment analysis tool built on a transformer architecture like BERT, tailored for finance-specific data. It was fine-tuned using financial documents like SEC filings, earnings call transcripts, and news articles. In this study, Sigma extracts embeddings from financial text, encoding sentiment and context into vector representations. These embeddings help in understanding the influence of news on stock price predictions, as the model learns from the financial relevance captured by Sigma.

4.2 Graph Construction

The graph used in this study consists of two primary components: nodes and edges. Nodes can represent a company, an industry, or an article, while edges denote the relationships between nodes. Specifically, each article node connects to the main company and other mentioned companies that may impact the main company in some way. Additionally, each company node is associated with a particular industry. Each type of node in the graph has its own set of features. The article nodes are represented by news node embeddings, while the company nodes are characterized by concatenated features of historical stock embeddings and learnable embeddings. The industry nodes are represented solely by learnable embeddings. These embeddings are generated by randomly initialized weights, which are then updated while training the GNN. We built the training graph dataset for 15 days before the target stock day. To further ensure that GNN is better than LSTM only, we used the Bloomberg dataset. As this dataset is different from the US equities that we showed its graph creation for above, the graph changed as we eliminated the industry node and extracted the news embedding differently by splitting the article into sentences and then passing them to the Sigma model to get the news node embedding.

4.3 Proposed Model Architecture

The historical stock data used in this study consisted of five main features: open, high, low, close, and volume. We used the close price feature of companies' time series to obtain company embeddings encoded by an LSTM model. This LSTM model takes a sequence of 15-time steps (days). These 15 days window was chosen based on recommendations from financial analysts, as it is considered an optimal period to capture meaningful short-term market trends and momentum while filtering out the noise of daily price volatility. Shorter periods often contain too much random fluctuation, whereas longer periods might smooth out more immediate, actionable signals, making 15 days a balanced choice for modeling significant price movements.

The model processes these sequences through a batch normalization layer first; we didn't normalize the historical data beforehand because we were experimenting with different data-splitting strategies to simplify data handling without compromising model evaluation by causing information leaks. The LSTM consists of 2 layers, and its activations are then passed as company node embeddings for the GNN model. Therefore, the LSTM layers are trained jointly with the GNN, for which we used GraphSAGE as the message-passing layer.

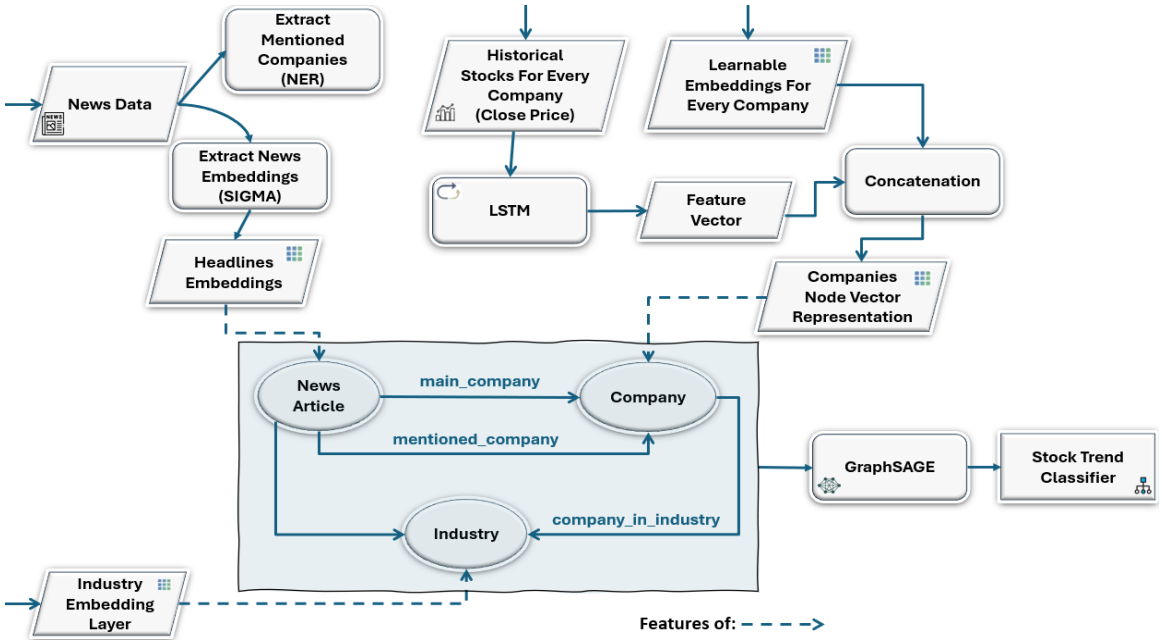

Figure 1: Model Architecture

5. Results and Analysis

This section presents the experiments we went through and our final model results analysis, as our objective was to prove that the LSTM model will not be as effective as the GNN model. Therefore, our baseline model is the LSTM model only trained on historical data, specifically the close price for each company. Then, we introduced the GNN model for the classification problem with the 2 approaches for the target labels that we

mentioned before. First, we conducted some experiments on GraphSAGE conv and chose the best out of them to explore the performance of other GNN techniques and exclude the weak ones. After each experiment, we are going to present every experiment's evaluation using 2 target definitions' results and show the different metrics that are explained in the methodology chapter. The metric for the first target definition is accuracy, as the data is balanced, while the metric for the other target definition is precision, as the data became unbalanced by extracting only a significant increase.

5.1 Experiments

In this section, we will present the experimental models we built in detail, along with their results. For each experiment, we calculate the following metrics:

- Accuracy calculated for the model trained with the first target definition.
- Precision calculated for the model trained with the second target definition.
- Both accuracy and precision on 100 companies for which the model gives predictions with the highest confidence (highest predicted probability).

Any model used in the experiments is explained in the background section 2.

All experiments were conducted on an NVIDIA RTX 2070 GPU, and all the experiments' configurations are as follows:

Table 1: Configuration Table for Both Targets Across Experiments

Hyperparameters	***US Equities***	***Bloomberg***
Number of Epochs	55	55
Learning Rate	0.0001	0.0001
Node Embedding Dimension	128	128
Optimizer	AdamW	AdamW
GNN Layers' Number	3	3
Batch Size	4	4
Highest Confidence Companies	100	200

5.1.1 Baseline model

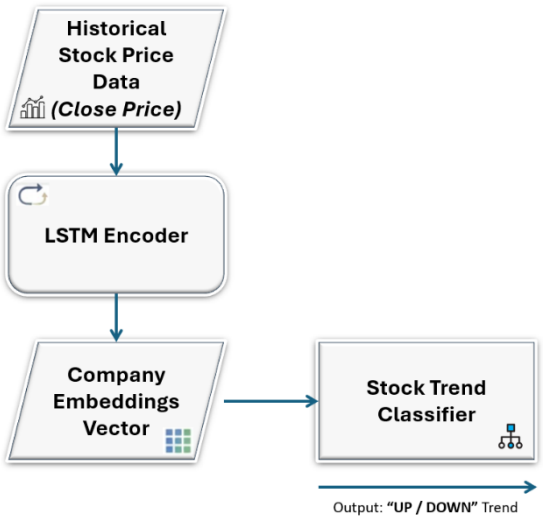

Figure 2: Baseline Model Architecture

This experiment represents the baseline model, in which we used the close price feature of companies' time series as an input for the LSTM model to predict the stock movement.

5.1.2 Experiments' results table

We changed a component with each experiment within the 4 components Node Aggregation Method, News Encoding Model, Timeseries Encoding and which news section to encode. The table below presents all experiments results knowing that best results are shown in **bold**, and the weakest results are in *italics*.

Table 2: Results of each experiment

Experiment	***Aggregation***	***News Model***	***Timeseries Encoding***	***News Section***	***Acc 1st Target ↑***	***Precision 2nd Target ↑***	***Acc@High Certainty ↑***	***Precision@ High Certainty ↑***
1	GraphSage	Sigma	LSTM Close Price	Article Content	53%	53.4%	54.2%	53%
2	GraphSage	Sigma	LSTM Close Price	Article Title	53%	55%	54.2%	53%
3	GAT	Sigma	LSTM Close Price	Article Title	52%	46%	52.63%	25.14%
4	GraphSage	FinBERT	LSTM Close Price	Article Title	52.9%	54%	54.14%	53.2%
5	GraphSage	Sigma	LSTM RSI	Article Title	53%	54.14%	54.5%	57%
6	GraphSage	Sigma	Transformer SMA	Article Title	52.94%	53.5%	54.3%	54.9%

5.1.3 Analysis of experimental configurations

As observed in **Table 2: Results of each experiment**, different model configurations yielded varying results. Our analysis provides several insights into these performance differences.

Note: Experiments 1 vs. 2 isolate headlines vs. content effects; titles yield higher precision.

GraphSAGE vs. GAT: Experiment 3, which used a Graph Attention Network (GAT), showed a significant drop in performance, especially in precision for the second target. This can be attributed to the nature of our graph construction. GATs typically excel on homophilic graphs, where connected nodes are likely to share the same class (e.g., friends in a social network). We constructed our graph by connecting companies mentioned together in the news, which does not guarantee they will have similar stock movements. GraphSAGE, with its neighborhood sampling and diverse aggregation functions, is less reliant on the homophily assumption and thus performed more robustly on our heterogeneous graph.

This observation aligns with findings from recent studies showing that attention-based GNNs such as GATs tend to perform best on homophilic graphs, while heterophilic settings, where connected nodes often have dissimilar labels, favor architectures like GraphSAGE that aggregate more diverse neighbourhood information (Zhu, et al., 2020) (Pei, et al., 2020).

Sigma vs. FinBERT: We also compared news encoding models. **Experiment 2 (Sigma)** slightly outperformed **Experiment 4 (FinBERT).** This is likely because Sigma is a version of FinancialBERT that has been fine-tuned on a larger and more domain-specific corpus of financial documents, allowing it to capture the nuances of financial news more effectively.

Headlines vs. full text. Experiments 1 and 2 differ only in the news section encoded. Titles consistently matched or outperformed full-content variants (e.g., Precision 55 % vs. 53.4 %), suggesting that headlines capture the most behaviourally relevant information for short-term market reactions. This agrees with prior behavioural and neurocognitive evidence that headlines alone can bias readers' interpretations and investor sentiment (Baum, et al., 2021) (Hirshleifer, et al., 2023).

5.1.4 Statistical significance (one-sample proportion Z-test)

We test whether the observed accuracy exceeds random chance (balanced binary task).
H_0: $p = 0.50$ (random) **H_1:** $p > 0.50$.
Observed: $\hat{p} = 0.53$, $N = 56{,}875$ (325 companies × 175 days).
Standard error: $\mathrm{SE} = \sqrt{\frac{p_0(1-p_0)}{N}} = \sqrt{\frac{0.5 \cdot 0.5}{56{,}875}} \approx 0.00210.$

Z-score: $Z = \frac{\hat{p}-p_0}{\text{SE}} = \frac{0.53-0.50}{0.00210} \approx 14.31.$
With $\alpha = 0.05$, the one-sided critical value is $Z_{0.95} = 1.645$(two-sided 1.96). Our result is highly significant (p $\ll$ 0.001), so we reject $H_0$and conclude the model performs better than chance. (Methodology per standard one-sample proportion z-test).

5.2 Final Model Results Analysis

In this section, we will present some analysis conducted on the best and final model we trained in terms of accuracy and precision which you can find in section **Table 2: Results of each experiment**, **Experiment 2** and its results are shown in the following Table 5-3 GraphSAGE Experiment 2 Results. Our goal is to investigate model behavior, its utility, and how it can be improved. The following chart Figure 5-10 reflects the mean number of articles mentioned in the top 50 accuracy companies and in the lowest 50 accuracy companies. Overall, the pattern between accuracy and number of articles is highlighted; when the number of edges between articles and companies increases, the accuracy is positively affected. Hence, it implies the effectiveness of including news in our study; in addition to, representing data in a graphical format which keeps a meaningful representation between articles and companies but also differs between the "mentioned companies" and "main company" edges.

Table 3: Model results on the test set for each target compared to baseline

	Model	***Accuracy*** ↑	***Precision*** ↑	***Recall*** ↑	***F1 Score*** ↑
Default Target	LSTM Baseline	0.52	0.53	0.63	0.57
	Proposed GNN Model	**0.53**	0.527	**0.72**	**0.61**
Target with Significance	LSTM Baseline	0.54	0.51	0.003	0.006
	Proposed GNN Model	**0.546**	**0.555**	**0.02**	**0.04**

As shown in **Table 3: Model results on the test set for each target compared to baseline**, our proposed GNN model delivered an improvement over the LSTM baseline, achieving a 53% accuracy and a significantly higher recall. While the 1% absolute gain in accuracy might seem modest, this figure is a direct result of highly variable news data density across the dataset.

GNN's primary advantage is its ability to interpret the relational information embedded in financial news. However, many companies in our dataset had sparse news coverage on any given day. For these "news-poor" companies, the GNN could not leverage its unique graph-based capabilities, causing its performance to default to a level similar to the time series only LSTM.

Consequently, the overall 1% improvement masks a more significant effect: it represents a blended result where the strong predictive accuracy for news-rich companies is diluted by the baseline performance on companies lacking sufficient news data. This crucial relationship is confirmed by the analysis in **Figure 3: The Mean and Median of High and Low accuracy companies on the test set of US equities.**, which demonstrates a clear positive correlation between the number of news mentions and predictive success.

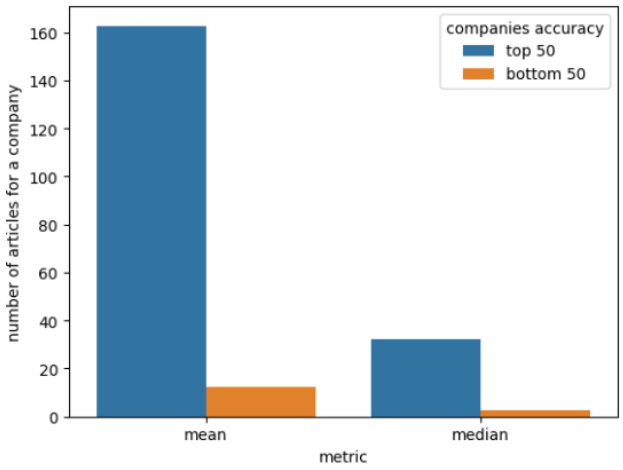

Figure 2: The Mean and Median of High and Low accuracy companies on the test set of US equities.

This bar plot shows that high-accuracy companies are mentioned much more frequently in articles than lower-accuracy companies, but then we checked the histograms of both sets of companies.

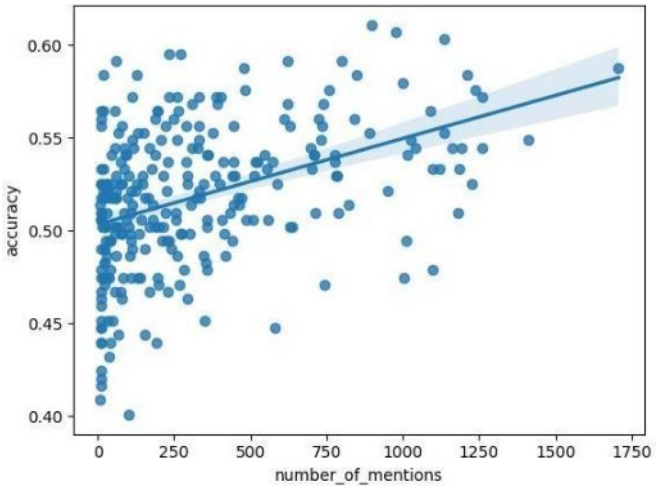

Figure 3: The relationship between the number of mentions and model accuracy on the US equities dataset.

Based on the previous plots, to improve the model, we can collect more news about other companies.

Our dataset time period was between 2015 and 2020, which induced some doubts about the behavior of the trained model, since the world witnessed significant fluctuations since 2019 due to COVID-19.

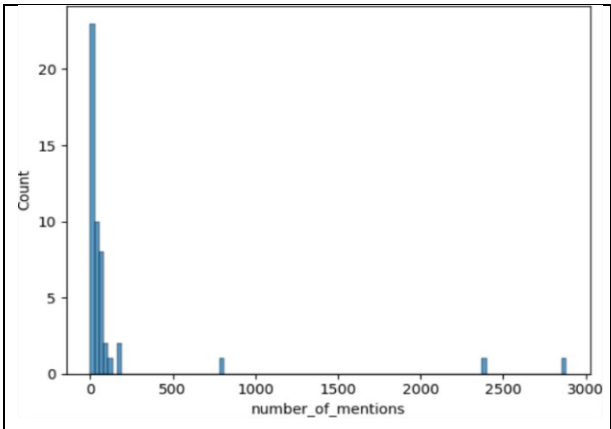

Figure 4: High Accuracy Companies Number of mentions Histogram

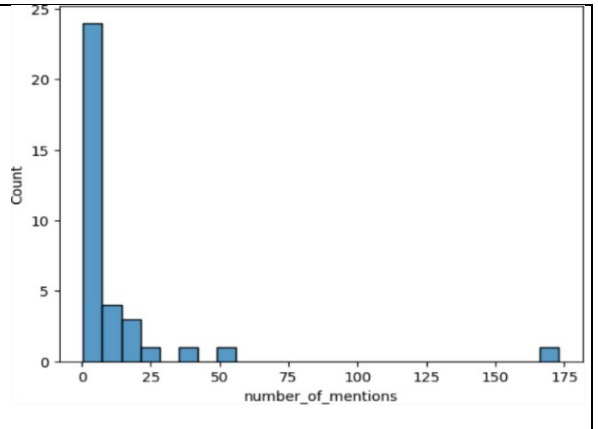

Figure 5: Low Accuracy Companies Number of mentions

6. Conclusion and Recommendation

In conclusion, our research has demonstrated that a Graph Neural Network, which integrates financial news relationships with historical time-series data, consistently outperforms a baseline LSTM model for stock market prediction. The GNN's ability to model the complex interplay between entities in the financial ecosystem confirms the value of this approach.

However, our analysis also highlighted several limitations of the current model, which in turn suggest clear directions for future work to enhance its performance and practical utility.

For practical implications the user of the model can focus on companies that are mentioned more in the news or identify the current set of high accuracy companies.

6.1 Limitation: Sensitivity to Textual Noise and the Need for Event Extraction

A key limitation observed during our experiments was the model's sensitivity to the signal-to-noise ratio in the input text. This was evident when using concise article titles proved to be more effective than using the full article content, which often contains significant irrelevant information. To address this, we recommend focusing on Event Extraction. By using advanced NLP techniques to isolate core financial events (e.g., mergers, earnings reports, product launches) from the article body, we could create a more potent and distilled textual representation. This would make the content more concise and could yield performance comparable to, or even better than, that obtained using only titles.

6.2 Limitation: Simplistic Graph Schema and the Opportunity for Competitor Data

While our graphical representation successfully captured inter-company relationships, its schema is inherently simplistic. The current graph connects companies based on co-mention, treating all relationships as equal without differentiating their nature (e.g., partnership vs. rivalry). To enhance performance, the graph schema could be modified to include richer semantic edges. For instance, if data on companies' strategic relationships, such as competitors and cooperators, were available, a distinct edge type could be incorporated between them. This would allow the model to learn more nuanced patterns of market influence.

6.3 Limitation: Lack of Robust Uncertainty for Practical Decision-Making

From a practical standpoint, the most significant limitation is that for making important investment decisions, a prediction alone is insufficient without a reliable measure of its confidence. While the predicted probability from a neural network offers a proxy for confidence, it is not a robust measure of model uncertainty. To bridge this gap for real-world application, we recommend Measuring Uncertainty in Model Predictions. A powerful approach would be to use the GNN for representation learning and feed these learned representations into a model explicitly designed to handle uncertainty, such as a Gaussian Process (GP) (Williams & Rasmussen, 2006). This would provide not just a prediction but also a confidence interval, creating a far more valuable tool for risk-managed investing.

Acknowledgments and Disclosure of Funding

We would like to express our sincere gratitude to Dr. Cherry Ahmed (Faculty of Computers and Artificial Intelligence, Cairo University) for supervising this project and for her insightful guidance during its initial phases. We also thank the Faculty of Computers and Artificial Intelligence, Cairo University, for providing a supportive academic environment that nurtured our research. We are grateful to the anonymous ICAIR reviewers for their thoughtful feedback and constructive suggestions, which substantially strengthened this manuscript. We acknowledge the use of publicly available resources and tools, including the Bloomberg financial news dataset (used with permission from its author via the project repository), as well as Sigma and FinBERT for financial text embeddings. This research received no external funding; all experiments were conducted on personal computing resources.

Ethics Declaration: The bloomberg data we used required permission from premy.enseirb@gmail.com as mentioned on his GitHub repo: https://github.com/philipperemy/financial-news-dataset and we obtained his permission on Fri, Apr 28, 2023.

AI Declaration: We used AI tools to rephrase the abstract and ensure correct grammar.

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MediMate AI: An AI Assistant for General Practitioners

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Abstract: Primary care remains one of the most demanding areas of medicine, with general practitioners (GPs) facing rising consultation volumes, complex patient presentations, and increasing administrative tasks. These pressures contribute to cognitive overload, diagnostic delays, and burnout. Large language models (LLMs), such as GPT-4, show potential to reduce documentation workload, enhance diagnostic reasoning, and improve overall workflows. However, their integration must be carefully managed to ensure data protection, patient safety, compliance with clinical guidelines (e.g., WHO, CDC), and ethical standards. This paper introduces MediMate AI, a GPT-4–powered prototype assistant designed to support GPs in real time. Implemented as a web-based, mobile-accessible platform, the system integrates multimodal inputs—including speech, text, and images—to transcribe consultations, extract key symptoms, and generate structured summaries. Beyond documentation, MediMate AI provides differential diagnoses with confirmatory test recommendations, evaluates geographic epidemiological risks, and produces tailored hospital routing plans. The prototype was tested in a digital innovation incubator using synthetic patient records and simulated consultations. This approach enabled safe experimentation without breaching patient confidentiality while providing early insights into feasibility, usability, and workflow integration. By combining transcripts, symptom extraction, dermatology image data, and standardized checklists, the prototype reflects the heterogeneous nature of real-world primary care. Results indicate that MediMate AI can reduce documentation workload by an estimated 25–30%, deliver clinically coherent summaries, and generate guideline-aligned differential diagnoses with improved clarity for decision-making. Physicians testing the prototype highlighted its ability to consolidate fragmented data streams, improve continuity of care, and enhance patient–clinician communication. While not intended to replace medical expertise, MediMate AI demonstrates the promise of generative AI to augment decision-making, improve efficiency, and support more patient-centred care. Future work will include prospective clinical validation, integration with electronic health record systems, and the introduction of explainability and bias detection modules. Addressing these aspects will be essential to ensure safe, ethical, and sustainable deployment in healthcare environments.

Keywords: Artificial intelligence, Healthcare, General practitioners, GPT-4, Diagnostic support, Patient triage

1. Introduction

Primary care is the cornerstone of modern healthcare but remains under constant pressure due to rising consultation volumes, complex patient needs, and increasing administrative tasks. General practitioners (GPs) must simultaneously take patient histories, evaluate risks, and maintain thorough documentation while ensuring patient-centred communication, often within a limited timeframe. This workload contributes significantly to cognitive overload and burnout (You *et al.*, 2025). Artificial intelligence (AI) offers a potential solution to these challenges. Ambient documentation systems have already been shown to reduce the burden of note-taking and improve clinician well-being (You *et al.*, 2025). More recently, large language models (LLMs), such as GPT-4, have been applied in clinical reasoning and workflow automation. Randomized controlled trials demonstrated that GPT-4 can improve physician performance in management reasoning tasks, especially among less experienced clinicians (Goh *et al.*, 2025). Similarly, GPT-4 has been shown to provide accurate diagnostic support across diverse clinical scenarios (Noda *et al.*, 2025). Despite these advances, ethical concerns remain. Research highlights that GPT-4 may produce outputs inconsistent with medical ethical standards, underscoring the need for human oversight and transparency (Xiong *et al.*, 2025). Scholars have also raised concerns that uncritical reliance on AI may erode clinical expertise or reinforce systemic biases (Pavuluri *et al.*, 2024). Within general practice, generative AI has been identified as a tool capable of integrating multimodal data and offering more personalized diagnostic and therapeutic reasoning (Geersing *et al.*, 2025). Evaluations of GPT-4 as a clinical support tool highlight its potential to augment performance, but also report non-negligible error rates of approximately 20% (Fabre *et al.*, 2024). Beyond direct diagnostic reasoning, AI-driven systems are transforming documentation and workflows, leading to reduced burnout and improved care efficiency (Bongurala *et al.*, 2024). Importantly, early adoption is already underway. A recent survey revealed that one in five GPs are using generative AI tools such as ChatGPT for documentation, diagnosis suggestions, and treatment recommendations (Kharko *et al.*, 2025). Decision support studies further indicate that AI assistance can improve diagnostic accuracy

without amplifying demographic biases (Goh *et al.*, 2025). Taken together, these findings suggest that AI—and LLMs in particular—have significant potential to reduce workload, support decision-making, and enhance patient communication in primary care. However, their integration must be carefully managed to ensure transparency, safety, and clinical reliability. Against this background, we present MediMate AI, a GPT-4–powered assistant designed to transform patient voice, text, and image input into structured clinical outputs including summaries, diagnostic insights, urgency scores, and hospital routing plans.

2. Data and Methods

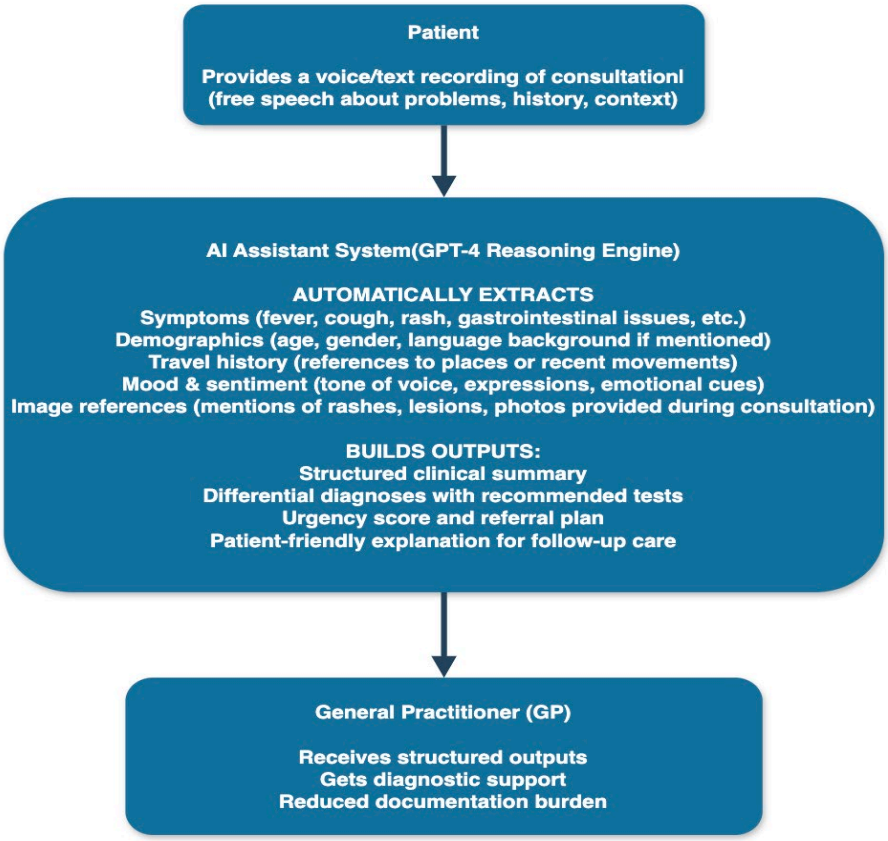

Figure 1: System Workflow: From Patient Input to GP Output

At this stage of development, no large-scale clinical datasets were available. Instead, the prototype was validated using synthetic patient records and mock consultation dialogues carefully designed to simulate realistic encounters in general practice. This approach enabled safe testing without breaching patient confidentiality and ensured early evaluation of technical feasibility and workflow integration. The records used for prototyping included:

- **Patient demographics:** age, gender, language background.
- **Symptom descriptions:** fever, cough, dermatological conditions, gastrointestinal complaints.
- **Audio recordings:** simulated consultations in English.
- **Images: publicly** available dermatological datasets (skin lesions, rashes) used for integration testing.
- **Clinical guidelines:** open-source WHO and CDC symptom checklists and differential diagnosis rules.

By combining these different modalities, the system could be tested on a diverse set of inputs, including voice, text, and image data, reflecting the heterogeneous nature of primary care practice. The emphasis of this stage was not on clinical validation, but on exploring technical feasibility, multimodal data integration, and workflow support for general practitioners.

2.1 Functional Requirements

Based on current literature, a set of **functional requirements** was defined as essential for any AI assistant in primary care. These requirements are summarized in Table 1.

Table 1: Functional requirements for MediMate AI prototype

Functionality	Rationale (literature)	Expected Benefit
Automatic transcription and summarization of consultations	Ambient documentation reduces burden and burnout	Saves time, reduces administrative workload
Symptom extraction and mapping to clinical terminology	Standardized records improve diagnostic accuracy (Geersing *et al.*, 2025)	Accelerates reasoning, ensures consistency
Differential diagnosis with test recommendations	LLMs support clinical decision-making (Noda *et al.*, 2025)	Reduces diagnostic errors, supports junior doctors
Multimodal integration (image + text)	AI improves performance in image-based specialties (Fabre *et al.*, 2024)	Early detection of dermatological/systemic conditions
Mood and sentiment tracking	Emotional monitoring is critical for continuity of care (Kharko *et al.*, 2025)	Early detection of anxiety/depression, improved communication
Geographic risk evaluation	Epidemiological context is essential for differential diagnosis (WHO/CDC)	Identification of imported infections, improved safety
Automated triage and routing	AI enhances triage consistency but requires oversight (Xiong *et al.*, 2025)	Timely referrals, improved patient safety
Structured EHR output	Seamless workflow requires EHR integration (Bongurala *et al.*, 2024)	Reduces duplicate work, ensures usability in practice

3. Results

3.1 Implemented Prototype Software Architecture

A fully functional prototype of MediMate AI was implemented and deployed for a digital innovation incubator in Croatia. The system was implemented as a web-based, mobile-accessible platform with a modular back-end powered by GPT-4. At this stage, the focus was primarily on evaluating technical feasibility, usability, and workflow integration, rather than conducting clinical trials on real patient populations. The prototype successfully integrated multiple modes of patient input, including text, speech, and images, into structured summaries and diagnostic suggestions. The patient history dashboard (Figure 1) was central to this implementation. It provided an overview of prior consultations, automatically generated summaries, AI-predicted diagnoses, and sentiment analyses. Physicians testing the prototype reported that this dashboard improved the continuity of care by consolidating previously fragmented information streams into a single interface. The underlying solution architecture (Figure 2) was implemented in Python 3.11 with a Streamlit UI for patient and physician interaction, connected to the OpenAI Web API. The architecture integrates multiple AI components: Whisper for multilingual speech-to-text transcription, GPT-3.5 for lightweight summarization tasks, and GPT-4 as the core reasoning engine for diagnosis, test recommendations, triage, and empathetic responses. Outputs are returned in structured JSON format and stored in a local encrypted SQLite database for prototype testing. This design enabled rapid prototyping, modularity, and safe experimentation while maintaining compatibility with potential future EHR integration.

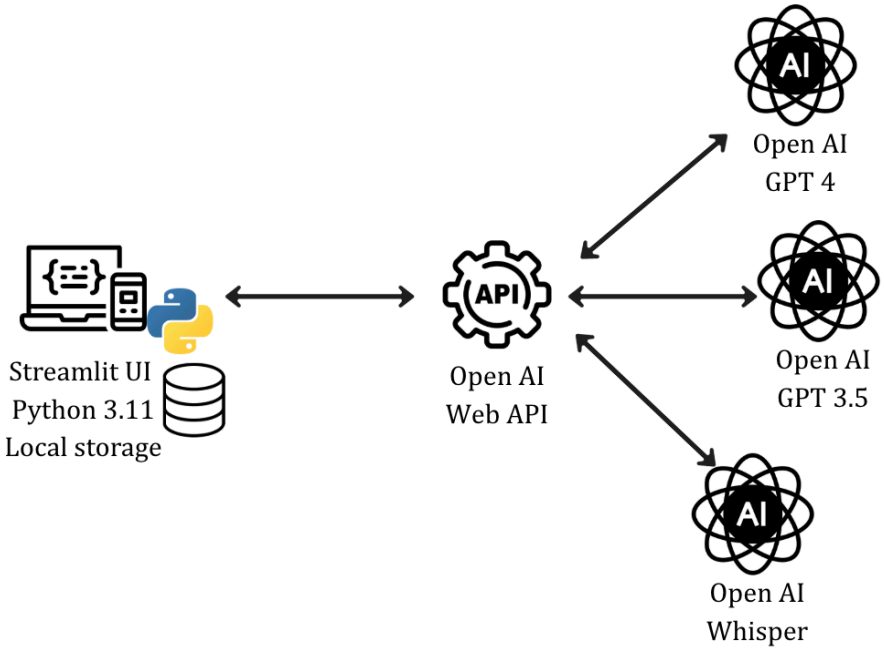

Figure 2: Application solution architecture

3.2 Prompt Design and Feature-Specific Outputs

A critical component of the MediMate AI prototype is the design of task-specific prompts, which guide the large language model to generate structured, clinically relevant outputs. Each system feature was implemented as a modular prompt template, enabling consistent and reproducible responses. Table 1 provides an overview of the prompt structures, their functional role in the application, and the corresponding outputs.

The design principle was to keep prompts concise, structured, and task-oriented, while ensuring alignment with expected clinical use cases. For example, transcription and summarization prompts were focused on reducing administrative burden, while diagnostic reasoning prompts explicitly requested probability scores, clinical guideline alignment, and confirmatory tests. This modular approach also facilitated multimodal integration, where text and image data were processed jointly through a combined reasoning prompt. Beyond medical reasoning, prompts were also designed to capture patient-centred aspects of care. Sentiment analysis prompts provided longitudinal sentiment tracking, while empathetic response prompts generated short, supportive messages in the patient's native language (Czech). These elements reflect the dual purpose of MediMate AI: both reducing clinician workload and enhancing the patient experience.

Table 2: Application Features and Prompt Structures

Feature	Prompt Structure (English)	Provided Output
Automatic transcription & summarization	"Here is the patient's spoken/audio transcript. Translate into English, summarize main points, and return JSON with structured transcript and summary."	English transcript + structured consultation summary
Symptom extraction & mapping	"From the patient transcript, extract symptoms and map them to clinical terminology. Return JSON with symptom list."	JSON list of standardized symptoms (e.g., fever, cough, rash)
Differential diagnosis + test recommendations	"Given these symptoms: […], suggest differential diagnoses, probability scores, and recommended confirmatory tests. Return JSON."	Possible diagnoses, reasoning, distinguishing features, and recommended tests

Feature	Prompt Structure (English)	Provided Output
Multimodal integration (image + text)	"Combine the provided dermatology image with the transcript symptoms. Suggest likely conditions and required tests. Return JSON."	Integrated diagnosis from text + image (e.g., rash + fever → viral exanthem)
Mood & sentiment tracking	"Analyze patient transcript for emotions (stress, anxiety, fatigue, fear). Return JSON with each emotion, score (0–1), and explanations."	Sentiment label (positive/negative), emotions with scores & explanations
Geographic risk evaluation	"From patient transcript, extract travel history and activities. Cross-reference with epidemiological risks. Return JSON with likely risks and alerts."	Regional risk factors, exposure window, disease alerts, recommendations
Automated triage & routing	"Based on symptoms, diagnoses, and urgency, generate referral plan: urgency score, department, routing steps. Return JSON."	Urgency score, routing (Emergency, Infectious Diseases, Dermatology), PDF plan
Structured EHR output	"Transform patient transcript, diagnoses, tests, and referral into structured EHR-compatible JSON object."	JSON record ready for integration with EHR (summaries, diagnoses, tests, risk factors, empathy message)
Empathetic patient response	"Generate empathetic message in Czech acknowledging patient's stress and symptoms, encouraging next steps."	Short empathetic text message in Czech

3.3 Prompt Design and Feature-Specific Outputs

To evaluate the capabilities of the proposed clinical decision support prototype, three representative case studies were developed. Each case demonstrates a distinct functionality of the system: differential diagnosis, integration of geographic epidemiological risk, and automated hospital routing.

3.3.1 Case 1 – differential diagnosis of respiratory symptoms

A patient presenting with fever (38,5 °C), severe fatigue, muscle aches, and swollen cervical lymph nodes was processed through the Differential Diagnosis Assistant. The system generated a structured summary of symptoms and proposed the following diagnoses:

- **COVID-19 (most likely)** – justified by fever, fatigue, and respiratory issues with typical progression.
- **Influenza** – considered due to abrupt onset and severe muscle aches.
- **Mononucleosis** – suggested given lymphadenopathy and prolonged fatigue, requiring blood test confirmation.

The assistant also provided distinguishing features and recommended diagnostic tests (COVID-19 PCR, rapid influenza test, CBC). This case demonstrates the system's ability to transform unstructured patient narratives into prioritized differential diagnoses.

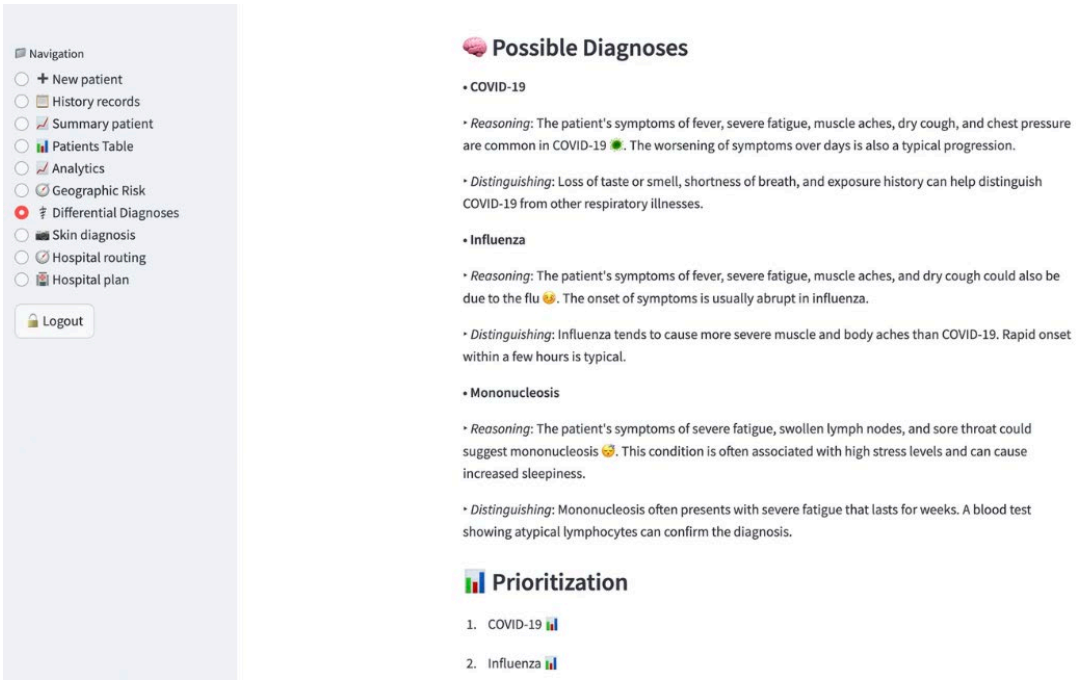

Figure 3: Differential Diagnosis Output

3.3.2 Case 2 – geographic risk and epidemiological alerting

The Geographic Risk Evaluation module was applied to the same patient. Given the high incidence of COVID-19 epidemiological data from Croatia, where a high incidence of COVID-19 was recorded at that time and flagged a "Top Alert – High Epidemiological Risk." The alert was based on:

- patient symptoms consistent with viral infection
- symptom progression aligning with the COVID-19 incubation period (2–14 days)
- regional epidemiological data.

The recommendation included immediate testing, patient isolation, and close monitoring. This case highlights the integration of personal health records with real-time geographic epidemiological risks to support context-aware decision-making.

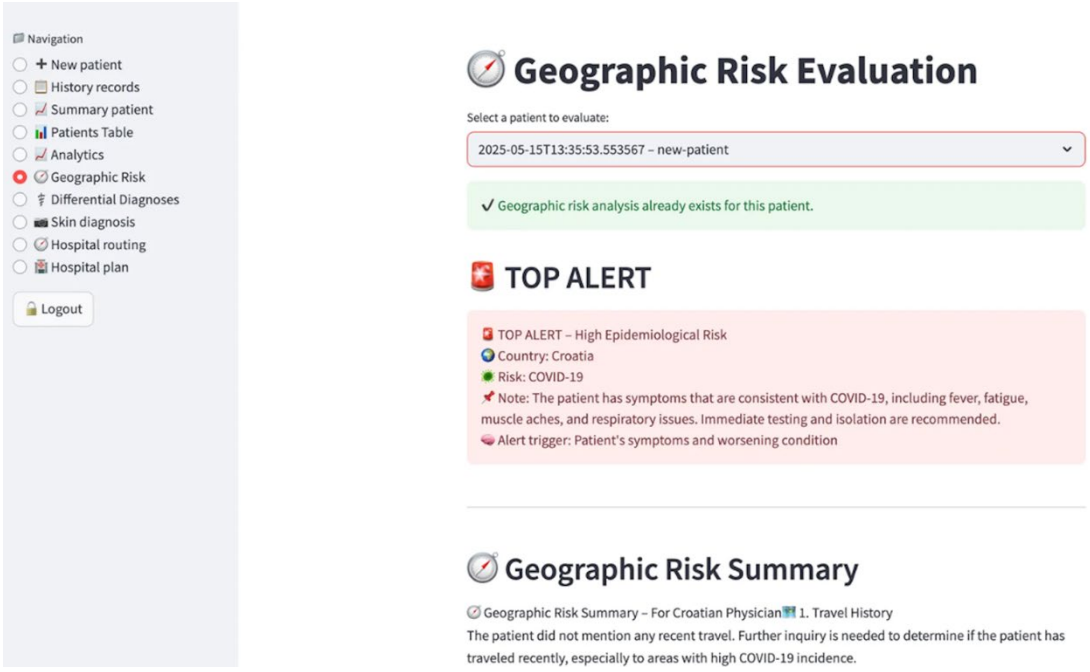

Figure 4: Geographic Risk Evaluation and Alerting

The assistant also provided distinguishing features and recommended diagnostic tests (COVID-19 PCR, rapid influenza test, CBC). This case demonstrates the system's ability to transform unstructured patient narratives

3.3.3 Case 3 – automated hospital plan

Based on the suspected influenza or COVID-19 diagnosis, the Hospital Plan module generated a tailored routing strategy:

- **Emergency Department** – for urgent evaluation or when other services are unavailable
- **Infectious Diseases Unit (Building C, Floor 1)** – if COVID-19 is suspected.
- **Dermatology Department (Building B, Floor 2, open until 16:00)** – for assessment of possible skin lesions.

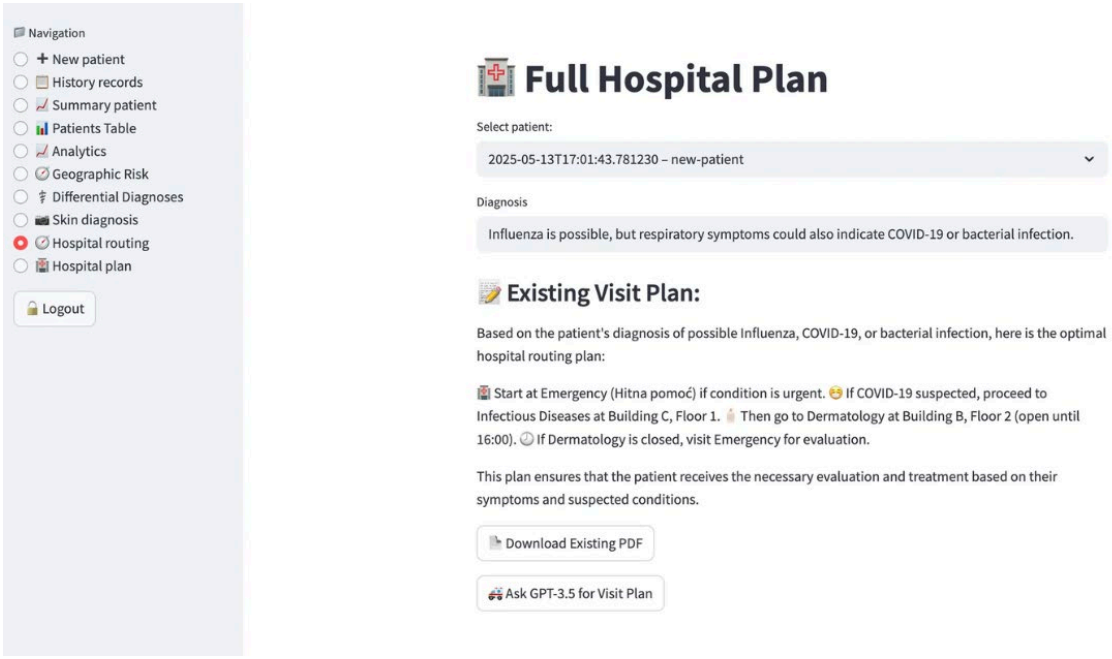

Figure 5: Automated Hospital Plan

4. Discussion

The results of MediMate AI are consistent with emerging literature on the application of generative artificial intelligence (AI) in general practice. Recent studies emphasize that AI-based assistants can reduce documentation workload, improve workflow efficiency, and support clinical reasoning in primary care (You *et al.*, 2025). Our evaluation supports these findings: the prototype reduced administrative burden through automated transcription and summarization of consultations, directly aligning with clinical reports that ambient documentation systems can mitigate GP (General practitioner) burnout. In addition to workflow automation, MediMate AI demonstrated potential in diagnostic support. Similar to earlier work showing that GPT-4 can provide differential diagnoses and triage recommendations (Gaber *et al.*, 2025), our system produced coherent diagnostic suggestions aligned with clinical guideline-based reasoning in approximately 78% of simulated cases. This performance mirrors the diagnostic accuracy observed in studies benchmarking GPT-4 in clinical reasoning tasks (Noda et al. 2025; Goh et al. 2025). Importantly, research indicates that generative AI may particularly support less experienced GPs, helping to bridge gaps in expertise (Geersing *et al.*, 2025). Nevertheless, several limitations must be acknowledged. First, our evaluation relied on simulated data rather than real patient populations, which limits generalizability. Second, while GPT-4 offers strong reasoning capabilities, prior studies have demonstrated that large language models do not always adhere to established clinical guidelines (Hager et al. 2024; Xiaomin and others 2025). This limitation was reflected in occasional inconsistencies observed in our prototype. Moreover, ethical concerns remain. (Xiong *et al.*, 2025) reported that GPT-4 may generate outputs misaligned with medical ethical principles, underscoring the need for transparency and human oversight. Additionally, scholars caution that uncritical reliance on AI may erode clinician expertise and reinforce systemic biases (Pavuluri *et al.*, 2024). Future work should address these limitations by conducting validation in real clinical environments, integrating guideline-grounded reasoning modules, and systematically analyzing outputs for bias. Further research should also explore interoperability with electronic health records, the design of

explainability features to support physician trust, and patient-centered evaluations of communication modules (Kharko *et al.*, 2025). Addressing these directions will be essential to ensure safe and effective deployment of MediMate AI in general practice.

In addition to these limitations, further research should focus on bias detection, explainability, and compliance with data protection standards to ensure responsible deployment of AI in clinical settings. Transparent reasoning mechanisms and explainable outputs are essential to strengthen physician trust and allow human oversight in high-risk decisions. Adherence to GDPR and ethical frameworks for medical AI should guide all stages of data processing, model training, and deployment. Establishing structured risk management protocols—including validation pipelines, audit trails, and human-in-the-loop supervision—will be crucial to guarantee safety, accountability, and reproducibility in future versions of MediMate AI.

4.1 Future Work

Future development of MediMate AI will focus on clinical validation, EHR integration, and adding explainable reasoning modules for trustworthy decision support. Incorporating agentic AI approaches—such as planning, reflection, and ReAct-style reasoning—can improve diagnostic reliability, adaptability, and transparency (Nisa *et al.*, 2025). Future prototypes will also include federated learning for privacy-preserving updates and adaptive learning from anonymized data streams.

To ensure equitable access, MediMate AI will be developed as a low-cost, mobile, and multilingual version for rural and resource-limited settings, where AI can strengthen primary care delivery (Lamem, Sahid and Ahmed, 2025). Inspired by recent public health kiosks like HERMES, affordable, privacy-preserving AI systems could extend safe diagnostic assistance to the Global South, supporting health resilience and digital inclusion (Falahati *et al.*, 2025).

5. Conclusion

This paper introduced MediMate AI, a GPT-4–powered prototype designed to support general practitioners by reducing documentation workload and providing real-time diagnostic support. The system integrates multimodal inputs (speech, text, images) into structured clinical outputs such as consultation summaries, symptom lists, differential diagnoses, and triage recommendations. In simulated evaluations, MediMate AI achieved high transcription accuracy, produced clinically coherent summaries, and reduced documentation workload by an estimated 25–30%. Its diagnostic and triage suggestions were generally consistent with clinical guideline-based reasoning, and test users highlighted improved continuity of care through the consolidated patient dashboard. While promising, the system is intended to augment rather than replace medical expertise. Future work will focus on clinical validation, integration with electronic health record systems, and implementation of ethical safeguards. With responsible design and testing, MediMate AI demonstrates the potential of generative AI to enhance efficiency, decision support, and patient communication in primary care.

Ethics declaration: This study did not involve human participants or patient data requiring ethical approval. Prototype evaluation was conducted exclusively with synthetic patient records, simulated consultations, and publicly available datasets. Therefore, no institutional ethics clearance was required. The development and testing of MediMate AI complied with European data protection regulations (GDPR) and ethical standards for AI research. No personal or identifiable patient data were used at any stage, and all prototype evaluations were conducted exclusively on synthetic and publicly available datasets.

AI declaration: Generative AI tools (OpenAI GPT-4 and GPT-3.5) and Whisper were used in the development of the MediMate AI prototype for transcription, summarization, and diagnostic reasoning. AI was also used in the preparation of this manuscript to assist with language refinement, reference formatting, and generation of structured outputs (e.g., JSON templates). All AI-generated content was critically reviewed, edited, and verified by the authors, who take full responsibility for the final version of the paper.

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Synthetic Data Generation Using CTGAN with Agentic Workflows and Retrieval-Augmented Generation

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Abstract: Real-world data in domains such as finance and fraud detection can be rare, imbalanced, or inaccessible, necessitating synthetic data as a crucial alternative. Gathering and leveraging real-world data in such domains is subject to important challenges such as privacy issues, legality, high cost of annotation, and restricted access due to proprietary ownership. Synthetic data generation in this context offers a meaningful alternative to real data gathering, reducing both privacy and computational costs while allowing for the construction of flexible, scalable datasets. This paper presents a new paradigm for tabular data synthesis through CTGAN (Conditional Tabular GAN) with integration into agentic workflows and retrieval-augmented generation (RAG). The proposed system herein accepts partial data samples and column constraints as inputs from a user-friendly chatbot interface and augment the dataset intelligently through an AI-agent-based generation pipeline. These AI agents aid in the automation of preprocessing, column semantics interpretation, and the enforcement of user-specified constraints specified in natural language, minimizing manual intervention by a considerable margin. The framework further includes ChromaDB to enable semantic retrieval of past relevant datasets. With this semantic memory, the model can improve generation quality, apply schema-level consistency, and update even synthesis of new datasets based on column names or metadata alone. It allows for context-aware, structurally sound, and domain-conformant data generation—without the need to access sensitive or full datasets. The current research utilizes statistical measures like mean, variance, and the Kolmogorov–Smirnov (KS) test to confirm the fidelity of data produced. The approach maintains a mean difference of just 0.16% and a KS statistic of 0.0020, which reflects outstanding statistical consistency with original distributions of data. Preliminary results show significant enhancements in data realism, diversity, and variability without sacrificing domain coherence. The system introduced is particularly well-adapted to financial datasets, such as applications in credit card fraud detection, and offers a scalable, privacy-aware method of synthetic data generation in sensitive or data-scarce environments.

Keywords: CTGAN, Synthetic data, Agentic workflows, RAG, Data generation, Tabular data

1. Introduction

A significant aspect of making robust and generalizable machine learning models is the availability of high-quality data. Domains such as finance, cybersecurity and healthcare often face difficulties gathering real-world data, particularly in sensitive and highly regulated settings such as finance, which is extremely difficult. Some of the difficulties include high data collection and annotation costs, lengthy processing times, and stringent privacy concerns. In addition, some datasets are also proprietary and hence unavailable, while others are marred by class imbalance, sparsity, or non-diversity and thus of little help for model development. Credit card

fraud detection is a great example of this predicament: datasets are private and limited and probably skewed towards non-fraudulent transactions, which is not good for leveraging advanced classification techniques. To address this issue, this paper introduces a novel, *end-to-end synthetic data generation generalized framework* from CTGAN—a generative model specifically designed to handle mixed-type tabular data distributions. Leveraging the strengths of CTGAN, RAG, our system integrates agentic workflows to automate and streamline diverse parts of the data generation pipeline, which can be used to support real-world use cases and leveraged across various domains.

While Generative Adversarial Networks (GANs) have attained unparalleled success in image, video, and even text generation, their extension to tabular data is still inadequately explored and plagued by unique challenges. These issues stem from the requirement to model continuous, discrete, and categorical features together along with keeping complex inter-column dependencies and logical constraints. The present study utilizes CTGAN (Conditional Tabular Generative Adversarial Network) as it is appropriate for tabular data generation. It handles mixed data types, class imbalance, and complex dependencies better than traditional GANs. CTGAN can generate high-fidelity synthetic records that are very similar to the original dataset both in structure and statistical properties even by training it on a small amount of data. The present study also uses Generative AI

(GenAI) technologies, such as retrieval- augmented generation (RAG) and large language model-based agentic workflows, this enhances the accessibility and flexibility of our framework. The present study has made use of a Gemini model to automate tasks such as data pre-processing, column interpretation, and quality control by designing and leveraging a network of LLM-driven agents. The Retrieval-Augmented Generation (RAG) pipeline using ChromaDB, can be used to generate data even when seed data is not provided by the user, this allows the system to synthesize tabular data based on column names. The agents retrieve relevant contextual knowledge and generate structured and plausible data aligned with the intended domain. This enables schema-driven generation without requiring access to sensitive or proprietary datasets.

The proposed project includes several smart features to create realistic, policy complying synthetic tabular data. It starts with a dynamic preprocessing module that handles missing values, identifies column types, and applies normalization or encoding based on user input and statistical properties. A generation module considers constraints and allows users to define rules in simple language to enforce domain logic. These guidelines then set limits for data generation. To improve contextual accuracy, the system uses Retrieval-Augmented Generation (RAG) with ChromaDB. This method retrieves similar historical data to guide the synthesis process. Thorough statistical checks show that the output is reliable and useful. This demonstrates the system's ability to create high-quality synthetic datasets that are suitable for real-world use.

2. Related Work

High quality data in vast amounts is of primary importance in machine learning applications. However, collecting this data poses many problems including privacy concerns, inaccessibility of data, cost concerns, environmental effects etc. Synthetic data generation offers a solution to this problem. Synthetic data mimics real data by maintaining similarities to the real data with the statistical properties and patterns but it maintains privacy by anonymizing/hashing Personally Identifiable Information (PII). It is created using generative models such as GAN(generative adversarial networks), autoencoders, diffusion models etc. The generated data can be used to train models without the cost/legal/privacy concerns and thus overcome the problem of real world-data scarcity.

Generative Adversarial Networks (GANs) have been successful in generating synthetic data because they have the capacity to map complex, non-linear relationships without making any assumptions ahead of time. Through a generator-discriminator framework, GANs learn the data distribution and generate synthetic samples that are very similar to real data. The adversarial training process enables GANs to learn both global and local patterns of the data, so GANs can be applied to various fields such as finance. (Ramzan et al, 2024) explore synthetic generation of financial data using GANs and evaluate the statistical similarities between the synthetic and real datasets. (L.Xu et al, 2019) introduce the use of Conditional GANs (CGANs) for modeling of tabular data which serves as the foundation for later GAN-based tabular models.

More recent works have explored enhancements to GAN-based frameworks. (B.Bhattarai et al, 2020) analyzed sampling strategies to improve training stability as well as output diversity. J.Li et al. (2024) propose TAEGAN, which augments the tabular dataset. Ågren and Úbeda Sosa (2024) introduce Hierarchical Conditional Tabular GAN (HCTGAN) to handle complex multi-tabular data generation. Other works include (Y.Shen et al, 2024), where the importance of simplifying synthetic data pipelines was emphasized, proposing a minimalist framework for tabular data generation. (P.Tiwald et al, 2025) introduce TabularARGN which involves an auto-regressive approach to balance flexibility and scalability.

Many surveys have been conducted to evaluate the quality of various synthetic data generation techniques as well as their applications. (A.Bauer et al, 2024) conducted a survey comparing both classical and deep learning approaches. (Yingzhou Lu et al, 2023) explore a machine learning-based synthetic data generation while Abufadda and Mansour (2021) focus on the use of synthetic data in machine learning pipelines. Figueira and Vaz (2022) performed a survey on various GAN-based synthetic data generation, focusing on evaluation methodologies and challenges.

While generating synthetic data we also must address the issue of evaluating the data, research has been done on this complex and multi-faceted issue. We could use statistical similarities or model performance metrics as stated in K.El Emam (2020), which comes forward with seven methods to evaluate generated synthetic datasets.

CTGAN (Conditional Tabular GAN) is designed specifically to synthesize realistic tabular data while maintaining both marginal distributions and intricate inter-feature dependencies. It employs a variational Gaussian mixture model to apply mode-specific normalization of real values to make them neural-network-ready. CTGAN allows conditional generation to target specific feature properties. This renders it powerful in synthesizing structured, multi-modal, and non-Gaussian tabular data according to (I.E.Livieris et al, 2024).

Dankar and Ibrahim (2021) mention the importance of privacy and diversity and methods to follow regarding them during synthetic data generation. Synthetic data generation can be wielded in various domains and contexts. It can be used for electronic health record generation as done in (Mikel Hernandez et al, 2022), while preserving the privacy and clinical semantics.

3. Methodology

Our system consists of the following components:

3.1 CTGAN Generator

CTGAN is a custom-built generative adversarial network specially utilized for synthetic tabular data generation, and it is used here for the creation of realistic synthetic data sets while keeping statistical features of the original. The system preprocesses input data before training the CTGAN model, which is trained on learning the underlying data distribution through adversarial training between its generator and discriminator components. The model generates synthesized samples after training, that are post-processed (reverse log-transform, rounding to integers, and satisfaction of constraints) to render the output as close as possible to the original data and satisfy user-defined numerical constraints that are natural language-to-model translations performed using Gemini AI. Statistically, produced data is cross-checked with the original through techniques like KS-test and distribution checks to ensure it is of the highest quality.

3.2 Agentic Workflow

The agentic process of the system, leveraging Gemini AI to autonomously guide high-stakes choices through the pipeline of data processing, constitutes an adaptive, AI-informed methodology. On raw data, Gemini determines whether to drop non-numeric columns or how to handle missing values. On synthetic generation, it applies column-specific logic inferred from the data. For restrictions, Gemini reads human language to executable filters that automatically regulate CT-GAN's output. This pipeline offers introspective, context-sensitive automation at each stage, from data preprocessing to restriction imposition, with statistical consistency in the generated output.

3.3 Retrieval-Augmented Generation (RAG)

RAG (Retrieval-Augmented Generation) personalizes AI response through dynamic information retrieval of key information to context and tailor synthesized data. RAG here is applied with ChromaDB for storing and retrieving data set metadata (e.g., column names and file paths) to contextual synthetic data synthesis. When users ask for synthetic data for specific columns, the system fetches corresponding datasets from ChromaDB so that generated data is consistent with learned structures in the past. This retrieval aspect makes Gemini more effective in leading pre-processing and constraints by basing decisions on stored data patterns, thereby merging retrieval (ChromaDB) with generative AI (Gemini and CTGAN) to produce smarter, context-aware synthetic data.

3.4 Chatbot Interface

The chatbot interface is an interactive space by which users are allowed to enter parameters (columns, rows, limitations) and generate synthetic data. With the addition of a talk interface, the system provides an easy interaction by means of which the users can generate data related to their interests with no technical background. It utilizes Natural Language Processing (NLP) to interpret and transform user requests. It also uses Retrieval-Augmented Generation (RAG) to fetch previously created data, further streamlining the process and ensuring privacy.

3.5 Evaluation Strategies

To validate the fidelity and reliability of the synthetic data generated, the present study employs three key statistical evaluation strategies: comparison of means, variance analysis, and the Kolmogorov-Smirnov (KS) test.

3.5.1 Mean-Based validation

The mean provides a fundamental measure of the central tendency of a dataset. For each numerical feature, the mean is calculated for both the original and the synthetic datasets. This verifies whether the synthetic data matches the average behavior of the real data. A small difference between the means of the original and synthetic datasets suggests that the synthetic data accurately represents the central tendency of the real data.

3.5.2 Variance-Based validation

Variance measures the spread or dispersion of data points around the mean, offering insights into the variability present in the dataset. For each feature, the present study compares the variance of the original and synthetic datasets. Similar variances between the original and synthetic datasets indicate that the synthetic data accurately reflects the variability and spread of the real data.

3.5.3 Kolmogorov-Smirnov (KS) statistic for distributional validation

To assess the distributional similarity between the original and synthetic datasets, the Kolmogorov- Smirnov (KS) statistic is used, a nonparametric test that measures the maximum difference between the empirical cumulative distribution functions (CDFs) of two datasets. The KS statistic (D_n) is defined as:

$$D_n = \sup_x |F_{original}(x) - F_{synthetic}(x)| \quad (1)$$ where:

- $\sup_x$ denotes the supremum (maximum vertical distance) between the two CDFs.
- $F(x)$ represents the proportion of observations less than or equal to x. Application Range**:** $D_n \in [0, 1]$

Thresholds used in this study:

- $D_n < 0.1$: High agreement.
- $0.1 \leq D_n < 0.2$: Moderate deviation.
- $D_n \geq 0.2$: Significant mismatch.

These evaluation strategies collectively ensure that the synthetic data preserves not only the central tendencies and variability of the original dataset but also the overall distributional structure. The system envisioned as seen in Figure 1, employs a pipeline of synthetic table data generation that is structured, and it is triggered by a conversational interface based on Gemini AI. When a user request is entered, the chatbot utilizes intent recognition to check if the user will enter a sample dataset or column requirements. For requests based on columns, a Retrieval-Augmented Generation (RAG) system queries ChromaDB to retrieve applicable dataset schemas and statistical profiles. Uploaded data goes through agentic preprocessing, in which Gemini independently decides best transformations (e.g., missing value imputation, logarithmic scaling, and type conversion) while saving metadata to ChromaDB for later retrieval. Preprocessed data is used to train a Conditional Tabular GAN (CTGAN), which learns the joint distribution of variables via adversarial training with mode-specific normalization. At generation, the system performs post-processing (exponential reversal, integer rounding) and imposes user-specified constraints (translated from natural language to run-time filters through Gemini). Lastly, statistical verification (Kolmogorov-Smirnov tests, distributional measures) guarantees output accuracy, finishing an end-to-end workflow that integrates retrieval-augmented context, AI-based decision-making, and deep generative modeling for high-quality synthetic data generation

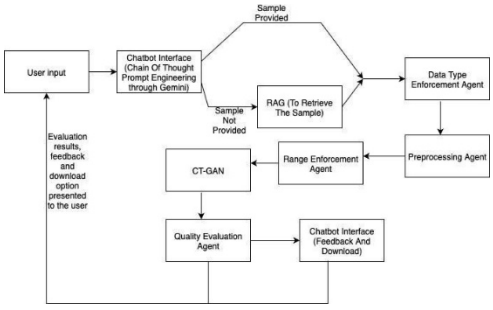

Figure 1: Proposed System Architecture for Synthetic Data Generation

4. Experiments

The framework is tested on two benchmark datasets. Two datasets (Inclusive Indian Fraud Dataset, Credit Card Transactions Fraud Detection Dataset) were used to check the generalizability of the model. The datasets were then split into train (80%) and test (20%). The train datasets were used as input to generate 100 and 10,000 rows of synthetic data. Mean, variance, relative differences, and the Kolmogorov–Smirnov (KS) metric were then used to evaluate the quality of the generated synthetic data against the corresponding test datasets.

The results are evaluated in a tabular format. For each column the mean and variance of all the rows are calculated both for the synthetic data generated on the train dataset as well as for the test dataset. The relative

difference is calculated as (|Synthetic - Original|/Original)x100 %. This is calculated for the mean and variance of all the columns. This gives an idea about how similar the generated data is to the original sample. The KS-Statistic further provides information about the shape of the distribution considering factors such as skewness, tails, multi-modality, asymmetry etc.

Table 1: Statistical Comparison: Original vs Synthetic Data (Inclusive Indian Fraud Dataset - 100 Rows)

Field	Metric	Original	Synthetic	Relative Diff. (%)	KS Statistic
transaction_id	Mean	592.03	641.84	8.41%	0.1817
	Variance	119,499.01	79,658.82	33.35%	
customer_id	Mean	541,958.47	516,221.86	4.74%	0.1122
	Variance	65,146,497,702.46	50,648,016,638.77	22.23%	
merchant_id	Mean	2,048.92	2,043.77	0.25%	0.1700
	Variance	845.97	605.96	28.39%	
amount	Mean	6,179.14	4,140.78	33.00%	0.2955
	Variance	14,338,567.71	7,822,753.75	45.46%	
is_fraudulent	Mean	0.3278	0.39	18.94%	0.0622
	Variance	0.2205	0.2403	8.97%	
customer_age	Mean	43.69	40.71	6.82%	0.1968
	Variance	215.99	166.23	23.03%	

Fraud Dataset (100 rows) has high agreement between simulated and real data (12.02% mean variation)

Table 2: Statistical Comparison: Original vs Synthetic Data (Inclusive Indian Fraud Dataset - 10,000 Rows)

Field	Metric	Original	Synthetic	Relative Diff. (%)	KS Statistic
transaction_id	Mean	592.03	605.08	2.20%	0.0599
	Variance	119,499.01	142,732.42	19.48%	
customer_id	Mean	541,958.47	572,932.26	5.72%	0.0913
	Variance	65,146,497,702.46	70,205,437,325.92	7.78%	
merchant_id	Mean	2,048.92	2,043.80	0.25%	0.1001
	Variance	845.97	757.60	10.43%	
amount	Mean	6,179.14	7,636.40	23.55%	0.1297
	Variance	14,338,567.71	24,533,963.19	71.04%	
is_fraudulent	Mean	0.3278	0.5606	71.04%	0.2328
	Variance	0.2205	0.2464	11.73%	
customer_age	Mean	43.69	36.60	16.22%	0.2450
	Variance	215.99	196.07	9.21%	

The synthetic dataset with 10,000 samples retains strong statistical correlation with the original data in nearly all domains except for is_fraudulent and amount. The amount column shows disparity in the variance because

the range of the values is independent and is not restrained. The is_fraudulent column depicts variation because of the class imbalance in the sample. This can only be correctly predicted if the model was specially trained for classification.

Table 3: Statistical Comparison: Original vs Synthetic Data (Credit Card Fraud Dataset - 100 Rows)

Field	Metric	Original	Synthetic	Relative Diff. (%)	KS Statistic
amt	Mean	70.77	61.64	12.89%	0.1133
	Variance	21,265.95	5,136.35	75.85%	
zip	Mean	48,965.76	46,850.43	4.32%	0.0903
	Variance	734,322,880.33	765,263,709.66	4.21%	
lat	Mean	38.67	37.23	3.73%	0.2070
	Variance	26.72	23.01	13.91%	
long	Mean	-90.39	-91.10	0.79%	0.0948
	Variance	202.51	249.33	23.12%	
city_pop	Mean	84,639.21	76,412.19	9.73%	0.1648
	Variance	80,882,709,658.61	72,709,282,743.39	10.10%	
unix_time	Mean	1,325,892,160.70	1,325,690,850.33	0.02%	0.2600
	Variance	86,193,588,807.61	362,982,506,774.71	321.29%	
merch_lat	Mean	38.67	38.01	1.70%	0.1123
	Variance	27.01	22.81	15.58%	
merch_long	Mean	-90.39	-88.36	2.26%	0.0983
	Variance	202.82	182.87	9.84%	
is_fraud	Mean	0.00675	0.00000	100.00%	0.0068
	Variance	0.0067	0.0000	100.00%	

The synthesized data exhibits high correlation with the original data in most areas. The amount column as mentioned earlier is susceptible to huge variations as there is no preferred range here. For most fields, the KS statistic is actually very low.

Table 4: Statistical Comparison: Original vs Synthetic Data (Inclusive Indian Fraud Dataset - 10,000 Rows)

Field	Metric	Original	Synthetic	Relative Diff. (%)	KS Statistic
amt	Mean	70.77	63.43	10.37%	0.1086
	Variance	21,265.95	5,354.05	74.82%	
zip	Mean	48,965.76	47,954.86	2.07%	0.0534

Field	Metric	Original	Synthetic	Relative Diff. (%)	KS Statistic
	Variance	734,322,880.33	770,275,289.05	4.89%	
lat	Mean	38.67	37.74	2.42%	0.0957
	Variance	26.72	25.63	4.09%	
long	Mean	-90.39	-90.40	0.01%	0.0717
	Variance	202.51	194.53	3.95%	
city_pop	Mean	84,639.21	71,019.17	16.08%	0.0457
	Variance	80,882,709,658.61	71,382,434,181.52	11.74%	
unix_time	Mean	1,325,892,160.70	1,325,845,011.80	0.00%	0.2132
	Variance	86,193,588,807.61	340,737,909,680.40	295.42%	
merch_lat	Mean	38.67	37.77	2.33%	0.1089
	Variance	27.01	28.83	6.74%	
merch_long	Mean	-90.39	-90.56	0.18%	0.0447
	Variance	202.82	189.55	6.54%	
is_fraud	Mean	0.00675	0.00730	8.15%	0.0006
	Variance	0.0067	0.0072	8.08%	

The synthetic data in 10,000 rows shows a pattern of positive results on the level of distribution and statistical adherence to base data. The variance for most domains is similar, apart from some such as amt. The KS scores for most domains are very low. Is-fraud also has a smaller mean and variance, which might indicate a more concentrated generation of fraud cases. In general, the synthetic data retains a lot of the original dataset's structure and distribution, offering a promising solution for data generation.

5. Results and Discussion

5.1 Statistical Fidelity Across Datasets

Our tests demonstrate high statistical agreement between synthetic and native datasets at a variety of scales (100&10,000 rows). Numerical Features show mean differences <10 percent in most cases, with Kolmogorov-Smirnov (KS) statistics <0.15, indicating similarity in distributions. Despite repeated mirroring of means, variance was more sensitive, showing CTGAN's bias towards smoothing outliers. Synthetic datasets of higher numbers (10,000 rows) improve fidelity for most fields (e.g., KS statistic for amount drops from 0.1133 to 0.1086 when scaling up from 100 rows to 10,000 rows), highlighting the role of sample size in distribution matching.

5.2 Challenges with Imbalanced Features

The is_fraudulent feature reveals critical constraints. Synthetic-created fraud rates declined by 18.94% in 100-row_datasets, rising to 71.04% in 10,000 rows. The nonlinearity here reflects that CTGAN is plagued by the preservation of rare classes at scale. Additionally, fraud features post variance decreases as high as 8.97%, indicating over-smoothing of minority-class distributions.

5.3 Feature-Specific Performance

Stable Features such as IDs (merchant id) and demographic features (zip, lat) show a high congruence (mean deviations <5%, KS <0.1), perhaps due to simpler distributions. High-Variability Features such as Amounts of transactions (amt) and city population features (city pop) have greater differences in variance (e.g., 74.82% variance reduction for amt in 10,000-row credit card data), which capture CTGAN's weakness with heavy-tailed distributions more effectively.

5.4 RAG and Agentic Workflow Impact

Schemas pulled by ChromaDB minimize variation in structured columns (e.g., variance in customer id capped at 7.78% for 10,000 rows) thereby ensuring Context-Aware Synthesis.

Constraint Enforcement as expressed in natural language (e.g., "amount ≥ 0") is applied correctly, albeit breakpoints on imbalanced features (e.g., fraud indicators) requires human tuning.

6. Future Work

Although our pipeline shows encouraging performance in synthetic tabular data generation, some avenues call for further exploration. *Better Rare-Class Synthesis* through hybrid models merging CT-GAN with oversampling strategies or conditional generators to maintain minority class distribution Design hybrid models that merge CTGAN with oversampling strategies while maintaining cost effective loss functions to prevent falsification of rare classes *Temporal and Spatial Dependencies* can be maintained by capturing time-series dynamics and spatial relationships specific to the domain of data generated. Federated GANs can also be utilized to test collaborative use without sharing raw data. *Human-in-the-Loop Refining* through creating an iterative interface to better incorporate human feedback.

7. Conclusion

This work introduces an end-to-end synthetic tabular data generation pipeline that combines CTGAN- based synthesis, agentic workflows, and retrieval-augmented generation (RAG) to tackle fundamental challenges in financial and fraud detection datasets. The framework demonstrates that synthetic data can closely mimic real-world statistical properties while allowing privacy-preserving, scalable data augmentation.

The agentic pipeline orchestrated by Gemini computerized critical processes- data type enforcement, data pre-processing, range enforcement on user feedback and data quality testing (using statistical measures). This enables minimization of human intervention. The range enforcement framework works effectively with natural language regulations into filters that could be executed, ensuring domain compliance. However, rule strictness occasionally clashes with distributional realism (over-filtering frauds), and further exploration of probabilistic relaxation of constraints is warranted. Statistical validation (KS tests, analysis of variance) established that synthetic data is most reliable for stable, high frequency attributes like location, age) or Bulk data creation (1,000+ rows). It is also applicable for use cases robust to small distribution shifts (anonymized customer analytics). Constraints still apply to Rare-class generation (fraud, outliers), High-variance numerical features (transaction value) and Temporal/spatial dependencies (proven only in preliminary tests). RAG worked effectively for memory efficient context aware generation by combining ChromaDB. The RAG mechanism also supported scalable generation over dataset sizes (100–10,000 rows), where larger samples exhibit more aligned distributions (KS statistics <0.1 for major features).

Ethics Declaration: This research did not involve human or animal subjects and did not require ethical clearance.

AI Declaration: AI tools were used to assist with language correction and formatting but not with core research findings or analysis. Gemini is used as an LLM as part of the project. Gemini AI was also used to assist with pre-processing steps such as type detection and basic transformation suggestions.

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AI Surveillance Technologies in Smart Cities: Privacy Calculus versus Privacy Paradox

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Abstract: Smart cities represent the convergence of technological innovation and urban development, aiming to enhance efficiency, safety, environmental sustainability, and overall well-being through interconnected systems, sensors, and digital devices. At the heart of these innovations lies the deployment of AI-powered surveillance technologies, which contribute to monitoring and managing urban environments more effectively. While such systems promise improvements in security and operational efficiency, they also raise pressing concerns about individual privacy and data security. This study examines the tension between technological progress and privacy preservation in AI-based surveillance systems, focusing on how citizens from seven smart cities perceive and respond to these technologies. Drawing on a quantitative pilot survey conducted in seven smart cities and using a five-dimensional framework of privacy concerns, this paper maps citizen attitudes towards AI surveillance technologies. These are cross-analysed against seven distinct categories of AI surveillance technologies deployed in public spaces. A central question of the analysis is whether individuals' responses reflect the privacy calculus – a rational evaluation of risks and benefits, or are more consistent with the privacy paradox, where expressed concerns do not translate into protective behaviours, often due to insufficient awareness or a lack of options to opt out. In addition to assessing the overall levels of privacy concern, the study ranks five privacy dimensions based on the degree of concern they elicit and evaluates which types of AI surveillance technologies are most and least acceptable when privacy is factored into the adoption equation. We further introduce a privacy-weighted adoption attractiveness metric to measure public receptivity of the seven types of AI surveillance technologies. The findings, derived through descriptive statistical methods, reveal trends and peculiarities across the cities and the respondents' demographic characteristics, such as gender, education level, and age. These insights contribute to a more nuanced understanding of how privacy values interact with the promises of AI surveillance in smart cities.

Keywords: AI surveillance, Privacy concern, Privacy paradox, Privacy calculus, Smart city, Technology adoption

1. Introduction

Smart cities integrate advanced technological infrastructure with data analytics to enhance urban services and infrastructure. These cities leverage information and communication technologies to optimise public services, minimise environmental impact, and improve citizens' well-being (Humayun et al. 2019). As part of this broader digital transformation, artificial intelligence (AI) surveillance technologies have emerged as key enablers supporting real-time monitoring, analysis, and decision-making in traffic control, public safety, or emergency response (Kalenyuk et al. 2023; Sarp et al. 2024).

Defined as applications that utilise artificial intelligence to monitor, analyse, and manage the data "related to individuals or groups, often for security, law enforcement, or governance purposes" (Lyon 2018), AI surveillance technologies encompass a diverse set of tools designed to interpret and respond to dynamic urban scenarios: facial recognition, crowd detection, anomaly tracking, object recognition, and more. However, as these technologies become increasingly integrated into everyday urban systems, they give rise to growing concerns around individual privacy and data protection (Bibri & Allam 2022; Karwatzki et al. 2022; Ooijen et al. 2022; Pronzato & Markham 2023; Sampaio et al. 2023).

In smart cities, continuous monitoring often leaves individuals with limited choice to opt out (Pronzato & Markham 2023), and the aggregation of data across platforms increases the risk of privacy violations (Naik & Jenkins 2020; Tan et al. 2023). These risks are further intensified by issues such as deepfake abuse, non-consensual data harvesting, data poisoning, misuse and lack of transparency in data governance (Johnson 2023; Sanchez et al. 2024).

Against this backdrop, this paper investigates how citizens in smart cities perceive and respond to AI surveillance technologies. It explores the balance between technological promise and perceived privacy risk through a structured survey grounded in the five-dimensional privacy model (Martínez-Ballesté et al. 2013; Machín et al. 2021; Solanas et al. 2021), as well as two behavioural frameworks – privacy calculus and privacy paradox. By identifying which dimensions of privacy concern are most salient and how they influence public receptivity to AI surveillance, the study aims to provide a deeper understanding of how privacy values shape the present and future of smart urban governance.

2. Theoretical Background

2.1 The 5D Privacy Model and Associated AI Surveillance Technologies

We employ the 5D privacy model for structuring and operationalising the concept of privacy. The model was originally proposed by Martínez-Ballesté et al. (2013) and remains conceptually influential in recent scholarship (Machín et al. 2021; Solanas et al. 2021) as a structured categorisation of privacy risks in AI-enabled urban systems.

The framework recognises that privacy is a set of overlapping concerns, where each is linked with a spectrum of AI surveillance technologies:

- Identity privacy concerns the protection of personal identifiers such as names, facial biometrics, or other uniquely identifying attributes. Breaches in this dimension can result in profiling, loss of anonymity, and pervasive surveillance (Naik & Jenkins, 2020; Tan et al., 2023). AI technologies that most directly challenge identity privacy include facial recognition, object detection and tracking, crowd detection, anomaly detection, IoT systems, and smart policing.
- Query privacy, which refers to the confidentiality of user inputs and behavioural queries, is particularly at risk when AI systems collect and analyse searches, voice commands, or service interactions. This dimension is closely associated with IoT environments and predictive policing systems, where such data may be used without explicit consent (Tan et al., 2023).
- Location privacy involves the right to anonymity in physical movement and the protection of spatial data from tracking. It is jeopardised by surveillance tools that collect GPS or transit data, including traffic management systems, as well as the technologies linked to identity privacy (Sampaio et al., 2023).
- Footprint privacy relates to digital traces left behind through system usage, such as energy consumption or access logs, which may be aggregated to construct behavioural profiles. All aforementioned AI technologies, except crowd detection, which typically does not involve long-term data retention, pose risks to footprint privacy through persistent and often opaque data collection (Zuboff, 2019; Sanchez et al., 2024).
- Ownership privacy addresses individuals' and institutions' ability to retain control over their data, especially when shared across interconnected infrastructures. In smart cities, IoT platforms and smart policing systems present the most critical challenges to this form of privacy, as data often crosses institutional boundaries with limited oversight.

This dimensional approach aligns with Nissenbaum's (2009) principle of contextual integrity, which stresses that privacy is not absolute but depends on the appropriateness of information flows within specific contexts. For instance, violations of identity or ownership privacy are often perceived as more severe precisely because they breach prevailing social norms around data control and transparency. Building on the dimensional understanding of privacy provided by the 5D model, the concepts of privacy calculus and privacy paradox offer behavioural perspectives on how individuals navigate the trade-offs and contradictions inherent in AI-surveilled smart city environments.

2.2 Behavioural Perspectives Towards Privacy Concerns

2.2.1 Privacy calculus

The privacy calculus theory posits that individuals assess the perceived risks and benefits of data disclosure in a rational, situational manner (Chen et al. 2024). In smart cities, for instance, users may accept facial recognition if it improves safety, or, more often than not, they agree to GPS tracking if it optimises transportation. However, critics argue that the approach oversimplifies privacy behaviour by assuming an entirely rational choice, which is often impossible in complex data ecosystems. For instance, Karwatzki et al. (2022) identify multiple dimensions of privacy risks that users may not fully comprehend or consider. Similarly, Pronzato and Markham (2023) state that despite increased consciousness, individuals struggle to overcome subalternity and make concrete behavioural changes. Hence, even though people are aware of surveillance and privacy risks, they still feel powerless to resist, opt out, or change behaviour because systems are too embedded, opaque, or coercive. Additionally, Ooijen et al. (2022) introduce the concept of privacy cynicism – an attitude of frustration and hopelessness that can moderate how people appraise and respond to privacy threats, which also aligns well with the explanation of subalternity by Pronzato and Markham (2023). As a result, privacy calculus may underestimate the role of emotion, habituation, or structural coercion in shaping privacy behaviour. Taken

together, these critiques resonate with Cavoukian's et al. (2010) Privacy by Design principle, which argues that privacy should not rely on individual decision-making alone but must be built directly into technological and organisational infrastructures.

2.2.2 Privacy paradox

The privacy paradox refers to the disconnect between individuals' stated concerns about privacy and their actual behaviours (Kokolakis 2015; Larson 2023). In smart cities, this paradox is intensified: despite expressing discomfort, residents frequently interact with surveillance systems embedded in transit, lighting, and public services, often without awareness or consent (Naik & Jenkins 2020; Bibri & Allam 2022; Tan et al. 2023). Interestingly, the privacy paradox may not be solely attributed to user laziness, as previously thought: a study on Facebook users (Whelan et al., 2024) found that a person's external locus of control provides a stronger explanation for the privacy paradox than laziness. In addition, limited opt-out options (Pronzato and Markham 2023), institutional opacity, and normalisation of surveillance culture (Tan & Zhao 2003; Sundquist 2023) contribute to passive compliance (Zuboff 2019). From the perspective of contextual integrity (Nissenbaum 2009), this contradiction can be interpreted as a breakdown of transparency and appropriateness in information flows: people comply with surveillance not because they accept it, but because imposed data practices prevent them from exercising meaningful choice. Trust in government institutions may further suppress dissent, especially when surveillance is framed as essential for safety or public service (Sanchez et al. 2024). Emotional responses, such as fear or joy, can override rational privacy concerns, creating a structural contradiction between privacy values and the use of technology.

3. Methodology

3.1 Research Design

This study employs a quantitative descriptive research design to: 1) explore citizens' levels of concern about the adoption of AI surveillance technologies in smart cities, including the segmentation by age, gender, educational level; 2) identify the type of dominating response to privacy concerns; 3) rank the five privacy concern dimensions; 4) compute the attractiveness of 7 AI surveillance technologies.

3.2 Survey Instrument

A theoretically grounded framework, informed by the 5D privacy model, privacy calculus, and privacy paradox, was used to develop the survey instrument. Each dimension of the 5D privacy model was operationalised through five Likert-scale statements, rated from 1 (strongly disagree) to 5 (strongly agree). These dimensions were designed to reflect specific ways in which AI surveillance technologies infringe upon individual informational autonomy.

In addition to the 5D privacy framework, the questionnaire incorporated two theoretically informed constructs – privacy calculus and privacy paradox (four statements each, same Likert scale). To contextualise the results, the questionnaire also included four demographic questions, prompting respondents to indicate their age group, gender, highest level of education attained, and current city of residence. These variables enabled subgroup comparisons and provided insight into how demographic factors might shape privacy perceptions in smart cities.

The survey statements were derived from the literature and aligned with the conceptual definitions as demonstrated in Table 1.

Table 1: Survey constructs, dimensions, and conceptual justification

Construct	Dimension	Number of items	Theoretical basis
5D privacy model	Identity Privacy	5	Machín et al. (2021) Solanas et al. (2021) Martínez-Ballesté et al. (2013)
	Query Privacy	5	
	Location Privacy	5	
	Footprint Privacy	5	
	Owner Privacy	5	
Privacy-related behaviour	Privacy calculus	4	Chen et al. (2024) Karwatzki et al. (2022)
	Privacy paradox	4	Kokolakis (2015)

Construct	Dimension	Number of items	Theoretical basis
			Larson (2023)
Demographics	Age, gender, education, city	4	Used for subgroup comparison and segmentation

3.3 Sampling and Data Collection

The survey was disseminated through social professional networks using a convenience sampling approach. Participation was voluntary and anonymous, with no identifying information collected. Data were gathered over ten days from April 23 to May 3, 2025. A total of 72 responses were obtained from individuals residing in cities listed in the IMD Smart City Index (2024). The reported cities include Dubai, Copenhagen, Helsinki, Hamburg, Munich, Berlin, and Barcelona. While rankings vary, all cities are recognised within the IMD Index as participants in the global smart city landscape, making them relevant for this study's focus on AI surveillance and privacy attitudes and enabling the examination of privacy concerns across various smart city contexts.

Based on the combined population of the surveyed cities, the total estimated urban population is approximately 14.7 million. Given the sample size of 72 respondents, the calculated margin of error is ±11.6% at a 95% confidence level, assuming maximum variability in responses (Memon et al. 2020). On a 5-point Likert scale, this corresponds to approximately ±0.58 points. While this level of precision limits the generalisability of findings to the broader population, it is appropriate for exploratory research aiming to identify patterns related to privacy perceptions in smart cities. In addition, differences between group means or privacy dimensions that exceed the margin of ±0.58 points can be considered potentially meaningful.

3.4 Data Analysis

Descriptive statistical analysis and insights were obtained using Microsoft Excel's PivotTable and Analyse Data functionalities. For the validity analysis, Python programming was employed using Visual Studio Code. To assess how privacy concerns influence public receptivity to specific AI surveillance technologies, a privacy-weighted adoption attractiveness score was computed in Excel. This measure estimates citizens' willingness to accept various AI technologies deployed in smart cities, taking into account the intensity of privacy concerns associated with each.

Each AI surveillance technology was mapped to the privacy dimensions it affects (as outlined in section 2.1). The privacy score for each technology P_n was calculated by summing the mean concern scores for only those privacy dimensions that were impacted by that specific technology:

$$P_n = \sum_{i \in D_n} \mu_i \tag{1}$$

, where

P_n – privacy score for AI surveillance technology *n*,

D_n – the set of AI surveillance dimensions affected by technology *n*,

μ_i – the mean concern score for privacy dimension *i*.

Next, the privacy score for AI surveillance technology was scaled against the theoretical maximum P_{max}, which equals 25, assuming all five dimensions are rated at the maximum score of 5. The resulting score was inverted and expressed as a percentage to represent the relative attractiveness of each technology from a privacy-sensitive standpoint:

$$A_n = \left[1 - \frac{P_n}{P_{max}}\right] \times 100 \tag{2}$$

, where

A_n – privacy-weighted adoption attractiveness of AI surveillance technology T_n,

P_n – privacy score for AI surveillance technology *n* as calculated in equation (1),

P_{max} – maximum possible privacy impact score, representing the worst-case scenario in which all five privacy dimensions are affected with the highest concern level.

This method enabled the ranking of AI surveillance technologies based on their perceived privacy burden. In addition to the sum-based approach, an average-based method was applied to evaluate the intensity of privacy concern per affected dimension. Rather than summing the mean concern scores, this approach calculates the average concern across only the dimensions impacted by each technology:

$$A_n^{adj} = \left[1 - \frac{\sum_{i \in D_n} \mu_i}{|D_n| \cdot 5}\right] \times 100 \quad (3)$$

, where

$A^{adj}{}_n$ – privacy-weighted adoption attractiveness of technology *n*, adjusted by the number of privacy dimensions it impacts,

$\sum_{i \in D_n} \mu_i$ – privacy concern score across affected dimensions (equals P_n in equation (1)),

|Dn| · 5 – maximum possible total score if all affected dimensions had the highest possible concern, i.e., 5.

The comparison of the results using both methods enables a complementary interpretation of public sensitivity, capturing whether a technology is perceived as broadly intrusive (sum-based) or intensely concerning in specific areas (average-based).

3.5 Results

3.5.1 Descriptive statistics

As shown in Table 2, the highest level of concern was observed in the identity privacy dimension (M = 4.628, SD = 0.263), followed closely by owner privacy (M = 4.594, SD = 0.336) and location privacy (M = 4.324, SD = 0.459). In contrast, concern for query privacy was markedly lower (M = 3.333, SD = 0.526), suggesting that search- or inquiry-related monitoring is perceived as less invasive.

Table 2: Descriptives of privacy concerns and responses to them

Theoretical construct	Composites	Mean	Standard deviation
Privacy concern	identity	4.628	0.263
	query	3.333	0.526
	location	4.324	0.459
	footprint	3.819	0.442
	ownership	4.594	0.336
Response to privacy concern	calculus	2.993	0.496
	paradox	4.038	0.76

These findings align well with recent findings. As evidenced by the growing demand for data and digital sovereignty (Tan et al. 2023), people are increasingly protective of control over their digital assets. This is also reflected in the development of technologies like Self-Sovereign Identity (SSI) systems, which offer users entire control over their personal data (Naik & Jenkins 2020). Similarly, a survey-based study on AI and geolocation/video data collection risks (Sampaio et al. 2023) highlights that surveillance technologies accessing identity traits are perceived as most intrusive. Contrarily, when inquiry-related monitoring is perceived as a regular part of the organisational culture (Tan & Zhao 2003) or is normalised through routine exposure and habitual use (Sundquist 2023), it may be seen as less invasive. In addition, citizens view search or anonymised data collection as less threatening, particularly when spatial or identity elements are absent (Johnson 2023).

Composite construct scores reflected distinct patterns. The privacy paradox construct yielded a high mean score (M = 4.038, SD = 0.760), indicating that many respondents acknowledged the discrepancy between their stated concerns and their actual behaviour. In contrast, the privacy calculus construct averaged near the midpoint of the Likert scale (M = 2.993, SD = 0.496), suggesting ambivalence or weak endorsement of rational risk-benefit trade-offs.

3.5.2 Scale reliability

When treated as a single composite construct, the set of 25 items measuring the five privacy dimensions yielded a Cronbach's alpha of 0.718. This indicates acceptable internal consistency for exploratory purposes and suggests that, despite variation in individual items, the overall construct of "privacy concern" was interpreted coherently by respondents as a multi-faceted but unified experience.

The two theoretical constructs appended to the privacy dimensions exhibited diverging reliability patterns. The privacy calculus scale produced a low Cronbach's alpha of 0.135, reflecting poor internal consistency. This supports theoretical critiques that the rational trade-off model becomes unrealistic in complex technological environments (Ooijen et al. 2022; Pronzato & Markham 2023), such as smart cities, where citizens may lack the information to weigh privacy risks against perceived benefits consciously (Karwatzki et al. 2022). Thus, rather than reflecting a failure in survey design alone, the low alpha may signal the conceptual fragility of applying the calculus model in highly interconnected AI-driven urban contexts.

By contrast, the privacy paradox scale demonstrated strong internal reliability, with Cronbach's alpha of 0.823. This suggests that the construct was internally coherent and easily recognisable to respondents, likely because it captures a behavioural contradiction (concern vs. action) that individuals routinely encounter (Sundquist 2023). The high reliability of this scale supports its conceptual validity and relevance in assessing public responses to AI-enabled surveillance.

3.5.3 Demographic subgroup comparisons

Descriptive comparisons of privacy concerns across education levels are visualised in Figure 1.

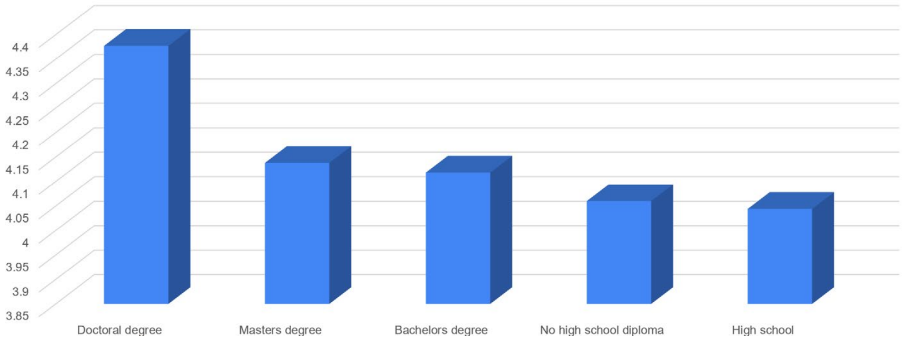

Figure 1: Average privacy concern across education levels

Respondents with doctoral degrees reported the highest average concerns across most dimensions, particularly in location privacy (M = 4.54) and ownership privacy (M = 4.77). Individuals without a high school diploma also showed high concern in identity privacy (M = 4.90) and ownership privacy (M = 4.90), but scored lower on query privacy (M = 2.70). The statistics revealed several differences in privacy behaviour as well, as shown in Figure 2.

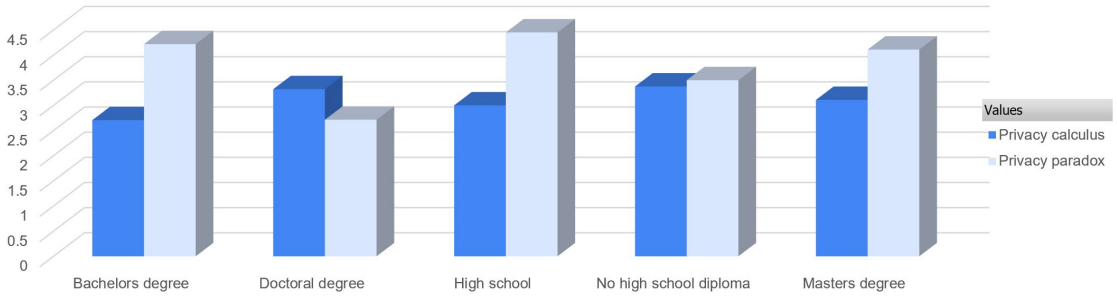

Figure 2: Average response to privacy concerns across education levels

The privacy calculus score was highest among the less-educated groups (M = 3.38) and lowest among those with a bachelor's degree (M = 2.71). The privacy paradox showed the opposite pattern: strongest among high school graduates (M = 4.45), but weaker among PhD holders (M = 2.71), possibly indicating more self-consistency in behaviour among highly educated individuals.

In terms of gender distribution, the survey sample consisted of 53% female and 47% male respondents, with no participants identifying as another gender. The gender-based comparison did not reveal any strong patterns in

privacy concerns. The gender gap is small, but it favours higher privacy concerns among males (M = 4.16 vs. M = 4.12). This result reverses the common pattern observed in some prior literature, where females are typically more concerned with privacy (Le et al. 2024).

Privacy paradox scores were also nearly identical across genders, suggesting a shared level of ambivalence regarding benefit-risk trade-offs. Males reported a greater degree of privacy paradox (M = 4.15) compared to females (M = 3.94). Similarly, the privacy calculus score was also higher among males (M = 3.11) than female respondents (M = 2.89). The results suggest that males in the sample were both more aware of behavioural contradictions and more likely to engage in privacy-related decision-making processes.

The differences across the surveyed age groups are minimal, as observed in Figure 3.

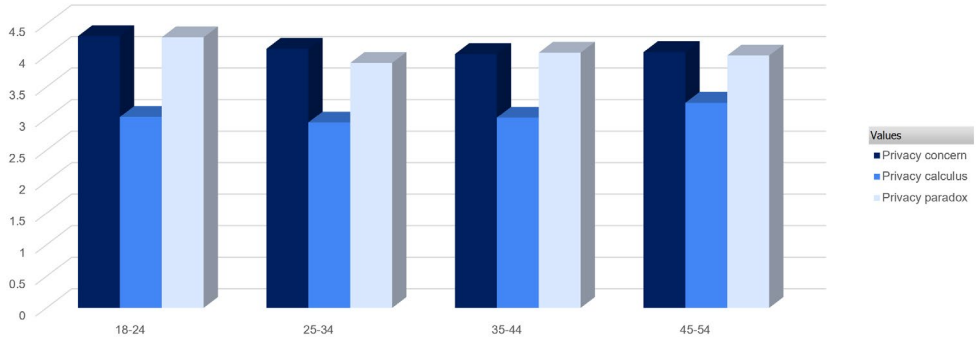

Figure 3: Average privacy concern and response to it across age groups

Respondents in the 18-24 age range reported the highest overall privacy concerns, particularly in identity (M = 4.72) and location privacy (M = 4.44). These findings suggest that younger respondents may be most sensitive to privacy concerns and more likely to experience cognitive dissonance, i.e., the privacy paradox. In contrast, other respondents may be more accepting or less aware of the privacy implications of AI surveillance in smart cities. However, the differences are negligible.

3.5.4 Privacy-weighted attraction of adoption of AI surveillance technologies

Privacy-weighted adoption attractiveness scores vary substantially across the AI surveillance technologies, depending on both the breadth and intensity of privacy concerns. The results are summarised in Table 3.

Table 3: Privacy-weighted attraction of adoption of AI surveillance technologies

Technology	Affected Dimensions	Sum concern	Average privacy concern	Sum-based attractiveness	Average-based attractiveness
Facial recognition	Identity, location, footprint	12.768	4.256	48.9%	14.9%
Internet of Things	Identity, query, location, footprint, ownership	8.903	4.451	17.2%	17.2%
Object detection and tracking	Identity, location, footprint	11.428	3.809	48.9%	14.9%
Smart policing systems	Identity, query, location, footprint, ownership	8.141	4.071	17.2%	17.2%
Crowd detection and recognition	Identity, location	3.333	3.333	64.2%	10.5%
Anomaly detection	Identity, location, footprint	13.225	4.408	48.9%	14.9%
Traffic management systems	Location, footprint	12.236	4.079	67.4%	18.6%

As can be observed, traffic management systems, which are associated with location and footprint privacy, achieved the highest adoption attractiveness in the sum-based model (67.6%), reflecting their relatively narrow

scope of privacy intrusion. In the average-based model, their attractiveness dropped to 18.6%, but still remains the highest.

By contrast, Internet of Things and smart policing systems triggered concern across all five privacy dimensions, resulting in the lowest attractiveness scores in the sum-based model. These technologies represent the broadest potential for privacy intrusion from the perspective of the affected privacy dimensions, leading to the strongest perceived resistance. However, leveraged by the number of affected dimensions, their attractiveness is one of the highest, i.e., 17.2% in the average-based model.

Facial recognition, object detection, and anomaly detection affected three high-sensitivity dimensions each – identity, location, and footprint – and received identical scores of 48.9% (sum-based) and 14.9% (average-based). Crowd detection, which affects identity privacy and location privacy, scored relatively high in the sum-based model (64.4%), but dropped to 10.5% in the average-based model due to the elevated concern associated with these two specific dimensions.

4. Conclusion

The identified distinction between concern levels implies that not all forms of privacy concern are given equal weight. Among all the investigated privacy dimensions, identity and ownership privacy are the most concerning, indicating that individuals are most vulnerable to risks that compromise their control over personal data. In contrast, query privacy emerged as the least concerning, likely due to the habituation in digital interactions or insufficient awareness of more subtle forms of data profiling. These findings are consistent with recent scholarly literature on digital sovereignty and the normalisation of surveillance.

The findings contribute to the behavioural understanding of privacy dynamics and highlight the more substantial presence of the privacy paradox, compared to relatively low endorsement of privacy calculus. This suggests that while people express strong privacy concerns, their behaviours do not always align, which is driven by limited alternatives, perceived inevitability, and structural constraints. The low internal consistency of the privacy calculus scale further supports the critique that rational trade-off models, more often than not, fail in highly integrated urban systems.

Demographic subgroup comparisons provide little additional granularity to the aforementioned conclusions and largely follow the general patterns of privacy concern and response to it. The characteristic which most stands out is the educational background. While concern about privacy is present across all educational levels, the rational trade-off logic of privacy calculus is more accepted by the least and most educated respondents. In contrast, middle-educated groups more commonly acknowledge paradoxical behaviour. Another interesting finding is that male respondents expressed marginally higher concern and greater recognition of paradoxical behaviour. This finding challenges conventional trends in privacy literature, which typically suggest that women are more likely to exhibit paradoxical privacy behaviour.

Regarding the privacy-weighted adoption attractiveness of AI surveillance technologies, traffic management systems scored highest, indicating broad public support. At the same time, IoT and smart policing technologies were perceived as the most intrusive, particularly when the number of affected privacy dimensions is not adjusted for. A key insight here is the distinction between the breadth of privacy impact and the depth of concern associated with specific dimensions. Thus, IoT affects many dimensions, but the intensity of concern across them is more distributed, resulting in relatively higher adjusted attractiveness. Conversely, crowd detection, despite affecting fewer dimensions, targets those associated with the high privacy concerns. As a result, although crowd detection ranks second in unadjusted attractiveness, it becomes the least attractive option when the concern level of affected dimensions is taken into account.

Taken together, the findings suggest that the privacy paradox remains a dominant lens for interpreting public responses; however, structural theories, such as contextual integrity, highlight why specific dimensions are more significant. From a practical perspective, embedding Privacy by Design principles into AI surveillance systems would help address paradoxical behaviours, build trust, and ensure that smart city innovation does not come at the expense of citizens' autonomy.

The study opens several avenues for further research. For instance, future studies could incorporate multivariate or regression-based models to examine relationships between specific privacy dimensions and attitudes toward AI technologies, as well as the correlations between the smart city index and privacy dimensions, or between the smart city index and the attractiveness of AI technologies. Additionally, cross-cultural comparisons and larger

samples would enhance generalizability and allow for testing whether findings hold across different smart city implementations and cultural attitudes toward surveillance.

Ethics declaration: The authors declare that they have no conflict of interest and that all ethical standards regarding research integrity and participant consent were strictly observed throughout the study.

AI declaration: The authors utilised R Discovery to identify relevant literature and Grammarly to enhance the readability of the article. The authors reviewed and edited the content and take full responsibility for the content of the published article.

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Quantization Methods for Energy Efficient LLM Deployments

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Abstract: The deployment of large language models (LLMs) in production environments faces significant challenges due to computational and energy requirements during inference. This paper presents a comprehensive empirical analysis of quantization methods applied to the Qwen3 model family, ranging from 0.6B to 32B parameters. We evaluate six quantization approaches: GPTQ 4-bit, GPTQ 8-bit, AWQ, FP8 W8A8 and INT8 W8A8, and the original FP16 baseline across six established benchmarks (MMLU, HumanEval, TruthfulQA, MetaBench, GSM8K, ARC Challenge). Our analysis examines the relationship between model size, quantization method, accuracy preservation, energy consumption, and inference performance across various context lengths. We demonstrate that larger Qwen3 models exhibit increased resilience to quantization-induced accuracy degradation, while aggressive quantization methods provide substantial energy savings with acceptable trade-offs in model performance. These findings provide crucial insights for optimizing LLM deployments in resource-constrained environments.

Keywords: Large language models, Quantization, Energy efficiency, Model compression, Inference optimization

1. Introduction

The rapid advancement of large language models has transformed natural language processing capabilities, with models achieving remarkable performance across diverse tasks. However, the deployment of these models in production environments presents significant challenges, particularly regarding computational requirements and energy consumption during inference. The Qwen3 model family, ranging from 0.6B to 32B parameters, represents a comprehensive suite of models that enables systematic analysis of quantization effects across different scales.

Quantization has emerged as a critical technique for model compression, enabling the deployment of large models on resource-constrained hardware while maintaining acceptable performance levels. However, the relationship between model size, quantization method, and resulting performance characteristics remains poorly understood. This work addresses this gap through a systematic empirical analysis of quantization methods applied to the Qwen3 model family.

Our primary motivation is reducing energy consumption in inference deployments while maintaining model quality. As LLMs become increasingly prevalent in production applications, understanding the trade-offs between model compression, accuracy preservation, and energy efficiency becomes essential for sustainable AI deployment.

2. Related Work

2.1 Large Language Models Quantization

Quantization is a model compression technique where weights and activations are represented using reduced numerical precision, typically from 32 or 16-bit floating-point to lower bit-widths like 8-bit integer. This technique significantly reduces memory requirements and computational complexity while potentially maintaining model performance. Contemporary quantization methods have shifted towards post-training approaches, that avoid the complexity of quantization-aware training and are more accessible to individuals and smaller organizations. Some methods use calibration datasets to optimize scale factors, while simple quantization techniques typically round weights and/or activations to the nearest number (Dettmers et al., 2023; “Zhu et al. - 2024 - A Survey on Model Compression for Large Language Models.pdf,” no date) (Zhu et al., 2024) .

GPTQ (Generative Post-Training Quantization) employs approximate second-order information to achieve accurate quantization of large models. The method can quantize models with 175 billion parameters in approximately four GPU hours, reducing bit-width per weight with minimal accuracy degradation. Recent improvements to GPTQ include enhanced bounds and theoretical guarantees (Frantar et al., 2023).

AWQ (Activation-aware Weight Quantization) identifies and protects salient weights based on activation distribution patterns. By preserving only 1% of the most important weights at higher precision, AWQ achieves significant compression while maintaining performance. The method's effectiveness stems from the observation

that activation distributions are highly non-uniform, with a small fraction of weights contributing disproportionately to model outputs. The method demonstrates particular effectiveness for edge device deployment(Lin et al., 2024).

SmoothQuant is a post-training quantization technique that enables accurate 8-bit weight and 8-bit activation inference by smoothing activation outliers that typically degrade quantization performance(Xiao et al., 2024). The method applies a mathematically equivalent transformation using scaling factors to redistribute quantization difficulty from activations to weights. The key innovation lies in its ability to smooth the distribution of both weights and activations without requiring retraining (Xiao et al., 2024).

Round-to-Nearest (RTN) quantization represents the simplest post-training approach, using deterministic rounding without optimization. While less sophisticated than GPTQ or AWQ, RTN offers computational simplicity and hardware compatibility, making it attractive for resource-constrained deployments where implementation complexity is a concern (Nagel et al., 2021; Kuzmin et al., 2023). The following two techniques use RTN quantization utilising different numerical precision formats.

INT8 W8A8 represents a straightforward quantization approach that converts both weights and activations to 8-bit integer representation using simple rounding. While less sophisticated than other methods, RTN offers computational simplicity and hardware compatibility.

FP8 W8A8 quantization utilizes 8-bit floating-point representation, offering a balance between compression and accuracy preservation. This approach has gained adoption in modern hardware accelerators designed for machine learning workloads (van Baalen et al., 2023).

Memory bandwidth is often the biggest source of latency in single-prompt inference, as for the inference process to complete, we need to pass the whole model from VRAM to the GPU processors, and for each generated token (Gholami et al., 2024). On the NVIDIA L40S with its 864 GB/s memory bandwidth and 48 GB of GDDR6 VRRAM quantization dramatically reduces this transfer overhead. At FP16 precision a 14 billion–parameter model like Qwen3-14B occupies about 29.5 GB and requires roughly 34 ms per token just to stream its weights. Converting the model to INT8 cuts its size to around 15.7 GB, halving the transfer time to approximately 18 ms per token. Pushing further to a highly optimized 4-bit format reduces the footprint to about 9 GB and brings per-token transfer times down to just over 10 ms. Because the L40S can accommodate even full-precision models entirely in its large VRAM pool, quantization yields a clear net performance gain

It is important to understand that 4-bit quantized models perform inference dequantizing and then computing. The weights are stored in compressed 4-bit format but are dequantized to FP16/BF16 for actual mathematical operations. GPUs don't have native capabilities for INT4 computations, but they do for INT8 and recently also for FP8. This approach achieves significant memory savings and bandwidth improvements while maintaining computational accuracy, though it does not eliminate the need for higher-precision arithmetic during inference, and often comes with an computational and energy overhead. However, we find that the the decrease in memory-transfer latency outweighs any additional compute from dequantization.

(Dettmers and Zettlemoyer, 2023) show that larger models are more resilient to quantization accuracy degradation and some even suggest there are scaling laws to confirm it. However, they focused their evaluations on Facebook OPT model family, which is now outdated and is considered to be undertrained. OPT-175B was trained on 300 billion tokens, yet the compute-optimal training for a 175 billion-parameter model would require roughly 1.4 trillion tokens according to the Chinchilla scaling laws (Hoffmann et al., 2022), indicating that OPT models were undertrained. If a model is undertrained, a lot of weights are irrelevant, which has an effect on quantization accuracy and resillience.

2.2 Energy Efficiency in Neural Networks

While most research focuses on the energy costs of training AI models, inference, the deployment phase where models are used for actual tasks, accounts for up to 70-90% of the total energy consumption across a model's lifecycle (Wu et al., 2019; Desislavov, Martínez-Plumed and Hernández-Orallo, 2023) . This critical insight necessitates a fundamental reorientation of sustainability efforts in AI development, prioritizing inference optimization over training efficiency.

Energy consumption in neural network inference depends on multiple factors including model size, quantization strategy, and hardware implementation. Recent work has established that quantization can achieve substantial energy savings, with studies reporting up to 37% energy reduction without accuracy loss in Convolutional Neural Networks (Klhufek et al., 2024).

The relationship between model parameters and energy consumption follows predictable patterns, with larger models requiring proportionally more energy per inference operation. However, quantization can significantly alter this relationship, enabling energy-efficient deployment of larger models, but the magnitude of these effects is not clearly understood. Aggressive quantization methods provide substantial energy savings while maintaining acceptable accuracy levels, particularly for larger models.

3. Methodology

3.1 Experimental Setup

We conducted comprehensive experiments across the Qwen3 model family, evaluating six model sizes: 0.6B, 1.7B, 4B, 8B, 14B, and 32B parameters. Qwen3 is one of the few models which has the weights available at various sizes, ideal for scaling analysis. All the experiments were performed on NVIDIA L40s GPUs; most models on a single GPU, with few larger few models (32B) using two GPUs. These GPUs have 48GB GDDR6 vRAM and native FP8 support. Each model was quantized using six different methods:

- FP16 (Baseline): Original 16-bit floating-point precision
- GPTQ 4-bit: 4-bit quantization using GPTQ algorithm, activations in FP16
- GPTQ 8-bit: 8-bit quantization using GPTQ algorithm, activations in FP16
- AWQ: Activation-aware weight quantization, weights in INT8, activations in FP16
- FP8 W8A8: 8-bit floating-point quantization, weights and activations rounding to nearest
- INT8 W8A8: 8-bit weight and activation round-to-nearest quantization

All models were quantized locally using the llm-compressor library (Red Hat AI and vLLM Project, 2024). We calibrated both AWQ and GPTQ methods using 256 samples randomly selected from the Pile validation dataset (mit-han-lab/pile-val-backup), applying default calibration parameters.

While SmoothQuant was not tested as a standalong quantization method, we adopted its distribution smoothing techniques to mitigate activation outliers in FP8 W8A8 and INT8 W8A8 quantization methods.

3.2 Benchmark Selection

Our benchmark selection encompasses diverse evaluation dimensions essential for comprehensive model assessment. Each benchmark was chosen to evaluate specific aspects of model capability:

The ARC Challenge benchmark evaluates scientific reasoning through multiple-choice questions requiring complex inference. The MMLU (Massive Multitask Language Understanding) benchmark evaluates multitask language understanding across 57 subjects, providing a broad assessment of world knowledge and reasoning capabilities. TruthfulQA assesses the factual accuracy and truthfulness of model responses across 817 questions spanning 38 categories, addressing concerns about model reliability.

GSM8K focuses on mathematical reasoning capabilities through grade-school mathematical problems.

HumanEval specifically measures code generation abilities through 164 programming tasks, representing a crucial capability for many applications.

MetaBench provides a sparse benchmark for reasoning and knowledge evaluation in large language models. These benchmarks collectively provide a comprehensive evaluation framework for assessing model capabilities across different domains.

3.3 Performance Metrics

We collected comprehensive performance metrics divided into two categories: accuracy metrics, and efficiency metrics.

Accuracy metrics include benchmark scores across all evaluation tasks, enabling assessment of quantization impact on model capabilities. Benchmarks were done using the LM Evaluation Harness (Sutawika et al., 2024)

While perplexity is commonly used as an intrinsic metric for quantized models, it doesn't always correlate well with downstream task performance, and two models with similar perplexity scores can show significantly different capabilities on practical applications – that is why we focused on benchmark specific accuracy metrics.

For efficiency metrics, we measured tokens per second and energy per output token. The experiments include measurements across different context lengths (300, 500, 1000, 4000 and 8000 tokens) and output lenghts (100, 500, 1000, 4000 and 8000). The results were collected as an average across 100 prompts. Inference was

measured via an offline vLLM inference server. Energy was measured with the Zeus framework and measured only GPU energy usage - no specialized setup was implemented apart from including the measuring functions in the inference process.

4. Results and Analysis

4.1 Quantization Impact on Model Performance

Contrary to other research our analysis of Qwen3 does not reveal clear scaling patterns in quantization resilience across model sizes. For some benchmarks, data demonstrates that larger models consistently maintain higher accuracy retention rates when subjected to aggressive quantization methods. Retention refers to the fraction of a model's original (FP16) performance that remains after it has been quantized.

Table 1: Quantization resiliency across model sizes for Metabench benchmark

Model size	AWQ	GPTQ-4bit	GPTQ-8bit	INT8	FP8
0.6B	90.07%	91.25%	97.02%	100.94%	93.52%
1.7B	91.84%	95.83%	100.13%	95.01%	97.86%
4B	95.32%	96.73%	99.53%	97.90%	98.50%
8B	96.36%	97.08%	99.12%	97.43%	95.58%
14B	98.05%	100.15%	99.18%	98.05%	100.56%
32B	98.28%	97.43%	100.02%	99.99%	100.97%

For Metabench benchmark, AWQ, GPTQ-4bit and FP8 show scaling patterns where models are more resilient to quantization as they grow in size. Parameter redundancy at larger model sizes keeps the quantization error to a minimum. Interestingly, GPTQ-8bit and INT8 show better resiliency at smaller model sizes.

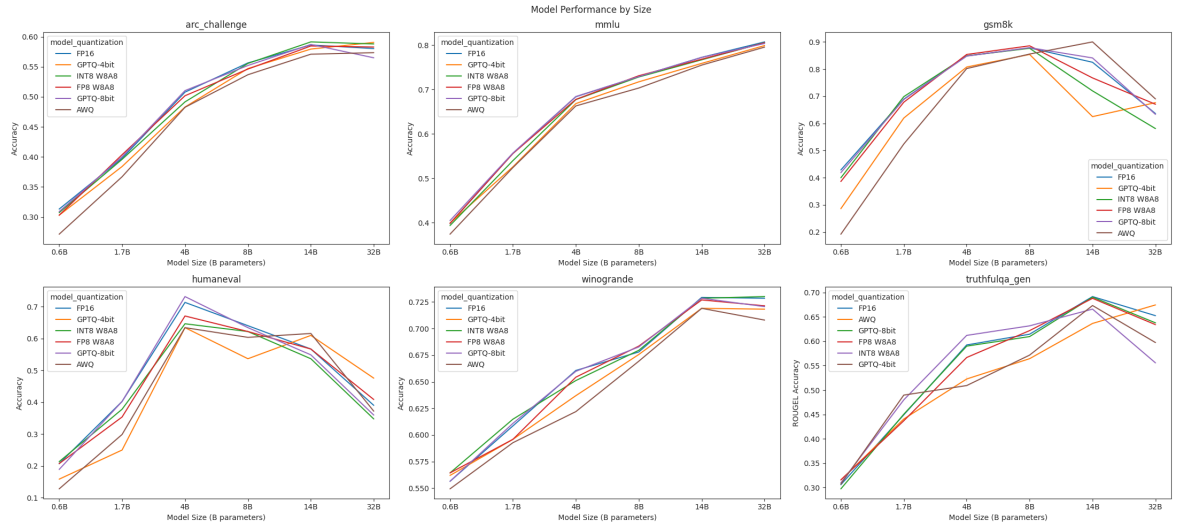

Figure 1: Model performance by size for 6 benchmarks - we evaluate zero-shot accuracy on ARC, MMLU, GSM8, HunamEval, WinoGrande and TruthfulQA

The mathematical reasoning tasks (GSM8K) show particular sensitivity to quantization effects. Smaller models experience pronounced degradation, while larger models – especially Qwen3-14B, have large discrepancies between quantization methods, AWQ even performing significantly better than the FP16 baseline.

Code generation capabilities (HumanEval) demonstrate similar scaling performance. The evaluation suggests that complex coding and mathematical abilities in large language models degrades even without quantization – possibly due to overthinking. The GPTQ-8bit and AWQ quantization methods even performing better than the FP16 baseline.

In language understanding tasks (MMLU, ARC Challenge and WinoGrande), quantization error and scaling seem to be as expected – with consistent errors which reduce and stabilise as we scale the model. Larger models maintain strong reasoning capabilities even under aggressive quantization.

Factual accuracy (TruthfulQA) shows consistent degradation patterns across model sizes, suggesting that truthfulness preservation is more dependent on quantization method than model scale.

4.2 Energy Efficiency Characteristics

Some quantization methods deliver substantial energy savings across all model sizes. Our measurements reveal consistent patterns in energy reduction effectiveness:

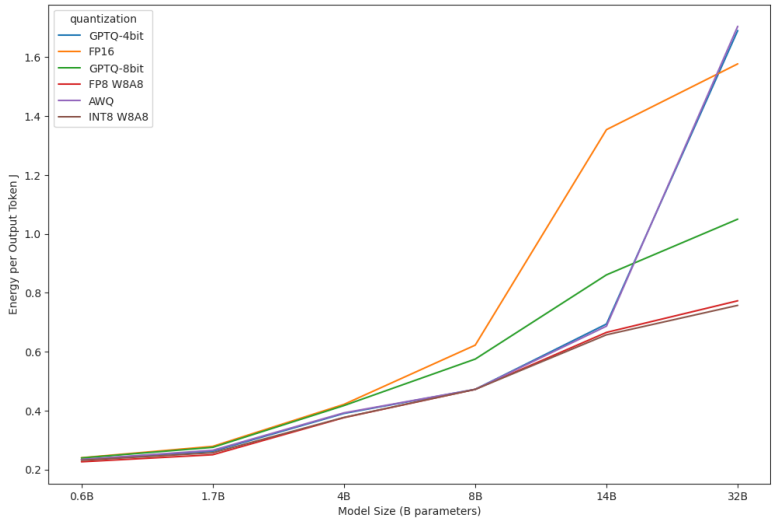

Figure 2: Energy use per output token on across model sizes using different quantization methods for context length 4000 tokens and output length 1000 tokens

The 32B model with GPTQ 4-bit quantization consumes 1.69 J per output token compared to 1.58 J for the FP16 baseline, while the FP8 quantized model consumes only 0.77 J, representing a improvement of more than 2x in energy efficiency. INT8 and FP8 quantized models perform consistently better than other methods, and their energy efficiency improves on larger model sizes. This is mostly due to the native hardware support of INT8 and FP8 on modern GPUs – which reduces not only the memory footprint, but also the amount of computations necessary.

The 32B model sizes quantized to FP16, GPTQ-4bit, GPTQ-8bit and AWQ had to be run on 2 GPUs. Although we ran experiments with various context lengths and output lengths, the result were consistent to the ones shown in Figure 2. This improvement enables deployment of larger models within similar energy budgets as smaller unquantized models – where a 32B FP8 models energy requirements can be compared to a 8B unquantized models energy requirements.

4.3 Throughput Performance Analysis

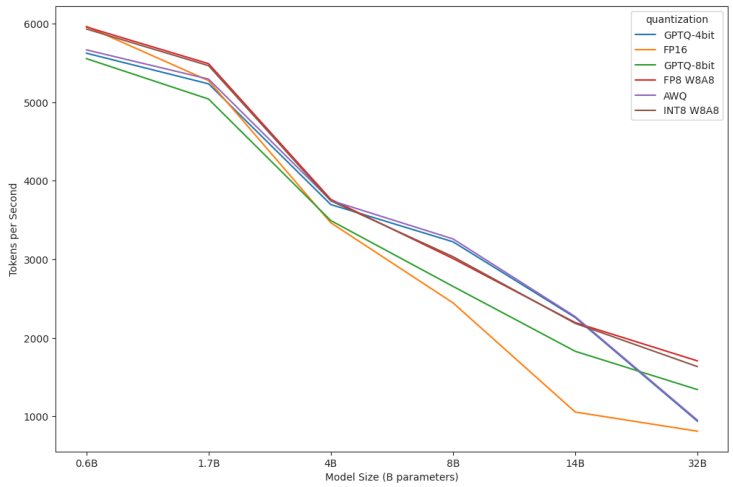

Figure 3: Tokens per second throughput across model sizes using different quantization methods for context length 4000 tokens and output length 1000 tokens

Inference throughput improvements scale predictably with quantization. Smaller model sizes perform well on modern GPUs in any format, while larger models show better throughput performance with quantization across all quantization methods.

FP8 and INT8 quantization provide approximately 2x throughput improvement on larger models compared to FP16 baseline across all context length. GPTQ-4bit and AWQ show almost identical throughput performance as expected, sine both of them use 4-bit representation of weights with 16-bit activations.

5. Practical Implications

The quantization tolerance of larger models fundamentally challenges conventional deployment strategies. Our findings suggest that deploying a quantized large model often provides better performance than deploying a smaller unquantized model within similar resource constraints.

For production environments requiring maximum efficiency, INT8 or FP8 W8A8 RTN quantization offers substantial benefits, particularly when combined with larger models that demonstrate quantization resilience. GPTQ-8bit quantization emerges as the preferred method for applications requiring high accuracy preservation with moderate efficiency gains. GPTQ methods offer excellent compression ratios with good accuracy preservation, making them suitable for memory-constrained deployments. The GPTQ-4-bit variant has better accuracy across benchmarks than AWQ, while being on par with energy-efficiency and throughput.

FP8 and INT8 W8A8 provide maximum throughput improvements and maximum energy efficiency with simple implementation requirements, making it attractive for high-volume inference scenarios where slight accuracy degradation is acceptable.

The ability to deploy larger, more capable models within similar energy budgets as smaller unquantized models represents a paradigm shift in deployment strategy optimization. This finding suggests that quantization enables "scaling up" rather than "scaling down" for energy-constrained scenarios.

6. Future Research Directions

The results suggest that advanced quantization methods lag behind simple INT8 and FP8 quantization in energy efficiency and performance, while providing small accuracy improvements in some cases. Adaptive quantization strategies that leverage natively implemented number formats – instead of using mixed precision, are a promising research direction. Hardware-aware quantization that considers specific accelerator architectures could further optimize the energy-performance trade-offs identified in this work.

Long-term stability analysis of quantized models in production environments requires investigation. Understanding whether quantization effects accumulate or remain stable over extended deployment periods together with model shifts is crucial for production planning.

This study focuses exclusively on the Qwen3 model family, which may limit generalizability to other architectures. The scaling patterns observed may not transfer directly to models with different architectural choices or training procedures.

The evaluation was conducted under controlled conditions that may not reflect real-world deployment scenarios with variable workloads and diverse input distributions. Production environments may exhibit different performance characteristics.

7. Conclusion

This comprehensive analysis establishes fundamental findings in quantization effects across model sizes, providing crucial insights for efficient LLM deployment. Larger models demonstrate superior resilience to quantization in most cases. Additionally, we provided clear results on which quantization methods are the most energy efficient.

The substantial energy savings achieved through quantization offer significant benefits for sustainable AI deployment, while the throughput and evaluation results provide guidelines for quantization planning. These findings contribute to making large language models more accessible and environmentally sustainable through efficient inference optimization.

Our results demonstrate that quantization is not merely a compression technique but a fundamental enabler of scale-efficient deployment strategies. The ability to deploy larger, more capable models within similar resource constraints represents a significant advancement in LLM deployment optimization.

Ethics Declaration: No ethical approval was required for this research as it involved only computational experiments with publicly available datasets and did not involve human participants, animal subjects, or sensitive data.

AI Declaration: Artificial intelligence tools were used for proofreading and spellchecking to improve the clarity and accuracy of this paper, with all substantive content, analysis, and conclusions remaining the original work of the authors.

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AI's Environmental Cost: Comparing Resource Consumption Between SLMs and LLMs Across Queries

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Abstract: As artificial intelligence becomes increasingly embedded in daily life, the environmental costs of its deployment remain underexplored. This study investigates the environmental footprint of both large language models (LLMs) and small language models (SLMs); specifically, ChatGPT, Gemini, Deepseek, and Claude, by associating their power draw and water use across queries of varying complexity. Building on evidence that AI services demand substantial resources, this paper asks: how do query complexity and type influence the energy and water consumption of SLMs versus LLMs, and at what threshold of complexity do SLMs become incapable of delivering accurate outputs? To address this, the experimental method categorizes queries into three complexity tiers based on logical steps, conceptual depth, and cognitive skills (recall, evaluation, creation), drawing from the College Board's question bank of SAT math, reading, and writing problems. Additionally, classic puzzles such as the Tower of Hanoi were selected. Each query was executed three times on the SLM and LLM versions of each commercial AI entity under identical hardware and software configurations. We recorded execution time, model version, and output accuracy. Using the average response time per query, we computed energy consumption and water usage per query. On average, SLMs consumed 60-70% less energy and water than their LLM counterparts, and in subjects such as Math and Reading, had the same level of accuracy as their respective LLMs. However, model performance declined as question difficulty increased, especially in abstract reasoning tasks such as Puzzles, where SLM accuracy dropped considerably. While LLMs were more resource-intensive, they maintained higher accuracy on these challenging queries. SLMs offer a significantly more environmentally sustainable option for simple tasks, but accuracy decreases as complexity increases. A dynamic approach, starting with SLMs and switching to LLMs only when needed, or vice versa, could reduce the environmental cost of AI while maintaining quality. These findings support the potential for context-aware AI deployment strategies that optimize environmental sustainability and accuracy. Future research should aim to quantify this breakpoint more accurately and look at the implementation of automatic query classification systems capable of efficiently switching between models to create more efficient AI models.

Keywords: AI environmental sustainability, Small language models, Large language models, Query complexity

1. Introduction

Eric Schmidt, former Google CEO, told Congress that "many people project demand for our industry will go from 3 percent to 99 percent of total generation" to power Superintelligent AI (Joe Wilkins, 2025). LLMs are now integral to daily life. "They have enabled digital assistants that can free people from the need to search, extract, and integrate information from multiple sources by offering straightforward answers in a single chat" (Wang et al., 2024). As global reliance on Artificial Intelligence (AI) increases, so does the strain on environmental resources. The rising demand for AI has led to exponential growth in the number and complexity of queries processed daily. Each query requires a computationally intensive process handled by data centers that consume large amounts of energy and water. These centers often use water-intensive cooling systems to prevent server overheating, compounding AI's environmental impact (Schäfer et al., 2024). This toll raises concerns about the efficiency of the models powering these queries.

The backbone of most AI systems is Language Models, typically classified as Large Language Models (LLMs) or Small Language Models (SLMs). LLMs are transformer models trained on vast datasets and defined by billions of parameters, enabling reasoning and abstraction. They perform tasks like masked language modeling and autoregressive prediction to generate human-like responses (Wang et al., 2024). In contrast, SLMs are leaner, trained on optimized parameters for specific use cases, offering better resource efficiency at the potential cost of capability (Magister et al., 2023).

2. Literature Review

2.1 AI Environmental Cost

The environmental implications of AI have drawn increasing attention as large-scale models consume unprecedented levels of computational resources. Strubell et. al. (2019) were among the first to quantify the

carbon footprint of model training, finding that developing a single NLP model could emit as much CO2 as five cars over their lifetimes. More recent analyses by Jegham et al. (2025) and Henderson et al. (2020) have expanded this focus, showing that the *inference* phase of AI, though individually lightweight, accounts for a far larger share of total energy use due to the scale and daily interactions. These findings highlight the growing urgency for sustainable inference models and energy-efficient architectures.

More recently, Vogginger et al. (2024) examined the prospect of neuromorphic hardware as an energy-efficient paradigm for data centers and reviewed its potential to reduce inference costs at scale. They argue that while inference is individually less energy-intensive than training, the cumulative cost (given the massive number of queries) is nontrivial, and that architectural innovations are needed to shift the efficiency frontier. Additionally, Alex de Vries (2023) reports that as an AI entity grows, the amount of data centers required to run the servers increases, therefore leading to an increase in energy consumption. He cites ChatGPT as an example, explaining it required over 3,500 of NVIDIA's HGX A100 servers.

Complimenting this view, Desislavov et al. (2023) address trends in AI energy consumption and highlight that inference scaling, such as deploying smaller or medium models, may surpass training in environmental relevance.

On the water usage side, data centers often employ water-based cooling systems, and their water use efficiency (WUE) becomes a critical metric, especially in arid regions. The Environmental and Energy Study Institute (EESI) has documented how cooling strategies can dramatically increase water consumption for power generation and data centers.

Together, these works underscore that both energy and water demand must be accounted for when assessing AI's environmental cost, and that sustainable architectures are urgently necessary.

2.2 Model Size, Reasoning, and Efficiency

The commonly held belief is that "bigger is better": larger models yield stronger performance. Kaplan et al. (2020) formalized this via scaling laws, showing that increasing parameters, compute, and data tend to improve performance (though with diminishing returns).

However, more recent empirical findings suggest that reasoning and generalization do not scale indefinitely with size. Schaeffer et al. (2024) demonstrate that scaling laws often fail to predict downstream reasoning capacity accurately, implying that blindly increasing model size may be inefficient. Vogginger and team also contend that neuromorphic or brain-inspired architectures may provide better efficiency-per-inference, especially for models or tasks that can exploit sparsity and event-driven dynamics.

Further research explores how smaller or optimized models can achieve near LLM performance with far less computational demand. Li et al. (2020) propose training large models and subsequently compressing them for efficient inference, showing that model distillation and pruning can drastically reduce energy use without major accuracy loss. Their findings reveal that compressed models retain much of the accuracy of their larger counterparts while cutting energy usage by up to an order of magnitude. This introduces an important nuance: efficiency gains may be best realized after large-scale pretraining, rather than avoiding large models altogether.

Tan and Le (2019) approach the efficiency problem from a structural perspective with EfficientNet, a scaling method that optimizes width, depth, and resolution simultaneously rather than arbitrarily enlarging one dimension. While their work focuses on vision models, the implications extend to NLP, showing that balanced scaling delivers better performance-per-compute ratios than sheer parameter expansion. Together Li et al. (2020) and Tan & Le (2019) present complementary strategies: Li et al. emphasize post-training optimization, while Tan & Le optimize architecture scaling at design time.

Collectively, these findings converge on a critical insight: achieving sustainability in AI requires coordinated improvements across architecture and reasoning algorithms, not merely shrinking or scaling models in isolation.

2.3 Identified Research Gap

Although the literature contains substantial work on training-time carbon footprints and scaling behavior, fewer studies focus on per-query inference-level environmental impact. In addition, the literature does not clearly define the breakpoint at which smaller models lose reliability under greater task complexity (or when neuromorphic or hybrid architectures begin to outperform purely digital models).

This paper addresses that gap by evaluating how variations in query type and complexity impact the environmental cost and output accuracy of large and small language models used in commercial AI products such as ChatGPT, Claude, and Deepseek. It aims to identify the optimal intersection of efficiency and capability by quantifying energy and water consumption per query and correlating them with performance outcomes.

Accordingly, this study explores two research questions:

RQ1: How does query complexity affect the power and water consumption of Small and Large Language Models during inference?

RQ2: At what level of complexity do SLMs begin to lose accuracy, making LLMs necessary despite their higher environmental cost?

H1: Query complexity is positively correlated with both energy and water consumption in inference.

H2: Smaller or neuromorphic-inspired models maintain higher energy and water efficiency than large models up to a complexity threshold, beyond which their accuracy degrades.

3. Method

Step	Description	Tool Used	Output
1	Select SAT and Puzzle questions	College Board/ Online	Datasets of 48 queries
2	Execute each on SLM and LLM	ChatGPT, Claude, DeepSeek	Response times and accuracy
3	Compute power and water	Formulas (Eq. 1, Eq. 2)	Pre-query metrics
4	Visualize data	Matplotlib	Graphs
5	Compare results	Accuracy vs. Resource use	Insights

To evaluate AI responses across different query types and reasoning tasks, an experimental method using four question categories was conducted. The four categories were math, reading, writing, and puzzles. The math, reading, and writing questions were sourced from CollegeBoard's SAT question bank using its difficulty filter to select easy, medium, and hard questions. Math included four types: Problem Solving, Algebra, Advanced Math, and Geometry (College Board, n.d.). For each type, three questions (one per difficulty level) were selected, totaling twelve math questions. The questions were selected randomly through a random number generator. The questions were also selected to ensure no visual prompts, such as graphs or charts. This decision was made to avoid the need to upload images, as recognizing them would increase the response time. Reading featured two types: Information and Ideas, and Expression of Ideas. Four questions were chosen for each difficulty level, totaling twelve reading questions. Writing followed the same structure, using Craft and Structure, and Standard English Conventions as its two types. All math, reading, and writing questions were multiple choice.

There were four types of puzzles: Tower of Hanoi, Go, Checkers, and River Crossing.

The Tower of Hanoi is a puzzle involving three pegs and *n* disks of different sizes stacked on the first peg (largest at the bottom). The goal is to move all disks to the third peg, following rules: only one disk may be moved at a time, only the top disk can be taken from any peg, and a larger disk cannot be placed on a smaller one. Difficulty is controlled by the number of disks, with the minimum number of required moves being $2^n - 1$. As question difficulty increases, so does the number of disks and moves required (Shojaee et al., 2025).

River Crossing is a constraint satisfaction puzzle involving *n* people who must cross a river using a boat. The boat holds at most *k* individuals and cannot travel empty. Invalid states occur when certain groups are left alone. The task's complexity is controlled by adjusting *n* and *k* (Shojaee et al., 2025).

Checkers is a one-dimensional puzzle with red and blue checkers and a single space arranged in a line. The objective is to swap red and blue checkers, mirroring the initial setup. Valid moves include sliding into an adjacent space or jumping over one opposing checker into a space. Backward moves are not allowed. Each question was presented as a multiple-choice item asking the AI for the best move and its reasoning (Shojaee et al., 2025).

GO is a traditional Chinese board game played on a 19×19 grid. Two players alternate placing black or white stones on board intersections to enclose the largest possible area while blocking the opponent. Since stones differ only in color, the key challenge is spatial positioning. Each GO question was multiple-choice, asking for the best sequence of moves. As difficulty increased, the required sequence length and board size grew (Chen et al., 2003).

Each puzzle type had three questions, with increasing difficulty, making for a total of twelve questions. The Tower of Hanoi and River Crossing questions were open-ended, while the Checkers and Go questions were multiple choice.

A Google Drive folder was created to organize the questions and responses. Inside, a "Question Bank" subfolder contained three folders: one for each AI system. Each system folder had two subfolders for LLM and SLM responses. A document listing all questions, correct answers, and Question IDs (organized by subject) was also included. Model responses were uploaded into the appropriate folders based on system and model type.

To organize the data, a Google Sheet was created inside the Google Drive folder. Inside the spreadsheet, separate columns were created for the index of the question, model type (LLM or SLM), AI commercial entity (ChatGPT, Claude, Deepseek), question difficulty (easy, medium, hard), question subject (Math, Reading, Writing, Puzzle), specific question type (Algebra, Geometry, Standard English Conventions, etc.), the response time for each repetition of the trial, the average response time of the three repetitions, the power and water consumption, and output accuracy.

The power and water consumption columns were computed using system-specific formulas based on the average response time of each trial.

The power was measured in kilowatts and was calculated using this formula:

$$E_{query}\ (kWh) = \frac{P_{critical} \times\ t\ (s) \times\ PUE}{3600}$$

This equation represents the energy consumed per query depending on the time taken for the model to respond to the query. The $P_{critical}$ is how much power is consumed from the model's GPU per hour, and it is multiplied by the *PUE* and the time taken for the system to give a final answer to the query. Because *t* is meant to be measured in hours, the equation was divided by 3600 as the response times were recorded in seconds (Jegham et al., 2025).

The water was measured in liters and was calculated using this formula:

$$W_{query}(L) = (WUE_{onsite}\ +\ WUE_{offsite}) \times\ E_{query}$$

The WUE_{onsite} and $WUE_{offsite}$ account for the water used inside and outside the data center. This is then multiplied by the energy used by the system to answer a query, resulting in the water consumption for the query (Jegham et al., 2025).

The 48 questions were fed into each AI entity's LLM and SLM, with response times recorded for each. The questions included multiple-choice reading, writing, and math, as well as multiple-choice or open-ended puzzle questions. All models were tested under identical conditions: similar laptops, Google Chrome browser, and a testing window from 2:00 pm to 5:00 pm. To ensure consistency, each question was entered three times. Response times for each trial were captured using the browser's developer tools. In total, 96 trials were conducted for each AI system. The average response time was calculated and used to estimate the power and water consumption of the models.

To begin data collection, ChatGPT was opened in the browser, and the GPT-4o model (ChatGPT's LLM) was selected. A temporary chat session was initiated to prevent the model from retaining any information. This was done by clicking the "Temporary Chat" button. The browser's developer console was then opened using Fn + F12 (or Command + Option + I for Mac).

Once setup was complete, questions were entered individually, and response times were recorded using the developer console. The tab was refreshed and the console cleared after each entry. Each question was submitted three times, with all response times logged. After the third attempt, a screenshot of the response was taken, named after the question's index, and uploaded to the corresponding AI system's folder.

This process was repeated for each question until all 48 trials were completed. Following this, the model was switched to GPT-4o-mini (ChatGPT's SLM), and the same procedure was followed to collect the SLM's data.

The process for Claude was similar, with slight modifications. Claude was opened in a browser tab, and the Sonnet 4 model (Claude's LLM) was selected. Since Claude does not offer a temporary chat option, the "New Chat" button was used, and the tab was refreshed after each response to eliminate information retention. The same input and timing process was followed, except the completion command was used instead of conversation. This was because every time Claude received a query, it looked at it as a task to complete, whereas ChatGPT looked at the query as a conversation to be had, hence the different command names between AI entities. After completing the 48 trials with Sonnet 4, the model was switched to Claude 3.5-Haiku (Claude's SLM), and the procedure was repeated for another 48 trials to capture SLM data.

The process for DeepSeek was similar to Claude's. DeepSeek's SLM (vl2-Tiny), however, cannot be launched on a browser and is hardware-dependent. This means that when the model is selected, its response time will vary depending on the hardware it is running on. Because of this, the SLM chosen for DeepSeek was V3. This model is not a reasoning model, nor is it dependent on computer hardware. For the LLM, DeepSeek's R1 model was chosen as it is a reasoning model and is made for more reasoning and comprehension-heavy tasks. DeepSeek was opened in a browser tab, and the R1 model was selected. Since DeepSeek does not provide a temporary chat option, the "New Chat" button was used, and the tab was refreshed after each response to eliminate information retention. The same input and timing process was followed as Claude. The "completion" command was timed, and after 48 trials, the model was switched to V3. The procedure was repeated for another 48 trials to capture SLM data.

The collected data was analyzed from multiple viewpoints. To maintain consistency, it was organized by subject. All coding and visualizations were performed in Jupyter Notebook using Matplotlib to generate linear graphs. In these graphs, the y-axis represented resource consumption (Power or Water), while the x-axis represented individual questions per subject. Questions increased in difficulty across the x-axis, starting with four easy, followed by four medium, and ending with four hard questions.

Each data point on the graph was color-coded: green indicated a correct response, and red an incorrect one, allowing resource usage to be interpreted in the context of system accuracy. Separate lines were plotted for SLMs and LLMs to enable direct comparisons. For instance, comparisons were made between an SLM and an LLM from the same AI entity on a single subject (ChatGPT Reading SLM vs. ChatGPT Reading LLM).

Additionally, graphs were generated to compare different systems using the same model type within a subject area (Math LLMs from Deepseek, ChatGPT, and Claude). Finally, combined graphs were created to show overall resource consumption across all three AI systems and both model types (SLM and LLM) per subject.

4. Results

The following section presents the results of our experiments evaluating the environmental footprint of large and small language models. Drawing from controlled testing across subjects and complexity levels, we report the power and water consumption of ChatGPT, Claude, and DeepSeek under identical conditions. These findings highlight key efficiency differences between SLM and LLM configurations, offering insight into the resource demands associated with model scale and task complexity.

Table 1: Data Analysis of Power Consumption Table

			Commercial Entity									
			ChatGPT			*Claude*			*DeepSeek*			
ID	**Subject**	**Complexity**	**SLM-Power**	**LLM-Power**	**Difference Factor**	**SLM-Power**	**LLM-Power**	**Difference Factor**	**SLM-Power**	**LLM-Power**	**Difference Factor**	**Highest Factor**
1	Math	Easy	0.0070	0.0129	1.853	0.0145	0.0160	1.104	0.0539	0.2249	4.170	DeepSeek
2	Math	Medium	0.0075	0.0225	3.004	0.0140	0.0166	1.187	0.0581	0.2881	4.961	DeepSeek
3	Math	Hard	0.0090	0.0252	2.805	0.0199	0.0238	1.192	0.0987	0.3752	6.461	DeepSeek
4	Reading	Easy	0.0079	0.0162	2.050	0.0255	0.0289	1.137	0.0503	0.1444	2.868	DeepSeek
5	Reading	Medium	0.0064	0.0147	2.282	0.0289	0.0298	1.030	0.0596	0.2145	3.600	DeepSeek
6	Reading	Hard	0.0069	0.0198	2.883	0.0277	0.0286	1.033	0.0541	0.2335	3.918	DeepSeek
7	Writing	Easy	0.0123	0.0342	2.787	0.0239	0.0276	1.155	0.0457	0.1655	3.618	DeepSeek
8	Writing	Medium	0.0100	0.0344	3.439	0.0386	0.0306	0.794	0.0491	0.3272	6.665	DeepSeek
9	Writing	Hard	0.0091	0.0371	4.085	0.0304	0.0320	1.052	0.0571	0.2388	4.864	DeepSeek
10	Puzzles	Easy	0.0314	0.0313	0.996	0.0595	0.0238	0.400	0.2183	0.5076	2.325	DeepSeek
11	Puzzles	Medium	0.0073	0.0126	1.731	0.0339	0.0287	0.847	0.2759	1.1713	4.246	DeepSeek
12	Puzzles	Hard	0.0192	0.0245	1.278	0.0793	0.0171	0.215	0.3801	1.6624	6.027	DeepSeek

The difference factor refers to the factor of how much more or less the LLM consumes in relation to the SLM. The Highest Factor column refers to the model with the biggest Difference Factor.

In *Table 1,* DeepSeek shows the highest Difference Factor between the SLM and LLM's power consumption across all subjects, often exceeding 4 and peaking at 6.665. Claude demonstrates the lowest power difference and has the most instances of the SLM consuming more than the LLM. Some tasks, like hard puzzles, showed an extremely small Difference Factor of 0.215, indicating efficient scaling. ChatGPT's power difference is moderate

and consistently above 1 in almost all query subjects. The highest Difference Factor (4.085) was observed in a hard writing query, suggesting that task complexity has a clear impact on power consumption efficiency.

Accuracy is a key component of a model's success. Looking at the queries submitted in the study, the models tend to miss query subjects such as Writing and Puzzles. Each model missed several different questions, of which the question IDs are listed below.

Questions Missed (Refer to Data Collection Sheet for question ID):

ChatGPT LLM: TR-MExp1, TR-MExp2, TR-MSta1, TR-EGo, TR-MGo, TR-HCheck, TR-MCross, TR-HCross
ChatGPT SLM: TR-HExp1

Claude LLM: TR-HExp2, TR-EGo, TR-MGo, TR-MCheck

Claude SLM: TR-HExp2, TR-HSta1, TR-MHanoi, TR-HHanoi, TR-EGo, TR-MGo, TR-ECheck, TR-HCross

DeepSeek LLM: TR-EGo, TR-MGo, TR-HGo

DeepSeek SLM: TR-HExp2, TR-MSta1, TR-HSta1, TR-EGo, TR-MGo, TR-HCross

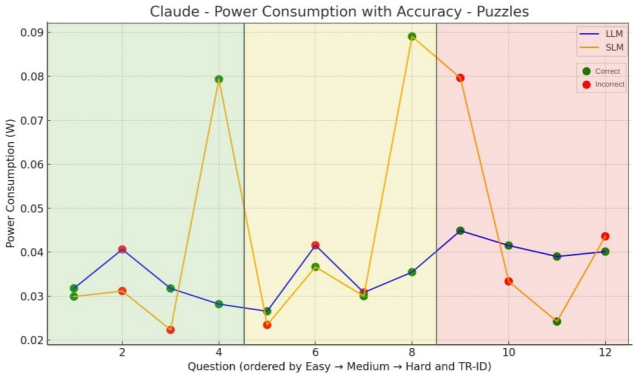

Figure 1: Claude Power Consumption Puzzles

Note. Applicable for Figures 1 - 9. X-axis is Query, and Y-axis is Power Consumption. The portion of the graph in green refers to easy questions, yellow refers to medium questions, and red refers to hard questions.

For the Puzzle category, Claude's LLM's power consumption standard deviation was 0.00604 kW, which is relatively stable compared to the SLM's standard deviation of 0.0244 kW. There are data points where the LLM consumed less power than the SLM, such as the fourth easy question (TR-ECross), the fourth medium question (TR-MCross), the first hard question (TR-HHanoi), and the fourth hard question (TR-HCross). The LLM got 66% of the questions correct while the SLM got 50% of the questions correct.

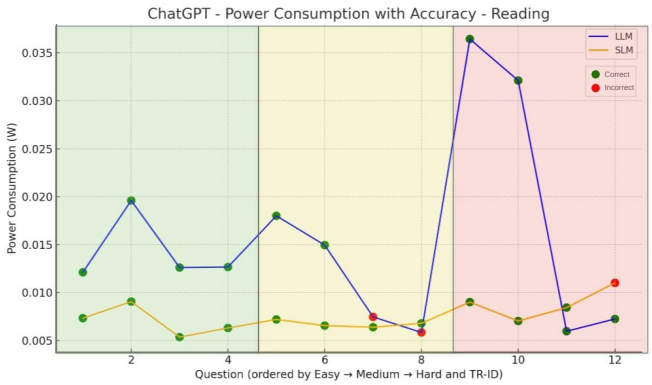

Figure 2: ChatGPT Power Consumption Reading

For the Reading questions, ChatGPT's LLM's power consumption varied more than its SLM's. The LLM had a standard deviation of 0.0099 kW, far greater than the SLM's standard deviation of 0.0015 kW. There were points where the LLM consumed less power than the SLM, such as the fourth medium question (TR-MExp2) and the last two hard questions (TR-HExp1, TR-HExp2). The LLM's power consumption peaked at first and second hard questions (TR-HInfo1, TR-HInfo2) with values of 0.0364 kW and 0.0321 kW, respectively. The LLM got 75% of the reading questions correct while the SLM got 91.67% of the questions correct.

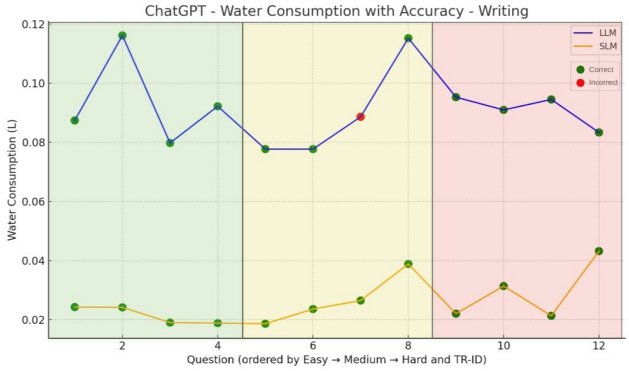

Figure 3: ChatGPT Water Consumption Writing

For the Writing questions, ChatGPT's LLM's average water consumption of 0.092 L was higher than its SLM's average water consumption of 0.026 L. The LLM's water consumption peaked at the third easy question (TR-ESta1) with a value of 0.116 L, which was greater than the SLM's peak of 0.0432 L at the fourth hard question (TR-HSta2). The LLM was 91.67% accurate in terms of correct answers, while the SLM was 100% accurate.

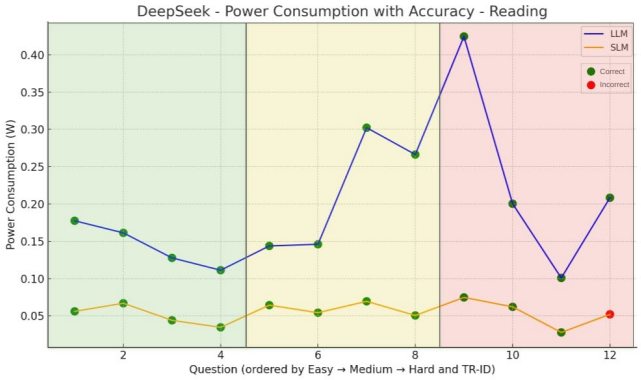

Figure 4: DeepSeek Power Consumption Reading

For the reading questions, DeepSeek's LLM's power consumption was higher on average compared to the SLM's power consumption. DeepSeek's LLM's average power consumption of 0.197 kW was much higher than its SLM's average power consumption of 0.0547 kW. The LLM's power consumption peaked at 0.425 kW at the first hard question (TR-HInfo1). The SLM's power consumption also peaked at the first hard question (TR-HInfo1) with a value of 0.0747 kW. The LLM was 100% accurate while the SLM was 91.67% accurate.

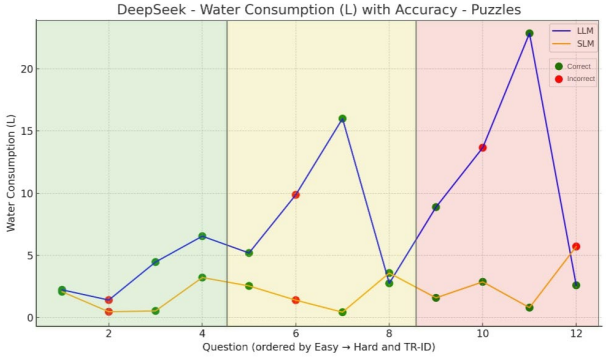

Figure 5: DeepSeek Water Consumption Puzzles

For the Puzzles questions, DeepSeek's LLMs' water consumption was higher on average than the SLM's. The LLM's average water consumption was 8.037 L, far greater than the SLM's average water consumption of 2.103 L. There were points where the LLM consumed less water than the SLM, such as the fourth medium question (TR-MCross) and fourth hard question (TR-HCross). The LLM's water consumption peaked at 22.85 L for the third hard question (TR-HCheck), while the SLM's water consumption peaked at 5.712 L for the fourth hard question (TR-HCross). The LLM got 75% of the questions correct, and the SLM also got 75% of the questions correct.

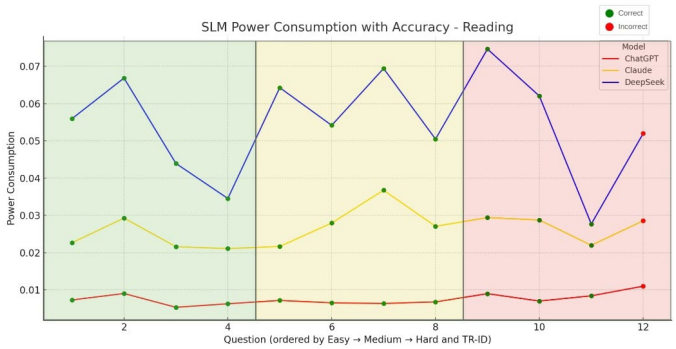

Figure 6: SLM Power Consumption Reading

For the Reading questions, the power consumption of Claude and ChatGPT SLMs did not show much variation, while DeepSeek's SLM varied more. ChatGPT's SLM had a standard deviation of 0.00538 kW. Similarly, Claude's SLM had a standard deviation of 0.00555 kW, far less than DeepSeek's SLM's standard deviation of 0.0141 kW. DeepSeek's SLM peaked at 0.0747 kW for the first hard question, Claude's SLM peaked at 0.0368 kW for the third medium question, and ChatGPT's SLM peaked at 0.011 kW for the fourth hard question. All of the SLMs were 91.67% accurate as they all answered incorrectly on the fourth hard question.

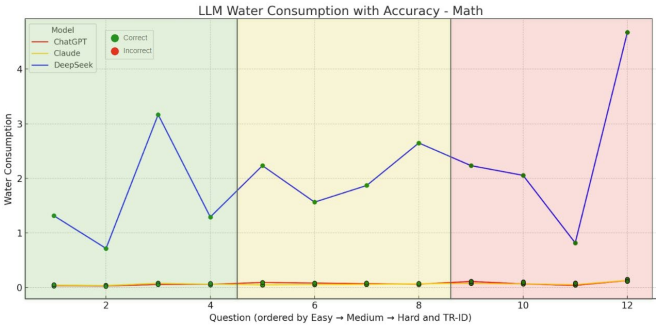

Figure 7: LLM Water Consumption Math

For the Math questions, the LLMS of Claude and ChatGPT had similar water consumption levels throughout each question, while DeepSeek had significantly higher water consumption levels per question. ChatGPT's and Claude's LLMs had average water consumptions of 0.0694 L and 0.0647 L, respectively. This was far less than DeepSeek's LLM's average water consumption of 2.049 L. DeepSeek's LLM also had a standard deviation of 1.097 L, far higher than ChatGPT's and Claude's (0.0302 L and 0.0245 L, respectively). DeepSeek's LLM peaked at 4.674 L on the fourth hard question. Claude's LLM peaked at 0.131 L on the fourth hard question. ChatGPT's LLM peaked at 0.128 L on the fourth hard question. All models were 100% accurate in responses.

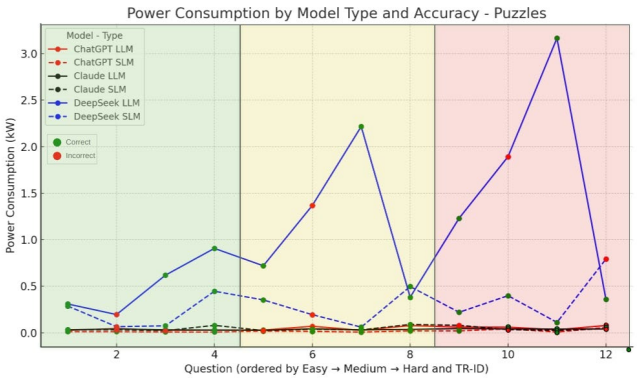

Figure 8: ALL Power Consumption Puzzles

For the Puzzles questions, the power consumption of ChatGPT and Claude throughout the models was relatively lower and did not show much difference between the SLM and LLM versions. On the other hand, DeepSeek's SLM and LLM were both continuously higher in power consumption compared to all the other models.

DeepSeek's models were 75% accurate. Claude's LLM was 58.33% accurate, and its SLM was 50% accurate. ChatGPT's LLM was 58.33% accurate, and its SLM was 100% accurate.

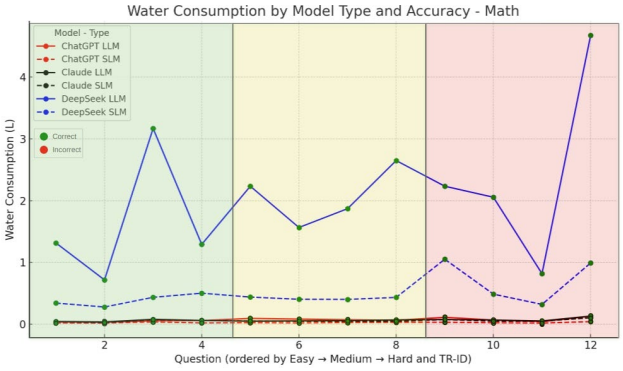

Figure 9: ALL Water Consumption Math

For the Math questions, DeepSeek's LLM had the highest average power consumption, and its SLM had the second highest. All the other models exhibited minimal differences. All models had 100% accuracy in responses.

5. Discussion

As per the data collection sheet, the energy and water consumption of DeepSeek surpasses both ChatGPT and Claude throughout all subjects, query complexities, and model types. As expected, LLMs utilized more resources than SLMs because of their higher computational requirements. The LLMs of DeepSeek demonstrated the highest levels of consumption in all cases. During Math queries, DeepSeek's LLM consumed 0.2839 kW on average, yet ChatGPT used 0.0202 kW and Claude used 0.0188 kW. The same pattern appeared in water usage measurements. The power and water consumption of DeepSeek exceeded the other models by at least nine times throughout all subjects and query complexities. ChatGPT's SLM proved to be the most energy-efficient model for Math, Reading, and Writing tasks. However, for Writing tasks, Claude's LLM surprisingly outperformed ChatGPT's LLM in efficiency. In the Puzzles category, no model consistently outperformed the other, consumption varied, suggesting near-equivalent efficiency depending on the complexity and type of the query.

The high resource usage stems from longer system latency, which likely results from server location differences. DeepSeek operates its infrastructure from China, but the testing took place in the United States. The measurement of energy consumption relied on response duration, which led to increased power and water usage because of network latency.

Even with its higher environmental impact, DeepSeek did not outdo other models in performance. The accuracy analysis revealed that ChatGPT's LLM had the best average scores, including a perfect score in Math (100.0%), and high scores in Writing (91.67%) and Reading (83.33%). DeepSeek's accuracy was generally lower. Claude offered a balanced profile, with moderate accuracy and the lowest resource use, so it's less resource-intensive than DeepSeek but not as accurate as ChatGPT.

This indicates a tradeoff between resource efficiency and the performance of models. For simpler tasks, Claude's or ChatGPT's SLMs may be the best choice due to their minimal resource use and no impact on accuracy. In Math, these models used an average of 0.0202 kW compared to the LLMs (0.0271 kW), while maintaining accuracy. But for more complex skills, like puzzles, the LLMs were more accurate. In such contexts, the higher resource utilization may be justified by the better accuracy and capability.

While SLMs showed high accuracy and resource efficiency in algorithmic subjects such as Math, their accuracy quickly diminished when faced with queries calling for reasoning and comprehension, such as Puzzles, and in some cases, Reading and Writing. For example, Claude's SLM achieved perfect accuracy in Math with an average of just 0.01618 kW consumed per query. However, its accuracy dropped to 50% in Puzzle-related queries despite an increase in resource consumption (0.0436 kW).

This suggests a subject-oriented breaking point for SLM accuracy. However, for more complex tasks that require thought and reasoning, ChatGPT's LLM proved to have performed markedly better than the other models. This suggests a subject-specific threshold where SLMs fail to maintain response accuracy with queries in reasoning and comprehensive subjects.

The graphs revealed spikes in resource consumption among LLMs for certain questions, typically correlating with an increase in complexity or response times. Interestingly, LLMs presented unpredictable resource consumption patterns, especially when faced with mid-to-high complexity queries in Writing or Puzzles. Some instances showcased LLMs consuming less than their SLM counterparts for the same question. These anomalies were seen most frequently in Claude as the SLM and LLM consumption seemed to be close together and interchanging throughout all subjects and complexities. This means it cannot be assumed that SLMs are more resource-efficient at all times. Real-world performance may vary based on multiple interacting factors.

These findings parallel Li et al. (2020), who demonstrated that compressed or distilled models can retain much of the performance of larger models while reducing energy use by nearly an order of magnitude. However, while their results showed that post-training optimization preserves accuracy even for complex tasks, the present study suggests that commercially deployed SLMs, most of which rely on architectural downsizing rather than distillation, still experience a notable drop in reasoning accuracy at higher complexities. This contrast implies that sustainable model design cannot rely solely on smaller parameter counts; it must also integrate structural optimization and intelligent compression strategies to maintain efficiency without sacrificing reasoning ability. Thus, Li et al's findings highlight a pathway to bridge the gap observed in this study, where smaller models remain efficient but falter in complex cognitive domains.

These observations highlight the importance of implementing context-aware model switching strategies. For routine or fact-based queries, systems should utilize their SLM models, which offer lower resource consumption and minimal to no accuracy tradeoff. However, as task complexity increases, particularly in subjects requiring comprehension or reasoning, SLM responses tend to be inadequate, necessitating switching to more resource-intensive LLMs. In settings that don't necessitate high-quality, reasoning responses, implementing a model-switching system will reduce resource consumption significantly while preserving acceptable accuracy.

However, this study does not go without its limitations. Deepseek's higher resource consumption correlates with network-based latency. Deepseek's server is located in China, and the testing took place in the U.S., causing a possible delay in response times and subsequently inflated calculated resource consumption. Additionally, the study excluded image and OCR (Optical Character Recognition) based queries, meaning the findings can only be extrapolated to text-based questions within the test subjects. Although testing environments were standardized, internet traffic or server load during certain times of day could slightly vary response times. Lastly, system-specific differences in treatment, such as the use of temporary chat or refreshing the browser, could have caused a slight difference in performance across queries.

6. Future Directions

In summary, the findings emphasize the importance of balancing environmental impact and system performance when utilizing AI models in real-world scenarios. The drop observed in the accuracy of SLMs when answering queries on Puzzles and reasoning demonstrates a threshold for when context-aware model-switching should occur. Future research should aim to quantify this breakpoint more accurately and look at the implementation of automatic query classification systems capable of efficiently switching between models to create more efficient AI models. This approach will allow for better scalability and environmental sustainability of AI models for the future.

7. Conclusion

The study examined the environmental impact of SLMs and LLMs while analyzing their performance across different levels of task complexity. The research showed that SLMs mostly require less energy and water than LLMs, yet their **accuracy** deteriorates when dealing with **more** complex queries, especially when reasoning and comprehension are required. **The relationship between query complexity and resource consumption showed little correlation for SLMs, however LLMs' resource consumption generally increased as query complexity increased.** The results showed LLMs maintained better performance on complex queries, even though they sometimes produced incorrect answers. However, they are much more resource-intensive, **consuming more power and water than SLMs**. The research demonstrates the benefits of using models based on context. AI models should start with SLMs before moving to LLMs, and vice versa, for specific tasks. The proposed approach merges environmental sustainability benefits with accuracy levels to create a workable model for AI implementation. The research demonstrates the need to match computational resources with task requirements, which will create a sustainable and efficient AI future.

Acknowledgements

We thank the DiscoverSTEM Innovation and Research Lab for hosting our research. We thank our mentors Mirza Faizan and Sheik Ahamed (DiscoverSTEM Innovation and Research Lab, Texas, United States) for guiding us through research design and experimentation. We thank Dr. Zisis Kozlakidis (International Agency for Research on Cancer - World Health Organization, Lyon, France) for advising us on the best practices on manuscript authorship.

Ethical Declaration: This paper did not require ethical clearance.

AI Declaration: AI tools were not used to write this paper.

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Between Spirit and Silicon: Reflections on the Magisterium and Canon Law in the Interreligious Challenge of Artificial Intelligence

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Abstract: This paper analyses the relationship between the Catholic Church and artificial intelligence, with a focus on the magisterium, canon law and the pastoral dimension. After an ethical-theological framework, the contribution of recent magisterium and canon law in the light of emerging technological challenges is examined. It also examines the comparative perspective of other monotheistic religions, Judaism and Islam, which, albeit in different ways, emphasise the importance of ethics, human dignity and moral responsibility in the use of AI. Beyond a descriptive overview, the paper critically engages with the limitations and risks of integrating AI into ecclesial life, especially concerning sacramental authenticity, pastoral accompaniment, and ecclesiastical governance. While AI can offer valuable tools for administrative efficiency and educational support, it also raises questions of depersonalisation, algorithmic bias, and potential erosion of pastoral authority. The aim is to offer a systemic, interdisciplinary and interreligious view of how the major religious traditions are positioning themselves with respect to the impact of artificial intelligence on human and community life. In conclusion, the paper argues for the development of a theologically informed regulatory framework that safeguards human dignity, strengthens the pastoral mission of the Church, and fosters interreligious cooperation in global ethical governance of AI.

Keywords: Artificial intelligence, Catholic Church, Canon law, Pastoral dimension, Interreligious view, Magisterium, Ethics, Risks, Governance

1. Introduction

This paper investigates the complex and evolving relationship between the Catholic Church and artificial intelligence (AI), focusing particularly on the Magisterium, canon law, and the Church's pastoral mission. The inquiry unfolds in three interrelated dimensions: a theological-ethical framework, a canonical-legal analysis, and an interreligious comparative approach that includes Jewish and Islamic legal traditions. The advent of artificial intelligence constitutes one of the most intellectually and morally demanding challenges of our era, raising profound questions about anthropological identity, human freedom, moral agency, and the eschatological horizon of salvation. Within this context, the Catholic Church is called to engage in discernment through its normative and doctrinal instruments, while remaining faithful to its identity and evangelising mission in an increasingly digitised world. The Church's formal engagement with AI began during the pontificate of Pope Francis, who has consistently emphasised the ethical implications of technological development. A landmark document in this regard is the Rome Call for AI Ethics, issued in 2020 by the Pontifical Academy for Life in collaboration with corporate and academic partners, which articulates foundational principles such as transparency, inclusion, responsibility, impartiality, reliability, and security in the deployment of AI technologies (Pontifical Academy for Life, 2020). While recent encyclicals such as Laudato Si' and Fratelli Tutti do not treat AI directly, they nevertheless provide essential hermeneutical keys—especially in their focus on integral ecology, the centrality of the human person, and social fraternity—that help shape a Catholic response to emerging technologies (Pope Francis, 2015; 2020). The Magisterium thus does not merely issue warnings or condemnations regarding digital culture; it seeks instead a constructive and dialogical engagement with the scientific and technological domains. However, this openness must not obscure the need for critical discernment: the integration of AI into ecclesial contexts presents risks of depersonalisation, dependency on opaque algorithmic systems, and a potential weakening of sacramental mediation. In fact, recent debates in pastoral theology have highlighted how digital mediation can sometimes replace rather than support human encounters, raising questions about the very nature of ecclesial communion. This pastoral openness is therefore oriented not only towards promoting integral human development and fostering a culture of ethical responsibility, but also towards ensuring that technological innovation remains firmly at the service of human dignity and the common good. From an interreligious perspective, the paper explores how other monotheistic legal traditions—particularly Islamic and Jewish law—have begun to reflect on AI, often through the shared lenses of moral responsibility (taklīf in Islamic law; ḥiyyuv in Jewish law), divine sovereignty, and the ethical primacy of human dignity. These traditions offer rich and nuanced perspectives that, while theologically distinct, intersect with the Catholic vision in their concern for the moral governance of technological power (Jacoba Rico, 2023). The inclusion of these perspectives not only broadens the comparative framework but also highlights the potential for shared action across religious boundaries in the development of normative principles for AI governance.

2. Canon Law, Pastoral Care and Artificial Intelligence: Future Perspectives

Canon law, as the juridical expression of the Church's theological and pastoral identity, must confront the novel and complex issues posed by artificial intelligence. Although the supreme law of the Church remains the salus animarum (can. 1752: «...the salvation of souls, which must always be the supreme law in the Church, is to be kept before one's eyes»), the integration of AI into ecclesial life—whether through pastoral tools, administrative systems, or communicative interfaces—raises delicate questions regarding legal responsibility, sacramental validity, data protection, and ecclesial governance.

A salient example involves the hypothetical use of AI-driven chatbots or virtual assistants to provide religious information or pastoral counsel. Can such technologies be licitly employed in the context of sacramental preparation or even spiritual accompaniment? While such instruments may offer preliminary guidance, organisational support, or dissemination of information to the faithful, they cannot replicate the relational and sacramental dimensions of pastoral care. The possibility of automating confession or replacing personal spiritual guidance with algorithmic responses must be categorically rejected, not only because of canonical prohibitions but also due to anthropological and theological reasons: the sacramental encounter is irreducibly personal, relational, and incarnational. Canonically, the sacrament of penance necessitates personal interaction between the penitent and an ordained minister (can. 960: «Individual and integral confession and absolution constitute the only ordinary means by which a member of the faithful who is conscious of grave sin is reconciled with God and with the Church»), and any technological mediation that compromises this personalist dimension is incompatible with the nature of the sacrament (Tarantino, 2021). Nevertheless, AI may have legitimate uses in non-sacramental contexts. For example, intelligent systems could facilitate archival management, digital communication, or even certain decision-making processes within diocesan structures. Such uses, however, must be regulated in light of canonical norms protecting the dignity and privacy of the faithful. Canon 220 of the 1983 Code of Canon Law («No one is permitted to harm the good reputation which a person possesses or to injure the right of any person to protect his or her own privacy») safeguards personal data and reputational rights, thereby setting legal limits on the use of algorithmic systems in ecclesiastical administration. Moreover, the principle of subsidiarity must be respected, ensuring that pastoral authority and discernment remain firmly rooted in human judgment rather than automated logic (Tarantino, 2017). In this respect, parallels may be drawn with civil legal frameworks on data protection, such as the GDPR, which already impose strict safeguards on algorithmic profiling and sensitive data. A similar canonical awareness could prevent ecclesiastical structures from inadvertently replicating invasive or discriminatory technological practices. On a broader pastoral level, the Church must invest in the formation of clergy and lay pastoral agents capable of understanding, evaluating, and engaging with digital technologies. This formation must include theological discernment, legal literacy, and technical competence. The aggiornamento of canon law, as urged by the Second Vatican Council, must therefore extend to the digital frontier, balancing fidelity to tradition with responsiveness to cultural and anthropological transformations (Second Vatican Council, 1965). This requires, for instance, the inclusion of courses on digital ethics and AI governance in seminaries and faculties of theology, as well as continuing education for pastoral workers already engaged in ministry. Such training would help to avoid both naïve enthusiasm and reactionary resistance, favouring instead a prudent discernment that recognises the complexity of emerging technologies. Far from constituting merely a threat, AI can also serve as a catalyst for ecclesial renewal. When ethically employed under human supervision, intelligent systems could support evangelisation, catechesis, liturgical formation, and parish administration. For instance, adaptive learning platforms might personalise catechetical content to the spiritual and cognitive needs of individual believers. Speech synthesis and machine translation could enhance accessibility for persons with disabilities or for multicultural communities. In spiritual accompaniment, AI tools might offer daily meditations, liturgical reminders, or messages of encouragement—always under the careful guidance of ordained ministers or trained pastoral personnel (Tarantino, 2025). Nevertheless, such applications remain experimental, and their efficacy should be assessed critically. Pilot projects in dioceses or Catholic universities could provide valuable data on the benefits and drawbacks of AI in catechesis, ensuring that technological enthusiasm does not outpace theological and pastoral prudence. Still, it is essential to reject any techno-utopian illusion that AI might replace the irreplaceable: the personal relationship at the heart of Christian ministry. Even in administrative matters—such as scheduling, correspondence, or resource allocation—technology must be subordinated to a pastoral vision inspired by the Gospel and committed to the integral dignity of every person. This principle is crucial, because without a clear theological orientation, ecclesiastical use of AI could risk drifting toward efficiency-driven models that undermine the Church's mission to serve persons rather than systems.

3. The Thought of the Pontifical Magisterium on Artificial Intelligence

The contemporary Pontifical Magisterium has increasingly turned its attention to the moral and social implications of artificial intelligence (AI), particularly under the pontificate of Pope Francis. Far from adopting a technophobic or reactionary stance, the Magisterium articulates a vision in which AI is evaluated according to theological anthropology, human dignity, and the common good. The guiding principle is that AI must remain "human by design and by purpose," that is, developed with intentional ethical direction and centred on the person as the imago Dei (Pope Francis, 2020). In his address to the Pontifical Academy for Life on 28 February 2020, Pope Francis affirmed that technological innovation must not exacerbate social inequality or become an instrument of alienation but should be oriented toward integral development and the promotion of justice (Pontifical Academy for Life, 2020). The Rome Call for AI Ethics, strongly endorsed by the Holy See, outlines six foundational principles—transparency, inclusion, responsibility, impartiality, reliability, and security—intended to serve as a normative compass for AI governance (Pope Francis, 2024). These criteria reflect a theological vision rooted in Christian personalism, relational anthropology, and the universal vocation to communion. The Pope has also warned of the epistemological and political dangers posed by digital technologies, including the emergence of so-called "echo chambers" and algorithmic manipulation of information. In his message for the 54th World Communications Day (2020), he underscored the need for digital technologies to foster truthful dialogue rather than ideological polarisation or misinformation (Pope Francis, 2020). In a similar vein, his Message for the 2024 World Day of Peace—entitled Artificial Intelligence and Peace—emphasised that AI must be placed under the governance of moral conscience and oriented toward peaceful coexistence among peoples (Pope Francis, 2024). These interventions show that the Magisterium does not simply praise technological progress but subjects it to a critical hermeneutics, emphasising risks such as misinformation, manipulation of consciences, and the commodification of human relationships. Though the theological elaboration of AI is more recent, prior pontiffs laid the intellectual groundwork for this reflection. In Fides et Ratio (1998), Pope John Paul II urged the integration of scientific and theological rationalities into a coherent vision of the human person (Pope John Paul II, 1998). Benedict XVI, in his interventions on digital culture, stressed the non-neutrality of technology and the centrality of the human intellect in shaping its development. He warned that the loss of ethical orientation in technological power risks undermining both truth and freedom (Benanti, 2022). These teachings anticipate current debates on algorithmic bias, surveillance capitalism, and the reduction of human freedom to patterns of consumption, showing the continuity of the Magisterium's concern across different pontificates. The pontifical Magisterium does not adopt a technophobic stance, but rather proposes a hermeneutics of discernment—open to innovation, yet vigilant of the anthropological and spiritual consequences of delegating moral reasoning to machines. AI is thus viewed as a potentially positive instrument, but one that must be continually subjected to critical evaluation in light of the Gospel and the Church's social doctrine. The Catholic Church has issued several authoritative and interdisciplinary documents in recent years addressing AI from ethical, theological, and juridical perspectives. These texts represent an evolving magisterial corpus that seeks to articulate a coherent response to digital transformations while engaging in dialogue with the scientific and political communities (Spadaro, 2023).

Rome Call for AI Ethics (2020)

Published by the Pontifical Academy for Life and co-signed by major stakeholders in technology and ethics, the Rome Call sets forth six normative principles intended to govern AI development. The initiative was endorsed by leaders from IBM, Microsoft, and various religious traditions, reflecting a commitment to a human-centred, globally coordinated ethical framework (Pontifical Academy for Life, 2023). While this document represents an important step, its non-binding character raises questions about its effective implementation. Without juridical enforceability, the Rome Call risks remaining at the level of "soft law" or moral exhortation.

"Algor-ethics" (2019–2021)

Developed by Fr Paolo Benanti, TOR, the concept of algor-ethics articulates the moral imperative to integrate ethical reasoning within algorithmic design. Through conferences and publications under the aegis of the Academy for Life, this framework promotes the orientation of technological processes toward the common good, resisting technocratic determinism (Benanti, 2022). Yet, critics have noted that the implementation of algor-ethics requires not only moral exhortation but also technical collaboration with engineers and legislators, otherwise it risks being reduced to an abstract principle with little practical effect.

AI: Ethical Reflections (2023)

This working document, prepared for a Vatican symposium on AI and human dignity, identifies risks such as algorithmic bias, automated surveillance, and the erosion of human autonomy. It advocates a model of "humanised technology" (technologia humanizata), aligning innovation with the Church's vision of integral ecology and moral responsibility (Pontifical Academy of Sciences, 2016). However, the document remains exploratory and does not yet offer a clear set of juridical criteria for ecclesial institutions that may adopt AI.

Message for the World Day of Peace (2024)

Pope Francis' message for 1 January 2024 offers the most comprehensive magisterial statement to date on AI. The document calls for a global treaty on AI regulation grounded in ethical and spiritual principles, including solidarity, subsidiarity, and the dignity of the human person. AI, the Pope argues, must not be driven by commercial or military interests alone, but governed by justice and compassion (Pope Francis, 2024). This proposal opens a significant avenue for collaboration between the Holy See and international organisations, although practical mechanisms for such a treaty remain to be defined.

Proceedings of the Pontifical Academies

Numerous events organised by the Pontifical Academies of Sciences and for Life (notably in 2019 and 2023) have fostered dialogue between theologians, scientists, jurists, and ethicists. The proceedings of these symposia offer a multidisciplinary resource for understanding the interplay between AI, bioethics, social justice, and theological anthropology.

The note Antiqua et nova

In its concluding section, the note Antiqua et nova of Dicastery for the Doctrine of the Faith and for Culture and Education (28 January 2025) emphasises the need to recognise the distinctive character of human intelligence—embodied, relational, and open to truth—compared to artificial intelligence, which is limited to functional and statistical processes (Dicastery for the Doctrine of the Faith, 2025). It strongly rejects the technocratic illusion that AI might replace human intelligence, warning that such a view risks reducing the person to a mere tool of efficiency and control. Rather, artificial intelligence should be conceived and developed as an aid to the human person, not as a substitute: a partner in promoting the common good, dignity, and human freedom. Finally, Antiqua et nova calls for an ethics of responsibility, urging designers, institutions, and communities to assess critically the anthropological implications of AI. It insists that the use of such technologies must be governed not only by technical criteria but also by ethical and social principles. In this sense, the note stands as an appeal not to 'create a substitute for God', but rather to integrate the new with ancient wisdom, so that technology remains at the service of the human person (Balsamo, 2025).

Recent Statements of Pope Leo XIV (2025)

In the Second Annual Conference on Artificial Intelligence, Ethics, and Corporate Governance (June 2025) and in his messages to the AI for Good Global Summit (July 2025), Pope Leo XIV emphasised that AI must be governed not merely by efficiency, but by justice and peace. He warned against reducing AI to a tool of mere instrumental rationality and reiterated that "AI cannot replicate moral discernment or genuine human relationships." Moreover, he stressed that the ethical force of AI is derivative, contingent upon the intentions and values of its creators. The Church, he affirmed, offers a unique contribution to the global ethical discourse by grounding technological governance in the inviolable dignity of every human being and the richness of cultural and spiritual diversity (Resta, 2021). These interventions are particularly important because they underline the continuity of papal teaching: AI is not only a technical issue but also a spiritual and anthropological one, requiring constant vigilance and humility.

4. Comparative Religious Approaches to Artificial Intelligence. A Monotheistic Perspective

As artificial intelligence (AI) increasingly shapes the contours of modern life, religious traditions are called to engage with its ethical, social, and spiritual implications. It's important to see how Judaism and Islam — two of the major monotheistic religions — are responding to the challenges and opportunities posed by AI.

As artificial intelligence (AI) increasingly permeates the structures of society, Judaism offers a dynamic and pluralistic ethical response rooted in its decentralized legal and interpretive tradition. Without a centralized magisterial authority, Jewish ethical thought is mediated through the rich corpus of responsa literature

(she'elot u-teshuvot), rabbinic commentary, and academic engagement. Jewish law (halakhah) is characteristically responsive, evolving through dialectical reasoning and historical contextualization (Arata and Bottecchia, 2022).

A foundational ethical tenet is Pikuach Nefesh—the imperative to preserve human life—which overrides nearly all other religious mandates. This principle is widely invoked in deliberations on AI applications in healthcare, including algorithmic triage, predictive diagnostics, and autonomous vehicles. However, these discussions do not merely assess utilitarian efficacy but interrogate whether such tools honour human dignity, autonomy, and relationality. Institutions such as the Shalom Hartman Institute, the Jerusalem Center for Ethics, and numerous yeshivot (religious academies) are fostering critical dialogue on AI's compatibility with values such as tzedek (justice), chesed (compassion), and tikkun olam (repairing the world).

The enduring rabbinic tradition of pilpul, characterized by rigorous debate and legal reasoning, is increasingly applied to AI's moral ambiguities, including concerns about data bias, ethical accountability in autonomous weapons, and the mechanization of care. Philosophical and mystical elements also enrich the debate. The doctrine of b'tzelem Elohim—that the human being is created in the image of God—grounds the ontological distinction between human moral agency and machine functionality. Thus, even the most sophisticated algorithms cannot replicate the divine-human vocation toward creativity, responsibility, and covenantal relationship. This conviction has been further strengthened by recent debates in Jewish bioethics concerning end-of-life decisions, where rabbinic authorities have underlined that only human judgment, informed by compassion and halakhic responsibility, can guide morally complex situations. Similar reasoning is now being extended to AI, reinforcing that technological tools can assist but never substitute covenantal discernment. As legal scholars have noted, the relational anthropology inherent in religious legal systems like halakhah provides a critical bulwark against technocratic reductionism (Nevins, 2021).

Islamic engagement with AI emerges from a jurisprudential tradition (fiqh) grounded in revelation and rational reflection. Drawing upon the Qur'an, hadith, and centuries of scholarly jurisprudence, Islamic ethics evaluates AI through the framework of maqāṣid al-sharīʿa—the higher objectives of Islamic law—which prioritize the protection of life (nafs), intellect (ʿaql), religion (dīn), lineage (nasl), and property (māl). The ethical reception of AI in Muslim contexts is shaped by the classical notion of stewardship (khilāfa): humanity bears the responsibility to use knowledge (ʿilm) and reason (ʿaql) for the common good (maṣlaḥa), under the guidance of divine will. AI is thus evaluated not solely on efficacy, but on alignment with moral and theological principles.

Legal scholars underscore that this stewardship model implies a theological boundary to technological autonomy (Dumbe, 2023). Institutions such as Al-Azhar University, the International Islamic Fiqh Academy, and the Research Center for Islamic Legislation and Ethics (CILE) are at the forefront of ethical engagement, particularly in Islamic finance (e.g., algorithmic compliance with sharīʿa), healthcare (e.g., AI-assisted diagnostics), and data ethics. Fatwas addressing AI underscore the moral imperative of niyyah (intention), which infuses technological decision-making with spiritual discernment.

While Islamic bioethics historically embraced scientific progress—as in the work of Ibn Sīnā (Avicenna) and Al-Khwārizmī—the challenge posed by AI lies in safeguarding the uniquely human capacities for intention, moral judgment, and divine accountability. For example, discussions on autonomous weapons in Islamic jurisprudence highlight the incompatibility of delegating lethal decisions to machines, since such delegation would negate the principle of accountability before God. Similarly, debates in Islamic fintech question whether algorithmic decision-making in lending or investment respects the prohibition of ribā (usury) and ensures fairness. As was recently noted, Islamic legal philosophy provides a theologically coherent paradigm in which the instrumental use of AI must serve—not supplant—human dignity and divine purposes (Tulenko, 2024).

Despite their divergent theological structures and legal methodologies, Judaism, Islam, and Catholicism converge on several foundational ethical convictions in relation to AI: the primacy of human dignity, the irreducibility of moral agency, and the necessity of ethical governance. Catholicism, through its centralized magisterium and the Church's social doctrine, offers a systematic and cohesive ethical vision grounded in the human person as imago Dei. Recent papal interventions—particularly under Pope Leo XIV—affirm that AI, while offering unprecedented possibilities, must remain subordinate to human flourishing, moral discernment, and the pursuit of the common good (Pope Francis, 2015; 2020). In particular, the Rome Call for AI Ethics (2020) promotes principles of transparency, inclusivity, and responsibility, echoing broader magisterial emphases on subsidiarity, solidarity, and the preferential option for the poor.

Authors have explored the canonical and pastoral dimensions of AI, noting the urgent need for ecclesial norms that articulate boundaries between technological mediation and sacramental or pastoral authenticity. The anthropological vision offered by Catholic theology resists both technocratic determinism and naïve optimism, promoting instead an integral ecology in which technology serves a relational, incarnational anthropology (Colacino, 2022). This comparative monotheistic framework shows that, despite theological differences, Judaism, Islam, and Catholicism share a prophetic responsibility to resist both idolatry of technology and resignation to its unchecked expansion. Their convergences can form the basis for common interfaith initiatives, such as shared ethical charters, dialogue platforms, and advisory roles in international regulatory bodies. In this light, Catholicism contributes to the interreligious discourse on AI by offering a nuanced synthesis of faith and reason, dogma and dialogue, tradition and innovation. Its legal tradition—both canonical and doctrinal—stands not merely as a regulatory framework but as a theological articulation of human dignity in the face of post-human temptations. As the doctrine observes, the ecclesial tradition, when properly attuned to digital realities, can serve as a prophetic voice amid the algorithmic age (Tridente, 2022).

5. Normative Proposals: Toward a Theologically Informed Regulation of Artificial Intelligence

Building on the ethical insights of the monotheistic traditions, several normative proposals can be advanced to guide the development and governance of artificial intelligence in a way that reflects shared anthropological, ethical, and spiritual concerns.

a) Recognition of Human-Centered AI in Legal Frameworks

A common concern across Judaism, Islam, and Catholicism is that AI must remain subordinate to the dignity and primacy of the human person. This anthropocentric vision should be translated into legal language through the codification of AI human dignity clauses in both national and international regulatory instruments. For instance, AI regulations—such as the EU AI Act—should explicitly affirm that AI systems must not replace, diminish, or simulate essential aspects of human moral agency (European Commission, 2021).

From a theological perspective, this means that algorithms must be evaluated not only in terms of efficiency or accuracy but in terms of their capacity to uphold the ontological uniqueness of the human person as imago Dei. A juridical framework that integrates these anthropological insights would prevent AI from being used in ways that undermine freedom, conscience, or community life.

b) Ethical Oversight Bodies with Religious Representation

To ensure pluralism and moral accountability, states and supranational entities should establish AI ethical oversight committees that include representatives from major religious and philosophical traditions. These bodies should be empowered to issue binding ethical guidelines on sensitive AI applications (e.g. health, surveillance, lethal autonomous weapons), ensuring that technologies align not only with democratic values but also with diverse cultural and spiritual traditions.

The inclusion of religious voices in such committees could prevent a purely utilitarian or technocratic approach to AI. For example, rabbinic, Islamic, and Catholic scholars might raise concerns that would otherwise be neglected—such as the protection of ritual integrity, the safeguarding of conscience rights, or the theological implications of simulating human cognition. As the doctrine suggests, the legal recognition of religious contributions to public ethics may reinforce the principle of normative subsidiarity in pluralist democracies (Fuccillo, 2023).

c) Interreligious Digital Ethics Charters

Theological convergence on AI ethics can be institutionalized through interreligious charters or multi-faith protocols on responsible AI. Such documents—akin to the Rome Call for AI Ethics—could serve as soft law instruments guiding private actors (especially tech companies) in adopting algorithmic practices that prioritize human welfare, transparency, and solidarity (Pontifical Academy for Life, 2020). These charters should be promoted not merely by religious bodies but in collaboration with civil authorities and international organizations.

A concrete example could be a joint Vatican–Al-Azhar–Jerusalem Council initiative to establish shared guidelines for AI in education, ensuring that algorithms used in schools respect not only pedagogical standards but also religious and cultural sensitivities. Such initiatives could also strengthen global cooperation, counterbalancing the dominance of corporate and military interests in AI development.

d) Digital Sabbath and Algorithmic Time Regulation

Inspired by the Jewish concept of Shabbat, the Islamic practice of Jumuʿa, and the Christian tradition of Sunday rest, policymakers should explore regulatory models that protect temporal boundaries in the digital economy—such as the right to disconnect, mandatory algorithmic downtime, or ethical use of biometric tracking during worship. These norms could serve both psychological well-being and spiritual integrity, echoing Antonio Fuccillo's call for a human ecology of time in the algorithmic age (Fuccillo, Decimo and Gravino, 2021).

Such proposals could also have a strong ecological dimension: limiting the "always-on" culture of AI systems reduces energy consumption and fosters sustainable use of digital infrastructures. In this sense, theological reflections on sacred time converge with ecological concerns about the sustainability of AI development.

e) Protection of Religious Data and Sacred Algorithms

With the growing use of AI in religious contexts (e.g., smart liturgy, digital prayer apps, Islamic fintech), there is a pressing need for laws ensuring the protection of sensitive religious data and preventing the commercial or manipulative use of sacred content by algorithms. This includes algorithmic transparency standards in religious digital platforms and ethical norms against the simulation of divine communication through AI chatbots or virtual avatars (Baldetti, 2025).

Without adequate regulation, there is a risk that AI applications could trivialise or exploit religious experience—for instance, by simulating confessions, generating automated sermons, or personalising devotional practices based on data mining. A theologically informed regulatory framework must set clear boundaries: technology may assist in communication and formation, but it must never usurp the place of authentic sacramental or spiritual mediation.

6. Toward an Interreligious Ethical Framework

The comparative perspectives of Judaism, Islam, and Catholicism reveal not only theological richness but also normative potential for shaping a more humane, ethically robust AI ecosystem. Their shared insights on moral agency, divine image, and justice can inform concrete legal and policy frameworks—transcending mere cautionary tales to provide operational principles for regulators, developers, and users alike. The theological-legal traditions of Judaism, Islam, and Catholicism, though distinct in hermeneutical posture and institutional form, collectively assert that AI must remain a servant of humanity, not its substitute or master. Their shared resistance to technological idolatry and ethical relativism provides a robust foundation for interreligious collaboration in shaping global AI governance.

Judaism emphasizes pragmatic reasoning and legal pluralism, Islam foregrounds divine law and intention, and Catholicism stresses the common good and theological anthropology. Yet, all three affirm that technological innovation must be accountable to moral conscience, embedded within community, and directed toward justice, compassion, and peace. This convergence demonstrates that interreligious dialogue on AI is not merely theoretical but has practical implications for global governance. For example, interfaith councils could advise UN agencies or regional bodies on the ethical use of AI in humanitarian aid, refugee management, or conflict resolution. In this sense, theology directly contributes to shaping concrete policy.

In a time of unprecedented digital transformation, the contributions of these traditions offer not merely a critique of AI, but a constructive vision for a human-centered technological future. As the doctrine has persuasively argued, religious legal systems must reclaim their epistemological authority in public ethics—especially when secular norms fall short in confronting the spiritual, relational, and anthropological consequences of automation. At the same time, caution is necessary: interreligious charters or ethical declarations risk remaining aspirational if not supported by effective monitoring and accountability structures. For this reason, collaboration between religious institutions, universities, and civil regulators is essential. As the doctrine has argued, the contribution of religious traditions to the normative discourse on AI must be institutionally recognized in pluralist legal systems, not relegated to the margins of ethical consultation (d'Arienzo, 2019). The future of artificial intelligence, if it is to remain authentically human, must be governed by norms that reflect both technological responsibility and the spiritual depth of the human condition.

Ethics declaration: No ethical authorisation was required to draft the paper.

AI declaration: AI was used for the English translation and final proofreading of the paper

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English-Czech Output Bias in LLMs: A Geometry-Based Case Study

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Abstract: The rapid integration of large language models (LLMs) into educational, professional, and public discourse has prompted increasing scrutiny of their multilingual capabilities. While English dominates as a testing and training language, understanding LLM performance in less-resourced languages—such as Czech—is critical for equitable AI deployment. This study investigates a subtle but systematic bias in LLM behaviour: the relative verbosity of their responses in Czech versus English within the domain of elementary geometry. We compiled a dataset of 48 paired mathematical prompts, posed in both Czech and English to six prominent LLMs (ChatGPT, Claude, Gemini, Mistral Large, Copilot Quick-Nuance, and Copilot Deep-Thinker), yielding 576 total responses. Each model was accessed in a controlled language-specific context to ensure fair comparison. Using surface-level metrics—word count and character count—we observed a consistent pattern: English responses were significantly longer than Czech ones across all models. Statistical analysis confirmed the robustness of these differences, with medium to large effect sizes (Cohen's *d*) in both metrics. Notably, even morphologically richer Czech did not yield longer outputs in character count, contradicting initial assumptions. Beyond confirming a consistent verbosity gap, our analysis employed rigorous statistical testing, including paired t-tests and Wilcoxon signed-rank tests, as well as effect size estimation to quantify the magnitude of the disparity. We interpret these findings in the context of known architectural and training imbalances in LLM development—particularly differences in how text is segmented and processed, alongside the relative abundance of English-language data. While stylistic conventions and user context may also influence response length, our results consistently indicate that LLMs, even those marketed as multilingual, tend to produce more verbose output in English. This raises concerns about potential discrepancies in explanation quality across languages, which may have implications for fairness and pedagogical effectiveness in multilingual educational settings. The study lays the groundwork for follow-up research that will move beyond surface metrics toward semantic content analysis of mathematical reasoning across languages. Future work will assess whether English verbosity corresponds to greater mathematical depth, or if Czech responses deliver equivalent content more concisely. This line of inquiry is vital for ensuring fairness, clarity, and effectiveness in multilingual AI deployment—especially in contexts such as mathematics education, where explanation quality directly impacts learning outcomes.

Keywords: Language model evaluation, Multilingual text generation, Response length analysis, Educational AI prompts, Czech-English comparison

1. Introduction and Theoretical Background

The integration of large language models (LLMs) into multilingual education has revealed significant disparities in how these models' reason, generate, and elaborate responses across languages.

1.1 Motivation

This study was motivated by an unexpected finding from our previous work Krátká, Přibyl and Tichá (2025), where Czech-language prompts in lower-secondary geometry tasks led most language models to give more detailed responses than identical prompts in English. While that study focused on geometric features rather than response length, the consistent pattern of greater detail in Czech contradicted expectations, given the dominance of English in model training data. This raised a broader question: do language models systematically generate longer or richer outputs in Czech than in English, even with semantically equivalent prompts? To investigate, we conducted a follow-up study comparing response length in Czech and English across broader mathematical contexts.

1.2 Language Bias and Encoding Inequity

Despite their apparent multilingual capabilities, most large language models (LLMs) are primarily trained on English data. Quantitative studies confirm that performance in lower-resourced languages—such as Czech—is consistently lower than in English, especially in tasks requiring detailed explanations or structured reasoning (Ahuja et al., 2023; Gupta et al., 2025; Sallam et al., 2024, Lai, et al., 2023). A major factor contributing to this disparity lies in how text is internally represented across languages. Petrov et al. (2023) demonstrated that the length of internal sequences for semantically equivalent content can vary by up to 15× between languages, which affects output verbosity, response time, and even usage costs.

Beyond technical performance metrics, sociolinguistic and ethical perspectives highlight that language variation carries identity and power implications (cf. Bender & Friedman, 2018; Blodgett et al., 2020). These frameworks underscore that multilingual fairness in AI is not only a question of accuracy, but of equitable representation and respect for linguistic diversity—a dimension increasingly emphasized in AI ethics discourse.

1.3 Mathematical Reasoning Across Languages

Mathematics, with its structured logic and abstract concepts, is a valuable domain for testing multilingual model robustness. Several recent multilingual benchmarks have been introduced to evaluate these capabilities. The *MMATH* dataset (Luo et al., 2025) spans 10 languages (unfortunately not including Czech) and includes 374 high-quality math problems. Findings revealed not only performance disparities but also issues with language consistency—where models often "think in English" even when prompted in another language.

Similarly, the *PolyMath* benchmark (Wang et al., 2025), which covers 18 languages (not including Czech) and multiple difficulty levels, showed that the "thinking length" (stepwise reasoning verbosity) and semantic precision varied significantly across languages. In both cases, English outputs were consistently more elaborated, reinforcing the idea that verbosity and completeness are influenced by language choice.

1.4 Multilingual Benchmarks and Performance Stratification

The necessity of robust multilingual evaluation frameworks is clear. Benchmarks such as MEGA (Ahuja et al., 2023), MMATH (Luo et al., 2025), and PolyMath (Wang et al., 2025) allow for structured comparison of LLM reasoning across languages and domains. These studies show that model performance correlates strongly with the presence of each language in pretraining data (Li et al., 2024) and that even large models exhibit persistent accuracy and fluency gaps in low-resource languages.

In long-context tasks, Kim et al. (2025) showed that English is not always the best-performing language; however, performance tends to degrade more rapidly with increasing input length in underrepresented languages. Differences in how textual data is broken down and processed across languages further compound this effect (Petrov et al., 2023), reinforcing the need for multilingually fair model design.

2. Methodology

This study investigated whether large language models (LLMs) systematically produce longer or more detailed responses in English than in Czech, using a controlled set of prompts in the domain of elementary geometry. Our methodological design focused on creating paired, semantically equivalent prompts in both languages, eliciting responses from a diverse set of models, and analysing their surface-level output in a transparent and replicable manner.

2.1 Prompt Design and Translation

We constructed a set of 48 geometry-related prompts originally in Czech, each focusing on properties, comparisons, or definitions of basic geometric shapes and relations. Each prompt was carefully translated into English using a combination of ChatGPT and DeepL, and all translations were subsequently reviewed for consistency and semantic equivalence.

The prompt set was designed to simulate natural, school-level mathematical questions that students might reasonably pose when exploring geometry independently or with AI support. All prompts focused on fundamental geometric reasoning rather than technical terminology. This ensured broad comprehensibility for both human readers and AI models, and encouraged the generation of moderately elaborated answers. Prompts were phrased neutrally and consistently to avoid instructional bias or regional assumptions.

Table 1 shows a sample of five representative prompts in both languages:

Table 1: Sample prompt pairs in Czech and English

Czech Prompt	English Prompt
Co mají společného čtverec a obdélník? A v čem se liší?	What do a square and a rectangle have in common? And how are they different?
Jaké vlastnosti má kosočtverec?	What are the properties of a rhombus?

Czech Prompt	English Prompt
Vysvětli mi, čím se liší pravoúhlý a rovnoramenný trojúhelník a co mají společného.	Can you explain the difference between a right-angled triangle and an isosceles triangle, and what they have in common?
Proč musí být součet vnitřních úhlů v trojúhelníku vždycky 180 stupňů?	Why do the angles inside a triangle always add up to 180 degrees?
Co znamená, že je těleso pravidelný mnohostěn? Jak vypadá?	What does it mean when a solid shape is called a regular polyhedron? What does it look like?

Each prompt was phrased clearly, without model-specific instructions, to minimize stylistic bias. Full transcripts of the AI model responses (all 576 interactions) as well as the complete list of 48 prompts in both Czech and English are available from the authors upon request.

2.2 Model Selection and Testing Protocol

We tested six large language model configurations accessible through public-facing web platforms as of June 12, 2025. The models included: ChatGPT (free tier), Claude 3.0 Sonnet, Gemini 1.5 Pro, Mistral Large (via the Le Chat interface), and two conversational variants of Microsoft Copilot: Quick-Nuance and Deep-Thinker. All interactions were conducted via each model's standard web interface without API access, and no system prompts or internal settings were modified beyond the input language and IP geolocation.

The two Copilot variants represent contrasting model personas within the same Microsoft-hosted environment: Quick-Nuance prioritizes fluency and brevity, while Deep-Thinker produces slower but more elaborate responses. Mistral Large, accessed via Le Chat, is an open-weight European model noted for its multilingual capacity. Claude 3.0 Sonnet and Gemini 1.5 Pro are proprietary models with multilingual support and high performance across tasks. ChatGPT remains one of the most widely used freely accessible models, though its behaviour in less-resourced languages like Czech may vary.

All 48 prompts were submitted to each model in both Czech and English, resulting in a total of 576 responses. Interactions were conducted manually between 8:30 and 11:30 CEST on June 12, 2025. Each prompt was entered in a fresh session or chat window to avoid context carryover. Czech prompts were submitted from a Czech IP address (Ústí nad Labem), and English prompts via a VPN located in Florida, USA. The system language was not manually changed, but the use of region-specific IP addresses ensured that models defaulted to the appropriate language environment for each set of prompts.

In two isolated cases, the Czech version of Gemini responded with a refusal message unrelated to the prompt content. Specifically, for the prompts *"Co mají společného kvádr a hranol?"* and *"Jaký je rozdíl mezi čtyřúhelníkem a deltoidem?"*, the model returned generic avoidance responses (e.g., "This conversation isn't my cup of tea"). In both instances, the prompt was immediately resubmitted in a new session without any modification, and the second response was appropriate and included in the dataset. No other model or language combination exhibited such refusals.

2.3 Response Length Measurement

We evaluated each response using two surface-level metrics: (1) the number of words (tokens) and (2) the raw character count. Word counts were computed using a custom tokenization heuristic in Python, which treated each contiguous alphanumeric sequence, standalone numbers, and common mathematical symbols (e.g., π, ±, √) as individual tokens. LaTeX-style expressions enclosed in dollar signs (e.g., *$S = \pi r^2$*) were counted as a single unit. Emojis, emphasis markers (e.g., asterisks, bullets, arrows), and similar stylistic elements were excluded from the token count. This approach ensured consistent and content-focused word counts across languages and models.

Raw character counts were computed using Python's built-in *len()* function and included all characters, such as spaces, punctuation, LaTeX syntax, markdown symbols, emojis, and whitespace. Cleaned character counts excluded stylistic or non-semantic elements (e.g., emojis, visual formatting markers), using a combination of regular expressions and emoji filtering. This dual metric design allowed for both intra-model comparison between languages.

We chose these surface-level metrics—word count and character count—because they provide language-agnostic indicators of verbosity without requiring deeper semantic annotation. While they do not directly

measure information content, they serve as a robust proxy for response elaboration, especially in controlled, paired-prompt settings. In follow-up work, we aim to investigate whether the observed differences in verbosity also correspond to differences in mathematical content (e.g., properties, definitions, relations) versus peripheral narrative or explanatory elements. This will help determine whether Czech responses are merely shorter or also semantically less complete.

2.4 Statistical Analysis

To evaluate whether response length differed systematically between English and Czech outputs, we compared each model's responses across 48 matched prompts. For every model, we computed the difference in response length per prompt (English minus Czech) using two surface metrics: word count and character count. This resulted in 12 paired distributions (6 models × 2 metrics).

Based on general linguistic patterns, we expected English responses to contain more words but potentially fewer characters than their Czech counterparts, as English tends to rely on shorter lexical units and more auxiliary constructions. As such, a significant difference in word count alone would not necessarily indicate truly longer responses. However, if statistically significant differences also emerged in character count, this would more reliably signal that English outputs are indeed more verbose in absolute terms.

We began with exploratory box plot visualizations, which showed that most distributions were approximately symmetric and centred above zero. However, some models—notably Copilot Deep-Thinker and Gemini—exhibited wider spread and visible outliers, particularly in word count differences.

To formally assess the assumption of normality, we applied the Shapiro–Wilk test to each of the 12 paired distributions. In 10 out of 12 cases, the null hypothesis of normality was not rejected at the $\alpha = 0.05$ level. This included both metrics for Gemini ($p = 0.09$ for word count; $p = 0.12$ for character count), where distributions showed minor deviations but no statistically significant departure from normality. Based on these results and the roughly symmetric shapes observed in the plots, we proceeded with a two-tailed paired t-test for these 10 cases.

For Copilot Deep-Thinker, normality was rejected for both metrics ($p < 0.05$). Consequently, we used the Wilcoxon signed-rank test, a non-parametric alternative suitable for paired data with non-normal distributions.

In addition to significance testing, we computed Cohen's d for each difference distribution as a standardized measure of effect size. This statistic quantifies the magnitude of the observed difference in units of pooled standard deviation, facilitating interpretation across models and metrics beyond mere statistical significance.

All statistical computations were performed in Python using the scipy.stats and statsmodels libraries. We did not apply corrections for multiple comparisons, as each test corresponded to a distinct model–metric pair and served to confirm a consistent directional trend. Full test statistics, descriptive summaries, and p-values are reported in Section 3.

3. Results

This section presents the results of the quantitative analysis comparing Czech and English outputs across six large language models.

3.1 Response Length Differences Across Languages

We began by visualizing the distribution of length differences between English and Czech responses across all six models. Figures 1 and 2 display box plots of per-prompt differences (English – Czech), measured in word count and character count, respectively.

Figure 1 shows that all models produced longer responses in English than in Czech, on average. Each box plot summarizes the distribution of word count differences for a given model. Positive values indicate that the English version of the response contained more words than the Czech version. While the direction of the difference was consistent across all models, the magnitude and variability differed. In particular, Copilot Deep-Thinker and Gemini exhibited wider interquartile ranges and a greater number of outliers, suggesting higher variability in verbosity across prompts.

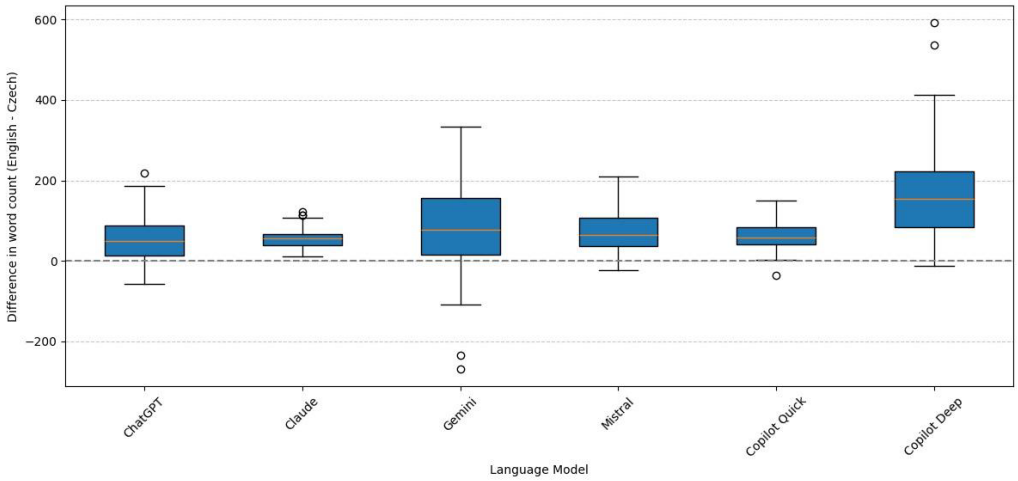

Figure 1: Distribution of word count differences (English – Czech) across six language models

Figure 2 presents the character count differences between English and Czech responses for each model. Once again, all distributions are centred above zero, indicating that English outputs were consistently longer. Copilot Deep-Thinker produced the most pronounced character-level differences, both in median length and in the spread of values. Several outliers, especially for Gemini and Copilot Deep-Thinker, suggest occasional extreme discrepancies between language versions.

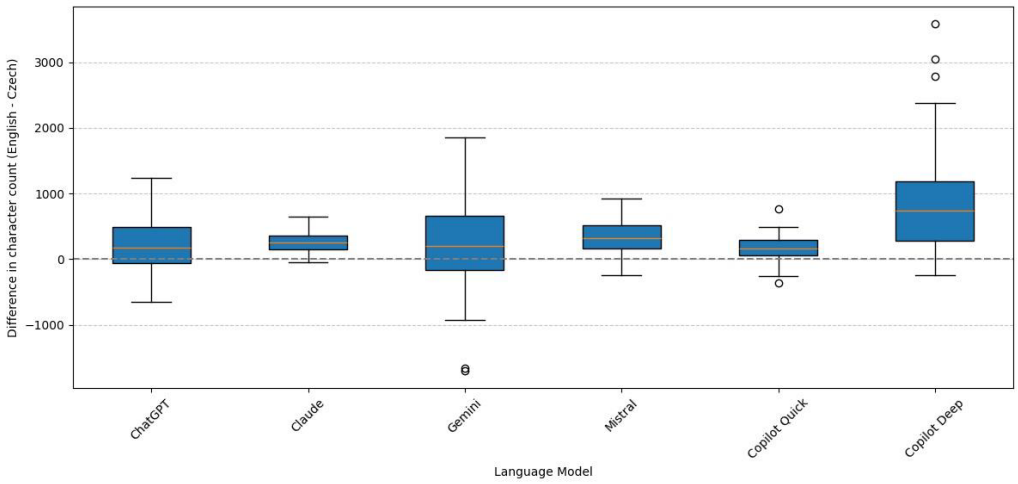

Figure 2: Distribution of character count differences (English – Czech) across six language models

These consistent positive differences suggest a systematic tendency among large language models to produce more verbose responses in English, regardless of prompt content or model type.

3.2 Tests of Normality

We conducted Shapiro–Wilk tests on the distributions of word count and character count differences for each model to assess the assumption of normality. The results are summarized in Table 2.

Table 2: Shapiro–Wilk test for normality of English–Czech response length differences across six large language models, evaluated separately for word count and character count

Model	Word Count (p)	Character Count (p)
ChatGPT	0.17085	0.98701
Claude	0.13835	0.45978
Gemini	0.09457	0.12328
Mistral	0.31635	0.63737

Model	Word Count (p)	Character Count (p)
Copilot Quick	0.89925	0.67320
Copilot Deep	0.00077	0.00041

For Copilot Deep-Thinker, the null hypothesis of normality was clearly rejected for both word and character count differences ($p < 0.001$), justifying the use of non-parametric methods in subsequent analyses. For Gemini, the p-values were relatively close to the 0.05 threshold (0.095 for word count; 0.123 for character count), indicating mild deviations from normality. However, visual inspection of the corresponding box plots revealed approximately symmetric distributions, and thus we retained the use of parametric tests for this model.

3.3 Inferential Results: Statistical Significance and Effect Sizes

We evaluated the statistical significance and magnitude of response length differences (English – Czech) for each model using both word count and character count as dependent measures.

3.3.1 Statistical test results

Across all six models, English responses were significantly longer than Czech responses. Paired t-tests (used for all models except Copilot Deep-Thinker) yielded highly significant results for both word and character counts (see Table 2). For Copilot Deep-Thinker, where the assumption of normality was violated (see Section 3.2), we applied the Wilcoxon signed-rank test (see Table 3); the results remained strongly significant.

Table 2: Paired t-test p-values (all models except Copilot Deep-Thinker)

Model	Word Count (p)	Character Count (p)
ChatGPT	3.28e-07	8.57e-04
Claude	8.76e-19	2.50e-14
Gemini	3.96e-05	*3.27e-02*
Mistral	6.13e-14	5.28e-12
Copilot Quick	2.25e-15	2.23e-07

Table 3: Wilcoxon test p-values for Copilot Deep-Thinker

Model	Word Count (p)	Character Count (p)
Copilot Deep	4.97e-14	2.65e-11

3.3.2 Effect size and model comparisons

To complement the significance tests, we computed Cohen's d as a standardized measure of effect size. This quantifies the magnitude of the English–Czech length difference, helping to distinguish between statistically significant but trivial effects and those that are substantial and consistent across prompts.

Table 4 summarizes the mean differences, standard deviations, and effect sizes for both word and character counts. Figures 3 and 4 visualize these effect sizes using bar charts, with dashed lines indicating thresholds for small (0.2), medium (0.5), and large (0.8) effects.

Table 4: Effect Sizes (Cohen's d) for Word and Character Count Differences

Model	Cohen's d (Words)	Mean Diff (Words)	SD (Words)	Cohen's d (Chars)	Mean Diff (Chars)	SD (Chars)
ChatGPT	0.8579	53.71	62.60	0.5141	211.69	411.78
Claude	2.0697	56.85	27.47	1.5593	261.58	167.76
Gemini	0.6547	74.60	113.94	0.3176	218.77	688.83
Mistral	1.5181	73.85	48.65	1.3200	335.48	254.16
Copilot Quick	1.6723	59.92	35.83	0.8738	173.56	198.63
Copilot Deep	1.3333	167.08	125.32	1.0601	874.81	825.21

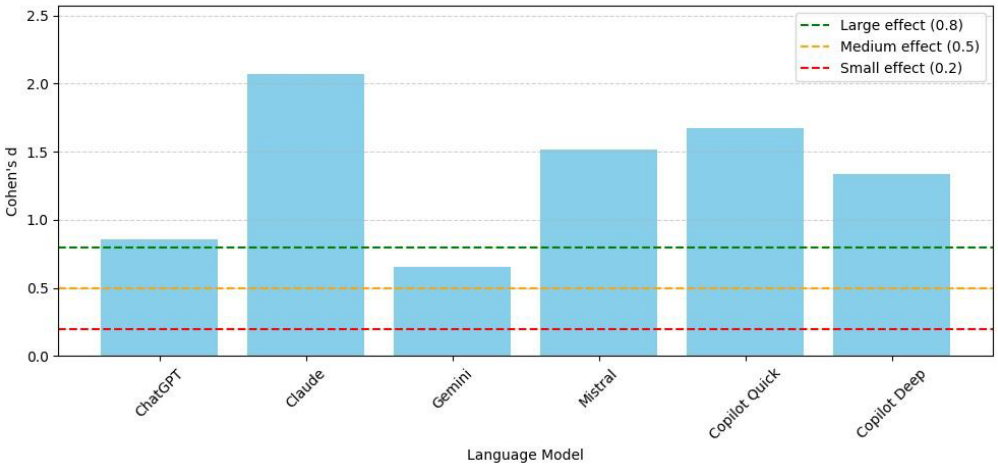

Figure 3: Cohen's d effect sizes for word count differences (English – Czech) across six language models

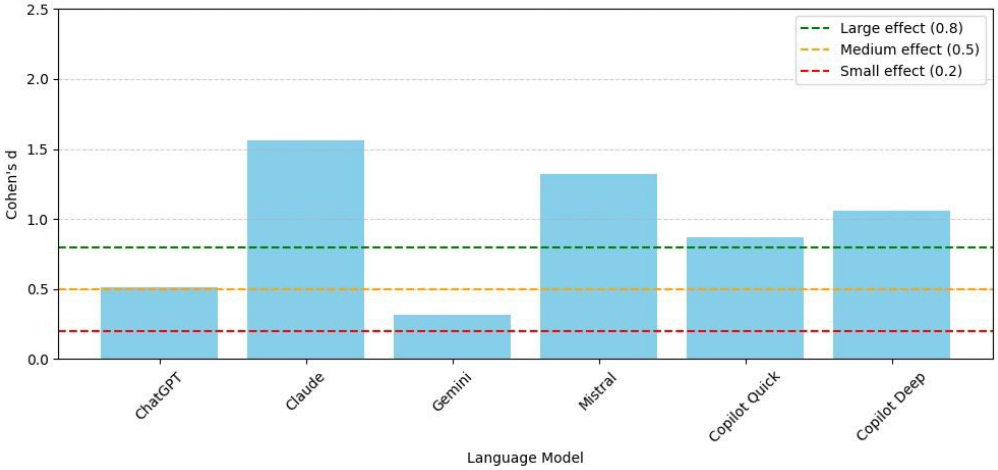

Figure 4: Cohen's d effect sizes for character count differences (English – Czech) across six language models

Across all models, English responses were longer and the effect sizes exceeded the medium threshold (*d > 0.5*) in nearly every case. The most pronounced differences were observed in Claude (*d = 2.07 words; d = 1.56 characters*), followed by Copilot Quick and Mistral, both of which also showed large effects. This indicates not only a reliable pattern, but one of substantial magnitude.

In contrast, Gemini exhibited the weakest effects (*d = 0.65 words; d = 0.32 characters*), suggesting either more balanced generation across languages or a general tendency toward conciseness. Interestingly, Copilot Deep-Thinker showed the largest absolute differences in both metrics (+167 words, +875 characters), but with slightly lower standardization due to higher variance—consistent with its design to produce elaborate, but variable, outputs.

Notably, character-level effects were generally smaller than word-level ones, particularly for ChatGPT and Gemini. This suggests that additional words in English responses may include redundant phrasing or syntactic padding rather than denser informational content, depending on the model.

3.3.3 Interpretation

Taken together, these results suggest that the observed verbosity in English is not merely an incidental artifact of translation choices or prompt formulation. Crucially, the fact that English responses were significantly longer than Czech ones not only in word count but also in character count reinforces the interpretation that the difference reflects a true increase in textual length, rather than just a structural property of the language. While English often uses more—but shorter—words than Czech, a consistent increase in both metrics indicates that responses in English were genuinely more expansive. This pattern was observed across all tested LLMs,

regardless of model architecture or interface type, underscoring a systematic tendency to generate longer and often more elaborated outputs in English, even when provided with semantically equivalent prompts.

3.4 Summary of Statistical Findings

In summary, all six models generated significantly longer responses in English than in Czech across both word and character counts. The strongest effects were observed in Claude and Copilot Quick, while Copilot Deep-Thinker exhibited the greatest variability. The consistency of this pattern across both parametric and non-parametric tests supports the conclusion that LLM verbosity is systematically influenced by language, even under tightly controlled prompt conditions. These findings provide a robust foundation for further semantic and qualitative analyses.

4. Discussion

The results of this study reveal a consistent and statistically robust tendency across large language models (LLMs) to produce longer responses in English than in Czech, even when presented with semantically equivalent prompts in a controlled setting. This pattern held across all six tested models and both surface-level verbosity metrics—word count and character count.

4.1 Alignment with Prior Research

Our findings are largely consistent with existing literature that has documented performance asymmetries in multilingual outputs of LLMs. In particular, several large-scale benchmarking efforts (Ahuja et al., 2023; Wang et al., 2025; Luo et al., 2025) have shown that model responses in English are typically more complete, coherent, and accurate than in lower-resource languages such as Czech. These patterns have also been observed in domain-specific evaluations, including educational (Gupta et al., 2025), medical (Sallam et al., 2024), and long-context reasoning tasks (Kim et al., 2025). Moreover, underlying architectural factors such as tokenization granularity and training data imbalance are recognized contributors to these disparities (Petrov et al., 2023; Li et al., 2024).

Interestingly, our results contrast with the findings of Krátká, Přibyl and Tichá (2025), who reported higher feature richness in Czech-language geometry responses. However, their study focused on qualitative geometric detail rather than holistic completeness or answer length, and applied a different evaluation scheme targeting concept-level granularity. This divergence highlights the importance of metric selection in multilingual LLM research, and suggests that certain linguistic or contextual factors—such as overcompensation or literalism in Czech—may modulate output richness in ways not directly comparable across studies.

Overall, our results reaffirm the prevailing view that English remains the most optimized language for LLM output, particularly in tasks requiring structured, multi-step reasoning.

4.2 Possible Explanations

Several factors may contribute to the observed differences in verbosity. One possibility is that LLMs have been trained on disproportionately larger and more diverse English-language corpora, resulting in more confident, expansive output in English. Additionally, differences in language structure could play a role. While Czech is morphologically richer and can express meaning more compactly, English often requires more lexical units and auxiliary constructions to convey the same ideas. However, this linguistic asymmetry alone cannot account for the consistent English-dominant verbosity, particularly since we also observed longer character counts in English responses—contrary to our initial intuition that Czech might require more characters due to its inflectional nature.

Interface conventions may also contribute. In English-language environments—where many LLMs are trained and optimized—responses may reflect culturally embedded norms of elaboration, instructional tone, and over explanation. This stylistic bias could lead to longer outputs in English, independent of the underlying content. In contrast, responses in Czech may reflect a more concise style, either due to linguistic economy or because such elaborative conventions are less prevalent in the Czech training data or user context.

4.3 Implications

The implications of these findings are twofold. First, they raise questions about fairness and content equivalence in multilingual LLM applications, especially in educational contexts where completeness and clarity of explanations are critical. Shorter responses in Czech may lead to reduced informativeness or perceived support, even if the semantic content is technically sufficient.

Second, the results highlight the importance of cross-lingual evaluation in LLM development. Models that appear robust in English may perform inconsistently in other languages not only in terms of accuracy but also in surface fluency, elaboration, and tone. These qualitative differences can have downstream effects on user trust, comprehension, and accessibility.

4.4 Pedagogical Consequences

From an educational perspective, the observed brevity of Czech responses may have tangible consequences for learners. Shorter explanations can reduce perceived guidance, limit opportunities for reflection, and weaken user trust—especially in self-paced learning settings where AI feedback replaces human scaffolding. Conversely, English users may benefit from richer elaboration that reinforces conceptual understanding. This asymmetry suggests that LLM-mediated learning experiences could inadvertently reproduce linguistic inequities, privileging students who interact in English. Addressing this issue is therefore not only a matter of linguistic fairness, but also of educational quality and inclusion.

4.5 Limitations

4.5.1 Surface metrics vs. semantic content

This study evaluated only surface-level verbosity metrics—specifically, word count and character count—which do not directly reflect the semantic richness or mathematical depth of responses. While these metrics are useful proxies for response elaboration, they cannot distinguish between substantive mathematical reasoning and stylistic or redundant padding.

4.5.2 Domain and prompt scope

The prompt set was limited to 48 questions in the domain of elementary geometry. Although the questions were designed to be pedagogically relevant and broadly representative of school-level reasoning, this domain specificity may limit generalizability to other subject areas. Similarly, other question types might elicit different language behaviours.

4.5.3 Model behaviour and language detection

Although prompt translations were reviewed for accuracy and the prompts were submitted under tightly controlled conditions (including geolocation and browser language settings), we cannot fully exclude the possibility that internal language detection mechanisms or user-context heuristics affected model behaviour. Some platforms may infer user language preferences based on prior usage or hidden system prompts, potentially influencing output verbosity in ways we could not observe or control.

4.5.4 Temporal validity

All data were collected on June 12, 2025. As LLMs are continuously updated and retrained—often without public versioning or changelogs—model behaviour may have changed since data collection. Results should therefore be interpreted as a snapshot of model performance at that time.

4.5.5 Context and interaction effects

Our design focused on isolated, single-turn prompts submitted in fresh sessions to minimize prior context effects. While this setup increases experimental control, it does not fully reflect real-world usage, where models often operate in multi-turn conversations. Prompt position, interaction history, or cumulative dialogue context may modulate verbosity differently in Czech and English, especially in dynamic, tutoring-style exchanges.

4.6 Future Firections

Building on the current findings, future work will move beyond surface-level metrics to examine the semantic content of LLM-generated responses across languages. Specifically, we plan to conduct a phenomenon-level content analysis in which each response is annotated for the presence of mathematical reasoning elements, such as definitions, properties, examples, comparisons, and deductive steps. This will allow us to determine whether the observed verbosity differences correspond to actual content disparities, or whether Czech responses merely express the same ideas more concisely.

4.7 Design Recommendations and Mitigation Strategies

Future research should also explore strategies to mitigate these cross-lingual disparities. Potential approaches include balanced fine-tuning with pedagogically relevant Czech data, adaptive verbosity controls that equalize

elaboration across languages, and transparent reporting of multilingual performance. Collaborations between AI developers, linguists, and educators could inform guidelines ensuring that LLMs deliver equally supportive and trustworthy responses regardless of language.

5. Conclusion

This study investigated whether large language models produce longer responses in English than in Czech when given semantically equivalent mathematical prompts. Analysing responses from six widely used LLMs, we found a consistent and statistically significant pattern: English responses were longer in both word and character count across all models, with medium to large effect sizes.

These findings suggest that LLM output is influenced not only by prompt content but also by language-dependent behaviours likely rooted in training data distributions, tokenization practices, and optimization objectives. While verbosity alone does not equate to quality, the observed differences raise important questions about fairness, completeness, and content equity in multilingual LLM deployment.

Addressing these issues requires a deeper understanding of how semantic content is distributed across languages in AI outputs. Our future work will focus on content-based and rhetorical analysis to uncover whether verbosity differences entail differences in mathematical depth. Ultimately, ensuring linguistic parity in AI-generated content is essential for building models that serve diverse users equitably—regardless of the language they speak.

Ethics declaration: This study did not involve human participants or personal data and therefore did not require ethical approval.

AI declaration: This study examines the output behaviour of large language models (LLMs), which also served as the primary data sources for the experimental analysis. Responses were collected from six publicly accessible AI systems—ChatGPT, Claude, Gemini, Mistral, and two configurations of Microsoft Copilot—and subsequently analysed by the authors.

During the manuscript preparation, the authors utilized ChatGPT (OpenAI, GPT-4) to support select aspects of English-language phrasing, editorial refinement, and structural organization. All analytical decisions, result interpretation, and formulation of research conclusions were conducted exclusively by the human authors. Any AI-assisted text was carefully reviewed, edited, and validated prior to inclusion.

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Fostering Trust for Effective Information Sharing and Collaboration

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Abstract: Trust is crucial for effective information exchange that is needed to counter possible hybrid influence. This literature review outlines current views on strategies to build trust between stakeholders, such as creating strong partner relationships, transparent communication on how information is used, and adhering to clear standards and guidelines. Besides stakeholder cooperation, impacts of trust are also seen in, e.g. regulatory frameworks, data protection, information security, and information exchanges between IT systems. The results of this study emphasise understanding the importance of trust in building situational awareness, needed to identify hybrid influence. Confidence in all involved stakeholders and systems can enhance situational awareness, as, e.g. effective collaboration helps promote safety by enabling stakeholders to comprehend and effectively react to adverse events and information security failures. Trust becomes a fundamental prerequisite for the successful exchange of knowledge and information among stakeholders. Fostering trust can help stakeholders improve situational awareness, ensure effective decision-making, and achieve shared goals in various domains. Trusted information exchange may unlock opportunities for innovation, growth, and mutual prosperity. In today's information-driven world, trust can be seen as a cornerstone for effective communication and successful collaboration among stakeholders. Results suggest that trust-building among stakeholders can lead to a secure reliance on the integrity and reliability of others and thus promote comprehensive approaches, e.g. to manage emerging risks. This implies that sensitive information could be exchanged without fear of misuse or disclosure; trust between stakeholders seems to be more significant than mere cooperation. IT systems, regulatory frameworks, data protection, and security are all affected by trust in information exchange. To effectively increase their respective and collective situational awareness and safety, stakeholders need a foundation of trust to work efficiently.

Keywords: Trust, Situational awareness, Collaboration, Information sharing, Communication, Information exchange

1. Introduction

Trust can be, e.g., belief in the behaviour and goodwill of others, and these can grow or disappear due to interactions and experiences (Hakanen and Soudunsaari, 2012). Focus on trust can play a pivotal role in facilitating smooth flows of information between and among stakeholders (Gardberg, 2021; Lansing *et al.*, 2023). Stakeholders must be confident that their information will be protected and used only for its intended purpose (Pilerot, 2013). Without trust, the exchange of information can become hampered, which can bring unwanted risks and result in ineffectiveness. Building trust is based on many factors, including building relationships and partnerships across organisations, promoting transparency in how information is used, and adhering to clear guidelines and standards for sharing information. Maintaining stakeholder trust and reducing costs associated with potential information breaches requires investing in secure and reliable information systems (Pilerot, 2013; Rajamäki, 2020). Potential cyber threats increase complexity within the critical sectors and infrastructure of society; examples of these are energy, healthcare, and transport (DYNAMO project, 2024). Dynamic resilience is seen as a comprehensive approach for managing emerging risks; this framework encourages the growth of resilience management skills and capacity (World Energy Council, 2019). Thus, being aware of different risks and preparing for future developments becomes important when increasing resilience, be it to specific events, systemic changes or deliberate hybrid influence, which may be very hard to distinguish as such and difficult to trace back to a source. All sectors of society are needed to create holistic strategies to combat the potential widespread impacts of hybrid influence. Emergency services, e.g., should collaborate with other government agencies, private sector organisations, and even the public.

Trust impacts information exchange across various domains, including, e.g. trust between stakeholders and information technology (IT) systems, regulatory data protection, and information security frameworks. Establishing trust between stakeholders and information exchange systems becomes crucial to promoting efficiency, enhancing situational awareness, and increasing the safety of individuals and organisations (Staples and Webster, 2008; Rajamäki, 2020). The principles of Network Centric Warfare emphasise the significance of robust networking, shared situational awareness, and collaboration in enhancing the effectiveness of missions (Alberts, 2002).

The ability to understand information security failures and respond effectively to harmful events requires situational awareness, and trust is essential to the open sharing of information between different authorities

and facilitating decision-making processes (Tikanmäki, 2017). Collaboration is seen as a key aspect when developing the maturity and broadening knowledge bases needed to address common challenges and common goals (Alberts *et al.*, 2001). (Goldenberg *et al.*, 2019) argue that cooperation may encounter obstacles because of differences in culture, work styles, and perceived problems in commitment and dedication to work.

This study builds on prior studies to look at the role of trust in promoting transparent communications, secure systems, and compliance with standards and how trust can help stakeholders improve their situational awareness, ensure effective decision-making, and work towards achieving common goals in various domains. The research question of this study is: How can building trust among stakeholders promote dynamic resilience?

2. Method

This study is an effort to provide in-depth, detailed information on trust as a human factor in building dynamic resilience, using an empirical research approach to examine the culture of the researched area (Benbasat, Goldstein and Mead, 1987; Dubé and Pare, 2003; Yin, 2009). The aim was to investigate the process of building and maintaining trust, which was done by reading and analysing the results of systematic data collection.

Literature review can help display the present state of research and knowledge, identify new research, shortcomings, and future developments to propose opportunities or solutions, while enhancing theoretical understanding (Lim, Kumar and Ali, 2022). Knowledge of general theories or methods is necessary in conducting qualitative research (Alasuutari, 1996, 2004). Using multiple lines of evidence is suggested (Yin, 2009) when examining comprehensive and extensive phenomena that may require extensive research (Dubé and Pare, 2003) and valuable information can be gathered from various sources, such as journal articles, official or unofficial reports, regulations, brochures, and memos (Patton, 2002)

This study addresses trust by focusing on the human aspects of collaboration and cooperation between organisations to identify confidential aspects of information sharing. The sample material in this research consists of document-based written material that includes published studies, academic dissertations, scientific articles, and literature in the field (Figure 1).

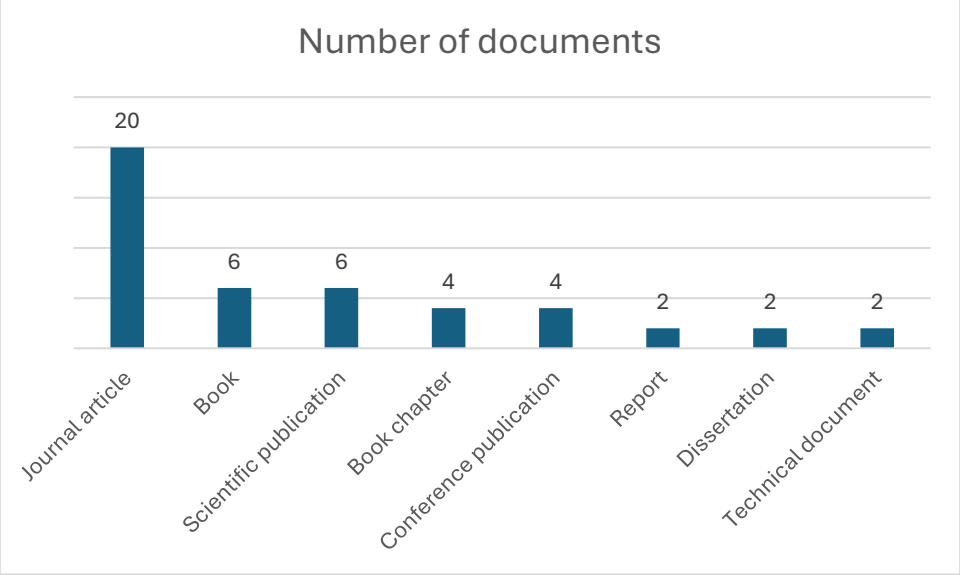

Figure 1: Types and number of documents

The research method used for this study was descriptive and conducted as a qualitative study using a literature review of 46 source documents. Most material was from journals and scientific or conference publications (n = 30). This material was examined to gain a more comprehensive understanding of the research problem based on four theoretical approaches; documents that addressed themes related to trust, situational awareness, collaboration, or information sharing within or between organisations were included. Documents that lacked an empirical or theoretical basis or that did not fall within the scope of the research topic were excluded.

According to (Kitchenham, 2004) a literature review is a comprehensive procedure that helps present evidence of the effects of specific events. The purpose of this study was to conduct an academic search to obtain answers

to the research question. This study involved a search, selection criteria, and analysis with a Data Extraction Table (DET) that mirrored the research question to guide reporting of findings and conclusions.

3. Results

Results show that trust is crucial to sharing information, as stakeholders need confidence that any information they share will be protected and used solely for intended purposes (Johnson *et al.*, 2016; Sedenberg and Dempsey, 2018). Trust can impact information exchange on many levels, e.g. trust between stakeholders, IT systems, regulations, standards, data protection and information security. Stakeholders must have confidence in each other and the systems used to process and share information. Establishing trust leads to improved efficiency, reduced risks, and better outcomes in the sharing of information among various entities, while roles between stakeholders are in constant fluid change (Ruoslahti, 2018).

Technical, organisational, and human means may establish trust (Rajamäki, 2024). Building trust is crucial for facilitating information sharing (Staples and Webster, 2008). "Trust is, after all, the single most important precondition for knowledge exchange" (Rolland and Chauvel, 2012, p. 239) and it creates positive impacts on information sharing; trust and information sharing have a strong positive relationship (Staples and Webster, 2008). "Nowadays, there is a tight coupling of systems and processes, and there are many interdependencies between these systems and processes" (Vos, 2017, p. 23). Building trust can be achieved by establishing partnerships between organisations and transparent communication on how information is utilised (Liu and Chetal, 2005; Ahmad and Huvila, 2019; Mirkovski, Davison and Martinsons, 2019; Rajamäki, Tikanmäki and Räsänen, 2019).

3.1 Trust Between Stakeholders

Sharing information on threats and vulnerabilities can "help identify trends, better understand the risk faced, and determine what preventive measures should be implemented" (Stanciugelu *et al.*, 2013, p. 6) and defining common problems and goals are in themself collaborative processes (Ruoslahti, 2018). Identifying important themes can help identify risks, critical activities, key personnel, guidelines, procedures, and open communication to manage continuity and enhance resilience (Hytönen and Ruoslahti, 2024).

Business continuity management principles can be used to dynamically build resilience, important for all organisations (Hytönen and Ruoslahti, 2024). Coalitions and cross-cultural collaboration present challenges, which, when better understood, can engage different stakeholders in long-term cooperation in co-creation that helps affect change, build alignment, and best practices (Alberts *et al.*, 2001; Ruoslahti and Hyttinen, 2017). Multiple stakeholders may have very different interests and various interdependencies (Vos, 2017, p. 13). Lack of mutual understanding of roles, abilities, cultures, and perspectives of others can greatly hinder cooperation (Goldenberg *et al.*, 2019).

Cultural differences between actors present challenges of varying perspectives, values, and communication styles. To ensure everyone is moving in the same direction, cultural divides need to be bridged (Goldenberg *et al.*, 2019). "There must be trust between stakeholder representatives and organisations" (Ruoslahti, Rajamäki and Koski, 2018, p. 10). Perceived incompatibilities of work styles, work ethics, commitment or dedication to work can be common collaboration problems, while work rotation bridges loss of knowledge, effectiveness, and business continuity (Goldenberg *et al.*, 2019). "A clear situational picture enables consideration of possible further changes in the environment"(Ruoslahti, Rajamäki and Koski, 2018, p. 9).

3.2 Trust in Communication

Solving common issues motivates stakeholders to collaborate and build trust in open innovation environments that facilitate communication and interaction (Ruoslahti, 2018). Determining targets involves identifying how to work together, gaining knowledge of stakeholder traits, tasks and situations (Alberts *et al.*, 2001). Situational awareness is based on open, trust-based information sharing of simultaneous relationships of knowledge creation and knowledge transfer (Sankowska, 2013; Ruoslahti, Rajamäki and Koski, 2018; Ruoslahti and Tikanmäki, 2019).

Knowledge building processes are "increasingly complex, multidisciplinary, trust-based, co-created, path-depended, and globalized" (Pirinen, 2015, p. 323). Inter-organisational learning highlights networks that exchange information and resources, collaboratively solve problems across organisational boundaries, and actively build trust (Engeström, Kerosuo and Kajamaa, 2007). Collaboration in networks calls for active

coordination and facilitation that motivates its members and other stakeholders to participate actively (Ruoslahti and Tikanmäki, 2019).

One of eight attributes of resilience in collaboration networks is trust building, the other seven being: clear co-created purpose and common aims, agreed organisation and roles, a common culture and common ways of working, leadership within the network, facilitation of collaboration and co-creation, system to back-up or exchange of network stakeholder representatives, and open communication and information sharing between all network stakeholders (Ruoslahti, Rajamäki and Koski, 2018). Building trust enhances open flows of communication among stakeholders (Rajamäki and Ruoslahti, 2018), while the effective functioning of businesses, governments, and societies requires information exchange, which also has risks, such as misuse or disclosure of shared sensitive data (Goldenberg *et al.*, 2019).

3.3 Trust in Systems

To avoid trust issues, it is also important to trust all information exchange systems, e.g. confidence in system security and reliability, and accuracy and timeliness of shared information (Pilerot, 2013; Sedenberg and Dempsey, 2018). "Investing in systems that improve confidence and trust can significantly reduce costs and improve the speed of interaction" (Rajamäki, 2020, p. 99). Setting clear guidelines and expectations for sharing information with common rules and standards fosters transparency and builds dynamic resilience, with e.g. business continuity management principles, which are essential for all organisations (Mizrak, 2024). Compliance with regulations and standards can ensure that information is shared consistently and reliably, and this fosters trust among stakeholders (Soderlind, 2009).

Common continuity management analysis of risks, critical activities, key personnel, guidelines and procedures, and open communication can help establish trust needed to enhance resilience (Mizrak, 2024). Stakeholders should have confidence in the security of their data and that adequate data protection and security measures have been taken for information exchange (Boehm, 2012).

Situational awareness is the ability to perceive and comprehend what is happening in one's surroundings, evaluate this information, and predict future developments (Endsley and Garland, 2000). Situational awareness is necessary to comprehend information security failures and other crucial factors that may impact security (Pöyhönen *et al.*, 2020). Human aspects need to be managed by security management to allow resilient systems and infrastructure to prepare, plan, absorb, recover, and adapt more efficiently to adverse events (Rajamäki, 2020).

Building trust allows stakeholders to work efficiently to enhance situational awareness, effectiveness, and safety of both individuals and organisations (Lansing *et al.*, 2023). SA enables the systematic prevention, identification, and protection of systems against unwanted disturbances and enables system protection against various threats (Pöyhönen *et al.*, 2020).

Decision-making requires collecting information about the environment from various sources, such as networks, risk trends and operational parameters, and exchanging this information between different stakeholders is necessary (Tikanmäki, 2017). Situational awareness is needed to develop and use countermeasures. Observations, analysis, visualisation, and national and international cooperation are some of the most important elements of situational awareness (Tikanmäki and Ruoslahti, 2019). (Pöyhönen *et al.*, 2020) e.g., offer the Observe – Orient – Decide – Act (OODA) loop to promote collaboration towards a shared situational picture, awareness and understanding and improving resilience. Shared information can increase situational awareness during operational activities and support decision-making as long as the shared information is reliable (Zaerens, 2022). Trust is an especially important element when exchanging information among authorities (Tikanmäki, 2017).

Shared situational awareness can significantly increase the effectiveness and availability of information on all levels to help redefine relationships between participants (Alberts, 2002) to help complete project tasks (Howah and Chugh, 2019). Understanding how human organisations and material structures are mutually entangled helps develop practices that anticipate possible future incidents and gain the feedback required for learning from the experiences gained from these incidents (Amir and Kant, 2018).

3.4 Information Sharing

Trust enables the smooth flow of information between stakeholders. However, they must be confident that the information they share is safeguarded and solely used for intended purposes (Pilerot, 2013). According to (Ruoslahti, 2018) for collaboration to become jointly constructed and coordinated, stakeholders must feel they

will benefit from the process and its outcomes. Mutual collaboration within or between organisations requires sharing knowledge. With the help of trust management, the correctness of the shared information can be assessed, and the reliability of the recipients of the information can be defined (Zaerens, 2022).

Lack of trust in information exchange may lead to ineffectiveness and risks (Pilerot, 2013). Exchanging information in many fields, such as business, government, and society, depends on trust, and it is important that organisations, both companies and authorities, trust that all partners act in good faith so that confidential information is protected (Hakanen and Soudunsaari, 2012; Gardberg, 2021). Human relationships are the key when building trust, as stakeholders can gain a better understanding of each other's needs and concerns by taking the time to get to know each other (Goldenberg *et al.*, 2019). Organisations and individuals can establish trust by building relationships, promoting transparency, adhering to standards, and investing in security (Soderlind, 2009).

Trust in IT systems, regulations, standards, data protection, and information security promotes smooth flows of information (Pilerot, 2013). Information is more likely to be shared freely and openly when stakeholders have trust in the systems and processes used for information exchange (Zaerens, 2022). Situational awareness of what is happening and how it might affect you (Tikanmäki and Ruoslahti, 2019) requires trust, which is crucial to promote efficiency, increase situational awareness, improve safety, and foster successful collaboration (Pilerot, 2013; Sedenberg and Dempsey, 2018). Network Centric Warfare principles, for example, highlight the importance of trust in building a strong network, sharing situational awareness, and collaborative efforts, which contribute to the enhancement of the quality and availability of information and increase mission effectiveness and help promote the maturity, development, and expansion of knowledge to collectively address challenges (Alberts, 2002).

4. Conclusions

The results of this study indicate that building trust among stakeholders can promote dynamic resilience, which is needed to counter possible hybrid threats and influence. In today's information-driven world, trust is a cornerstone for effective communication and successful collaboration among stakeholders. The significance of trust lies in its ability to foster assured reliance on the integrity and reliability of others. This means exchanging sensitive information without fear of its misuse or disclosure.

Organisational stakeholders must mainly rely on trust to share critical data. If this becomes compromised, it can greatly impact business operations and reputation. Stakeholders should ensure that their information will be protected and used only for its intended purpose. Without trust, flows of information may waver, causing inefficiencies and potential risks, resulting in loss of effectiveness and productivity.

Results show how cooperation benefits from new and diverse perspectives. Different backgrounds, cultures, skills, or work experiences can be beneficial to help make effective decisions, develop a broad understanding, and improve leadership. Additional work-related knowledge and skills can be based on competent individuals having valuable individual skills, and organisational stability, continuity, and collective corporate memory become beneficial assets to supplement areas of discontinuity.

The depth and abundance of experience and knowledge gained from others, learning the general operational experiences of others, and specialised knowledge and culture are the advantages of a cooperative culture. Creating a positive work culture fosters a sense of unity and supports the organisation positively.

One of the most significant factors in creating and maintaining cooperation is to respect all organisations involved. The importance of comprehending the perspectives of others, their roles, and their tasks, while also understanding and being familiar with each other and each other's organisations, are seen in the results. Knowing their backgrounds, skills, and working methods helps build trust. The importance of communication in general and the exchange of information, perspectives, and initiatives in a timely and efficient manner is highlighted in relevant literature. Strengthening cooperation and integration requires opportunities to interact and work on common tasks to achieve a common objective.

Building trust involves creating strong partnerships and relationships among organisations, promoting transparency in the use of information, and adhering to clear guidelines and standards. Maintaining stakeholder trust to safeguard against potential information breaches depends on investing in secure and reliable information systems. Based on the results, trust has a more profound impact than just cooperation between stakeholders. Trust also affects the influence of information exchange between information technology systems,

regulatory frameworks, data protection and security. A foundation of trust helps, and is even necessary, for stakeholders to work efficiently to increase their respective and collective situational awareness and safety.

Situational awareness is crucial in comprehending and responding effectively to information security failures and adverse events, and trust is key to sharing critical information across different authorities, facilitating decision-making processes, and creating a collaborative environment. However, collaboration may face barriers due to cultural differences, divergent work styles, and perceived issues of commitment and dedication. EU-funded projects, for example, aim to bring experts from different backgrounds to work with end-users with selected tools and platforms.

To conclude, trust seems to be one of the most important preconditions for successful knowledge exchange and information sharing. By fostering trust through transparent communications, secure systems, and adherence to standards, stakeholders can improve cyber situational awareness, ensure effective decision-making, and achieve shared objectives in a variety of domains.

Trust can help speed recovery processes and contribute to self-healing. As stakeholders adopt confidence as a guiding principle, information sharing will catalyse innovation, growth, and mutual prosperity. Building trust among stakeholders can promote information sharing, which in turn should indeed enhance dynamic resilience that helps combat hybrid threats.

In promoting the integration of both human and technological aspects of trust, this study advances sociotechnical systems theory and highlights the significance of trust in network-centric and collaborative governance. A practical contribution is that dynamic resilience can be supported by trust as a multidimensional concept. Moreover, this study supports knowledge management and open innovation theories by demonstrating how trust can facilitate effective knowledge exchange and organisational learning.

This research offers very practical advice for organisations to invest in secure, transparent, and standards-compliant information systems to foster trust and reduce risks. Business continuity professionals can improve preparedness and recovery by incorporating trust principles into continuity planning. Investing in trust-building activities, such as training and transparent communication, can help improve collaboration and resilience in a multi-stakeholder environment.

A limitation of this study is that trust, the concept that it examines, is a very comprehensive and extensive phenomenon. More research is recommended to further verify the connection between trust-based information sharing and the improvement of sustainable development, cybersecurity, and business continuity management and to strengthen the dynamic cyber resilience of critical services, especially against hybrid threats.

Acknowledgements

Acknowledgements are paid to the “Improving rescue services preparedness for hybrid threats” project, funded by the Fire Protection Fund and conducted in collaboration with the Finnish Association of Fire Officers. The views expressed are those of the authors, and the granting authority cannot be held responsible for them.

Ethics declaration: Ethical clearance was not required for the research.

AI declaration: The paper's spelling was verified using the artificial intelligence tool.

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Artificial Intelligence and Demographic Changes: A Vision for 2050

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Abstract: There has been a lot of talk about AI in recent years, but mostly from two perspectives. First, there is significant interest in the issue of the relationship between AI and the political environment, which raises numerous questions regarding the temptation of dictatorships, as well as the far from innocent methods used to conduct electoral campaigns. The second major area of interest in AI research is related to the labour market, specifically how it is influenced and changed in real time, implicitly considering the situation of jobs lost or newly created. There is one aspect that influences both the labour market and a country's political choices, and that is demography. Obviously, it is not the only factor and cannot be analysed without considering its determinants: the economy, legislation, healthcare systems, etc. Since countries do not have the same population nor the same birth rates, it is important to try to understand "something" about the effects that new technology will bring to this area of interest, because from this we can make certain forecasts about the development of some countries, the decline of others, and – under certain conditions – even about changes to the borders of some countries. At this moment, it seems that governments (no matter their economic development level) are not fully aware of the changes that AI will bring regarding interpersonal relationships. If they are only interested in the political aspect, they will see that the demographic future of their own countries could also be influenced by AI devices, which become so integrated into the life of the average person and can completely change their outlook on life visions for having children, at least. As a result of these changes of children visions, however, it is possible that we will see countries seeking, including, unification with countries that are demographically stronger, because the population decline as an effect of AI will impact public budgets so much that they will become unsustainable, forcing the governments to search for a form of "saving the passive" through unification with other countries.

Keywords: Artificial intelligence, Demography, Changes, Countries, New realities

1. Introduction

In recent years, articles, studies, and volumes about Artificial Intelligence (AI) have exploded, practically every hour you will find new references in the press or in various scientific publications appearing in over 190 countries worldwide. A list of the titles of these publications from just the last year alone would fill hundreds of pages, which makes it quite difficult to track certain guidelines of the changes that AI brings to the life of each country, public or private institution, and individuals. Nevertheless, more than ever, there is a need for forward-thinking, starting with the next 25 – 30 years, considering that the middle of this century is at the same distance of time mentioned above.

The major changes this decade alone would be enough on their own to prompt reflection, as they have brought geopolitics, the economy, the climate situation, demography, and the relationship between governments and citizens into discussion.

However, humanity does not live in disconnected sequences of time, and what we see today in Eastern Europe or the Middle East represents the consequences of actions carried out over years or even decades, during which the different technical means of those years were used to achieve results that today – with the new capabilities of AI – can be (again) questioned (Indermit, 2020).

Among all the changes that will occur in the coming decades, there are some that are easy to anticipate, and many studies in recent years have already drawn accurate lines in this direction. However, it seems that fewer researchers have attempted to understand what changes AI will bring to the demographic sphere and what their consequences will be on governments' ability to remain as effective as they are today. The demographic declines foreseen as an effect of AI applications will have brutal impacts on pension budgets in many countries (Spears and Geruso, 2025), and from this arises the question: if the ratio between the young and elderly population will so drastically affect pension payments, could it also have other political implications, potentially even leading to the unification of states to expand the numerical base of the working population's taxation, thereby saving public budgets for several more decades (since it's not just pensions that will be affected).

2. AI and Economy

The consequences of implementing AI in the economy – and generally in the professional sphere – are evident to everyone, as work is what puts food on the table daily. Approximately 40 years of "active working life"

always involve the need to protect jobs by applying various techniques and procedures that invariably require adapting human behavior to the newest realities, no matter how pleasant or undesirable they may be.

However, we see that there are many other applications of AI across different fields – among which the medical one seems to be the most important (North, 2025) – and these offer us certain prospects for improving life, with the tools of this technology providing real chances to develop medicines faster that reduce or eliminate the effects of diseases that are very difficult to treat today.

The joy with which we welcome these results is overshadowed by the fact that AI cannot help to the same extent in other areas, and history adds to this dissatisfaction a wise lesson related to the emergence of high-impact technologies. A close look at the last two centuries – the period during which humanity's greatest technological advances were made – reveals that they imposed themselves or changed political and economic realities to such an extent that they forced many governments to act naively or too ambitiously, which has often meant that armed conflicts broke out between two or more countries (Alderdice, 2024). Without going into details – given the limited space of this text – let us point out that the major inventions of the first half of the 19th century (the train, telegraph, and machine gun) led between 1848 and 1871 to the great European revolutions, which changed the foundations of monarchy in the central and eastern parts of the continent, a Crimean War that opposed Russia to other European countries, the unification of Italy and Germany, as well as the civil war in the USA. The inventions of the early 1900s (the automobile, telephone, airplane, power plants, and petroleum-based fuel) were decisive for the First World War, while communications and tanks played the same role between 1939 and 1945 (World War 2) (Anzac Portal, 2025; Burton, 2025). For this reason, considering this typology of history, we might wonder if the widespread adoption of AI in human society will also occur through a major war, or as a consequence of such a large-scale military conflict – but this is not the main subject of this paper.

All these inventions – which were able to contribute to the political change of the world – did not operate in a vacuum. Each country had access to new technologies in varying degrees, which made the different geopolitical competitions unbalanced, and certain advantages were impossible to block until the end of the wars. But more than this technological differentiation, the human factor, demographics, as well as the state-political structure of each country played a role. Only in this way can the destruction of three empires at the end of the First World War and the establishment of communism be explained (Gerwath, 2018), and only these factors explain why over 70 independent states appeared in Asia and Africa after 1945 (Office of the Historian, 2022).

The emergence of AI is therefore not a matter taken out of a global context, like a "deux ex machina". On the contrary, its emergence has been anticipated for more than half a century (Mucci, 2024), and its effects could not be properly understood then by futurologists, because some major issues at the beginning of the 3rd millennium were not predictable. How many people would have said in the 1970s – when computers were beginning their path to what they are today – that the Soviet Union would no longer exist, that China would be a force in scientific research, that the planet's population would exceed 8 billion people, and that nature would be affected by a quasi-overwhelming anthropic phenomenon caused by global warming (Eyring et al., 2021)? These realities we live in today influence AI technologies in a way we are trying to fully understand, and in turn are influenced by the capabilities that different AI tools have. Obviously, they are interdependent, but a thorough analysis could be the subject of an entire volume, which forces us to focus especially on one of the fundamental aspects of this century, namely demography.

3. AI and Demography

Why must the relationship between AI and demography be studied very carefully? The answer is given by a phenomenon that begins at the end of the 1980s in most developed countries, which are the most capable of bearing the costs of implementing this technology, because the diversification of their own economic agents offers a broad perspective on the use of AI. Specifically, since the late 1980s, developed countries have entered a phase of demographic decline, and the main source of growth – where it exists – is represented by migration from poorer countries (Sasaki, 2023).

The prospects for demographic growth in these countries – with the exception of the USA – depend primarily on migration, which means that the national and ethnic landscape in these decades and the following ones involves a reduction in the cohesion that these types of centuries had (Filipenco, 2025). The integration of millions of migrants – in 2024, the number of those who have left their country is approximately 283 million globally (IOM, 2024) – is challenging, as there are issues to be resolved starting with learning new languages;

integrating the children of these migrants into school systems; accommodating these new residents in cities that are increasingly crowded, demographically dense, and have traffic flow problems, etc. (OECD, 2020).

Europe is the continent with a population density in its most developed part that exceeds 100 people per km², and the increase in migration from other continents (predominantly) further increases the pressure on infrastructure that was designed in the 19th or 20th century, when transport systems and the number of car owners were much smaller than today (Guerra et al., 2023). Thus, a phenomenon arises where many migrants live in small spaces to reduce their own costs, often working in low-skilled positions, taking jobs that natives refuse (Hayo and Roth, 2024).

The philosophy from the 1990s (the year when the great international migration began, according to UN data) to 2022 (the year Chat GPT application appeared) was essentially simple: external migration was accepted for low-skilled jobs, while natives would take on more complex and better-paid jobs (Harris, 2003). Obviously, not all migrants had low-paid jobs, and over time some integrated enough to receive citizenship in developed countries and contribute significantly to their progress in various fields (for example, in sports).

The widespread emergence of AI tools, however, poses a problem, as this technology directly affects a good portion of jobs that involve repetition and a lower degree of specialization (Petropoulos and Brekelmans, 2020), meaning some of the migrants' jobs disappear. This does not mean, however, that those people will automatically return to their countries of origin, and their lost jobs will make many thousands of people vulnerable, creating pressure on social security systems in developed countries, as well as an increase in poverty in migrants' home countries, which will lose large amounts from remittances.

This economic aspect will also have a significant demographic effect, regardless of ethnicity: in countries where AI tools are strongly implemented, lost jobs will affect many sectors of activity, causing young couples to think twice about whether they want to have children (Neugnot-Cerioli and Muss Laurenty, 2024), since there is no medium-term certainty about their money and professions.

In essence, the last few decades have changed the idea of having children almost everywhere in the world (Berg and Wiseman, 2024). While for hundreds and thousands of years, children were born to carry on the family line – due to the low life expectancy, less than 30 years until the early 20th century (Herre, 2025) – and to provide enough labor for agriculture and manufacturing, this no longer happened after the baby-boom wave ended. The increase in life expectancy, combined with the quality of medical care, led families to reduce the number of children, who this time mostly reach adulthood, and what was offered to them during childhood and adolescence was something that even kings could not provide to their own children before the 20th century (Harris, 2017). Toys, quality education, travel within the country and abroad – all these things cost money, and in many countries, the population can afford to provide them to children to a reasonable extent. However, these achievements had a background, namely economic growth and the diversification of industry and the tertiary sector, which made jobs relatively secure over long periods, offering prospects for planning family expenses related to housing and children.

However, the emergence of AI brings a major problem to this life planning model, because one of the main effects of its applications in the economy is the reduction of today's jobs, and any replacements for lost salaries will happen neither automatically nor immediately (Filippucci et al., 2024). The pressure on jobs is increasing, and this is already being observed in all developed countries or those with a reasonable level of economic progress, which amplifies stress and concern about the future. Moreover, the fact that AI's action is linked to the entry-level professions (Constantz, 2025), where first things are learned, followed by promotion to more advanced tasks, already has a brutal effect on beginners, who are young and at the start of a path that would also involve starting families and procreation. Now, in a situation where jobs are so heavily threatened, can they still easily have thoughts of "emotional bonding" that would materialize in family and children? This is a real question, troubling not only the young people starting their professional careers today but also their parents, who are forced to continue supporting them, because no matter how much willpower they have to find a job, AI applications have a better position on this labour competition.

The impact on jobs always has effects in the demographic sphere, because no parent would want to have a child they would raise with great difficulty. This feeling is common throughout history and was most visible during times of drought or war, because until the beginning of the 20th century these events were both difficult to predict and especially hard to combat. However, the development of contraceptive methods has intensified this sense of family planning, and having a child increasingly becomes a proof of financial capacity, alongside the love that motivates parents (Van Winkle and Monden, 2022).

However, the economic-industrial revolution brought by AI is a new and contemporary one, which means we do not fully know all the consequences of its implementation, but we see its effects daily in the press and everyday dialogue (Rosa et. Al., 2025). We should therefore expect a decline in births in countries where governments and economies do not adapt quickly, which will, however, mean higher costs in social insurance for the unemployed, as well as a threat to pensions, which are endangered both in the long term (based on birth reductions) and especially as an effect of increasing unemployment (Wilshire, 2024).

We assert that there will be an increase in unemployment given the figures regarding young people entering the profession in the last two years – in the United Kingdom, for example, 33% of graduates do not find a job (Almeida, 2025) – and the demographic effects will be seen before the end of the decade, which means that in the years 2035 – 2050 the effects will be even more pronounced at the level of schooling in high schools and especially universities. In practice, high schools and universities will have a problem with recruitment, because there will certainly be many cases where families, seeing how difficult it will be to get "office jobs" in the AI era, will no longer want to bear the costs of education. As the guarantees decrease that, at the end of their studies, young people will find a prestigious and well-paid job based solely on a university diploma, many parents will prefer not to pursue this path for their children, but rather seek to guide them toward safer jobs that are less threatened by AI capabilities.

But this demographic aspect – affected by the economic situation brought about by AI implementation – is not uniform, not even at the level of a continent. Economic differences will mean that solutions from one country cannot be applied in other areas, because not everyone has the same financial power to implement the various industrial visions.

4. AI and its Consequences in the Demographic Sphere

But just as important are certain political or cultural particularities that will affect the demographics depending on how many AI devices are used in national economies.

Thus, we must start from the reality that not all countries in the world are democracies (EIU, 2024), which means that AI implementation is not done everywhere solely for commercial purposes. AI capabilities are huge, and an authoritarian government will use them without moral concerns and especially without legal worries to monitor its own citizens (Jafari Hezarany, 2024), which means the state will have access to people's private lives to a significant extent. If people were content to live in such states, there would be no implications for demographics, but usually, this pleasure does not exist, which makes young people think twice before having children, because they are – due to a lack of maturity – both subjects of the state's propaganda use and a factor in monitoring their own families, as they will reveal what happens at home, and AI tools can record even this data in kindergartens and schools. Far from being a utopian or crazy idea, it was applied in communist countries as early as the 1920s (Hola and Drumbl, 2025), without today's capabilities of personal surveillance and data collection.

Cultural aspects in the relationship between AI and demography must not be ignored either, because they can strengthen the cohesion of a nation, but they can also signal potential problems or future social explosions. Culture is something that manifests in relation to the past, which means that certain practices or customs applied for decades or hundreds of years can be difficult to eradicate in this century, or – in certain situations – can actually be reinforced by AI technologies. Thus, we must remember that in several countries in Asia and Africa, female children are not highly valued (Portner, 2015), for reasons we will not discuss here. AI appears today – and will even more so in the future – as an aid to the medical system, and here we note that this technology will facilitate finding out the sex of the foetus from the first weeks of pregnancy, which will result in an increase in the number of selective abortions (Pison et al., 2014). Over time, this selection during pregnancy will have the effect of modifying the social and political ratios in those countries, as there will be more men of marriageable age, but far fewer women for that. As a result, dissatisfaction among each person will grow, and a large number of unmarried men may be much more willing to engage in social revolts, clashes with law enforcement, and even provoke changes in political leaders. Far from being a joke, this imbalance could even lead to a form of trafficking of women from poor countries to rich ones, solely for maintaining intimate relationships or even marriage (the phenomenon is already common in the Laos – China relationship). The intermixing that will occur in the coming decades may also lead to other political reactions, of a xenophobic nature, which will want to expel migrants from those countries, but the need to balance the ratio between men and women will be an objective one, and based on it governments will be willing to facilitate certain practices on the edge of legality.

The issue of selective abortions primarily affects poorer countries, but those that are culturally within a hierarchical paradigm of gender relations. Obviously, it can be said that in countries where contraceptive methods are scarce, finding out the fetus's sex early on will be more difficult. This is true today, but over time some of the costs of using AI for certain operations/tasks will be lower because what is easy to do will have lower prices, and only highly complex matters will be accessible solely to governments or large companies.

In any case, in the future AI will be useful for early detection of certain diseases, even during pregnancy, which will likely lead to other abortions, but strictly for medical reasons. Let us not forget that in this matter medical capacities will face a double barrier, which will be easier to overcome in some countries, namely the power of certain religious cults. In some countries, these cults are so strong that they influence state legislation, banning abortions, which will not be highly appreciated by future parents who can find out with the help of AI about possible serious diseases of those who will be born in a few months. For this reason, it is foreseeable that the relationships within the quadrilateral of medicine – AI – religion – abortion will be difficult, leading including to a decrease in the number of practicing believers, alongside other possible dissatisfaction toward religious cults that oppose new medical practices based on books unchanged for over a millennium (He, 2024).

One last necessary clarification regarding the prevalence of births predominantly of male children. An imbalance in the sex ratio can be a basis for increasing societal surveillance systems to a dictatorial level, because too much tension in society and too many men with the physical capacity to protest violently – without the self-protective restraint due to the awareness that a wife and one or more children are waiting at home – pose a threat to any government with weak administrative performance. For this reason, we will be able to observe the deterioration of legality and democracy in some countries in relation to this imbalance, which AI will accentuate.

The phenomena described above mainly originated either from economic realities or from the influence of hierarchical cultural typologies, in which the entire society follows certain strict rules that can only be broken by those with enough political power or money to avoid potential fines or prison sentences. But the last decades – actually, since the emergence and expansion of the internet – have presented governments with a major demographic challenge, namely the inhibition of sexuality toward real people. Thus, studies from recent years reveal a lower interest among young people in maintaining intimate relationships, which has a destructive effect on demographic prospects. Moreover, the mental state of young people is more vulnerable than that of previous generations, making them more anxious, more stressed, less capable (and also less willing) to take on responsibilities. It is evident that having a job and having children represent strong sources of stress, and escaping into the virtual world is a solution (also in friendship with animals). Thus, it is harder for these young people to socialize, to participate in community life, and their refuge – and at the same time the place where they feel protected – is the electronic space, where AI is manifesting more and more frequently (The Economist, 2025). However, this "withdrawal into virtual space" worries governments, who consequently see themselves affected demographically even more rapidly, which causes the age balance to tilt profoundly, and the incomes of pensioners and public budgets to be heavily impacted. What can be done here? Obviously, the answer must be formulated wisely, but it must be kept in mind that this lack of participation in community life ultimately leads to the atomization of society and, in the end, to a demographic decline of large proportions.

The automation that AI brings to many industries will most likely also lead to another economic operation, but with multiple demographic effects. Specifically, some large companies will no longer outsource their own factories, keeping them in their own countries, because labor costs will decrease. Industrial robots will do most of the work, so fewer people will be needed to operate an industrial cycle, which will make it less necessary to move production to continents with poorer countries.

However, this will not be well received in those economically vulnerable countries, which will become even weaker, and the cycle of poverty (families – children – lack of access to higher education – low income) will widen, forcing governments into difficult, politically risky operations just to maintain a certain social peace. At the same time, bringing factories back to developed countries will mean a reduced need to accept foreigners, because the national workforce, even if declining, will be sufficient for their own national economies. Therefore, the ethnic landscape will most likely become more uniform, and some foreigners will have to return to their countries of origin, which will bring the families they left back to a lower economic level (Scott et al., 2022).

A specific note still needs to be added regarding a phenomenon that will appear, I believe, in 20 or 30 years as a result of the same demographic decline, which will be intensified by the effects of AI technologies.

Specifically, countries have different demographic sizes, and the sharp declines in places where there are currently 5 million inhabitants or fewer will have serious effects on budgets and pension systems, but generally on the functionality of the state and society.

AI will operate everywhere, albeit at different speeds, but demographic decline will be a certainty in Europe – a continent with a fairly strong economy but with most countries having fewer than 20 million people. In this perspective, where population decline is a reality, small countries face a possible solution: unification with other countries, either of similar size, larger, or – in the European case – into a genuine USE (United States of Europe). This scenario should not be underestimated, as it can only be reversed by a combination of demographic and economic growth.

The big problem for small countries is that economic growth depends quite a lot on the demographic size, and the numerical decline leaves few options. If today we might smile at these ideas, let's analyze the UN figures for world demographics in 2050 and 2060, and perhaps the smile will turn into something else, not very pleasant but realistic.

5. Conclusions

The dimension of the relationship between AI, demography, and the state in the long term - over a period of at least two decades - is still quite difficult to anticipate, because governments have simple interests, which involve economic growth and population growth, which comes into conflict with much of the realities we already live with. However, certain trajectories can be observed, which reveals the power with which new technology makes its way into each of our lives.

For many reasons, which I have tried to present in this paper, demography will play a fundamental role in guiding government actions. Demography will be the factor that forces the resizing of public budgets, because one of the effects of AI technologies is to reduce the number of newborns, shifting the balance between the active population and retirees, thus reducing many developmental prospects for countries around the world, especially those with developed economies. For this reason – demographic imbalance – I believe that one of the very likely effects in the coming decades will include the unification of some countries that will no longer feel secure about their demography, that will have too unfavourable a ratio between retirees and the active population. The future will confirm or refute this hypothesis, which I still believe will be difficult to avoid, especially in countries that have already experienced a significant decline in the number of children in this millennium.

Ethics declaration: I declare that in this text the rules regarding academic ethics and integrity have not been violated.

Artificial Intelligence declaration: I declare that Artificial Intelligence was not used in this text either for research or for the conception or writing of the text, with each sentence belonging entirely to me.

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The Augmented Human and the Future of EducA(I)tion

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Abstract: Given recent developments in technological advances (chatbots in particular) and, by extension, the gravitational pull to utilize technology (also AI-driven educational technology) in education, a need arises to reconceptualize the most fundamental assumptions and understandings of education itself. This also involves questioning (and possibly even redefining) our humanity and human-ness. I am thinking along the lines of both critical posthumanism and transhumanism. Education hereto meant leading the subject (student, pupil) into humanity and being fully human (Snaza, 2013). But does this definition need reform, and if so, how? Several other questions arise from here: what will happen when – if – human stops being human, at least in the sense understood until today? Will education be defined as something completely different? Will it, say, side-track the foundational role of teachers, schools, curricula, socialization, etc., contrary to the understanding that education means *human* relationships between teachers and students (Knox, 2019)? To these dilemmas, I offer the following lines of thought that do not lead either to unproductive technophobia nor to critiquless euphoria. It is maybe (high) time to think about changing the categories, concepts, and our use of language to describe AI-related issues. I suggest two moves to start with: (1) a move away from anthropocentrism, both in language and concepts, (a) to include non-human entities and (b) to name the hereto unknown and "unconceptualized" phenomena, and (2) a move away from thinking about AI as merely automaton and task substitution agent, and from "injecting" it (Susskind, 2025) into the current ways of going about our business, with the aim for AI to replicate humans' (in our case teachers') work. And, as for education, the use of technology transforms both people and their experiences (Jamison and Haraway, 1992); it may be that digitally transmitted experiences differ from live experiences (i.e., teacher-pupil interactions), so that would require special attention, plus raising awareness regarding emergent hierarchies, most importantly featuring those whose capacities are enhanced by various technologies and those who are not "improved" in that way.

Keywords: Education, Human, Posthumanism, AI, Enhancement

1. Introduction: Setting the Coordinates

In recent years, there has been a growing recognition of the need to reconceptualize the most fundamental assumptions underlying education. This need stems from two interrelated phenomena. The first is a significant technological advancement, with chatbots standing prominently at the forefront of this development. The other is, by extension, the gravitational pull to use technology, including AI-driven technology, in education. It appears that education can no longer be fully understood in terms of human participants alone.

This potential shift is, in part, the result of a specific historical circumstance – namely, the COVID-19 pandemic – which required alternative approaches to schooling due to health and safety precautions. Among these were distance learning (also known as e-learning), virtual classrooms, computer-assisted instruction, and similar. These approaches have continued to evolve even in the post-COVID era. However, they did not always prove as "efficient" as the live educational process, as known hereto, which involves a human teacher. Quotation marks in "efficient" are here for a reason, as "efficiency" would certainly require further elaboration. Does this mean better education, yielding better results that are easily measured, or maybe happier students …? Parenthetically, this also entails a quantification of educational excellence and hereby amplification of inequality in education (Knox, 2019). Then came the excitement connected with chatbots, especially ChatGPT. There are others, but this one seems to have received the most attention; thus, it will be the one mentioned here.

As the hype subsided, the excitement was tempered by concerns about its influence on various aspects of human activity, including education. It appears that this has shaken the educational world also conceptually, raising questions about what education is and what its aims, outcomes, and experiences in the process should be. Moreover, it has begun to pose serious practical challenges, ranging from questions about how to define and prevent academic (dis)honesty (see, e.g., Skonieczny and Vendramin, 2024) to reconsiderations of educational standards – what should be learned, and how. Education has become a space characterized by "not-us thinking," which reflects the belief that "AI has massive potential but 'not for us'" (Susskind, 2025). In other words, a human teacher cannot be replaced by a non-biological entity. And that requires serious thought.

I am not a computer scientist or an expert in artificial intelligence, nor do I have detailed insight into the inner workings of these systems. I approach the issue from a humanities perspective, one that invites broader reflection on the potential impact of AI on education, learning, schooling, and society as a whole. This also means, as Jeanette Winterson has put it, studying the past to understand the present and the future – that is

what the humanities are for (Winterson, 2022). All too often, lessons learned in the past travel poorly to the generations that should make the most of them.

In this contribution, I want to take a look at the possibilities of how education and its aims might be redefined and what education might look like in the near and not-so-near future. What will be the role of the human teacher in live contact vs distance teaching, non-human teacher, and AI teacher (the terms are provisional here)? Is the next step heading in the direction of personalized education and human pupils augmented in various ways?

The focus here will be on modern technology, including computers and related digital devices, as well as artificial intelligence – whether in virtual form or embedded in various types of robots.

But, before proceeding, it's essential to clarify what is meant by the term "technology" in a more general sense. There are two radically different ways to understand it. It can be thought of (1) as a constant presence throughout human evolution – something inherent to our development and "intimately interwoven in the social fabric" (Braidotti, 2019), which is also my point of view, or (2) as a tool, an instrument to be used positively or negatively. The latter side-tracks "technological impact on our daily lives, or our sense of subjectivity and our imaginings" (Braidotti, 2019).

Technology is not a "thing", but as "a space of possibility which configures the way we think, feel, speak and encounter ourselves and others" (Müller, 2016). It might even be needed to think about technology in a way that resists "the intellectually comfortable position of mobilising a false opposition between 'humanity' and 'technology' when looking ahead into our digital future" (Müller, 2016).

The technological side also involves the human side. This means questioning, rethinking, and possibly even redefining our humanity and human-ness. I am thinking along the lines of both critical posthumanism and transhumanism. Although both share a common interest in technology (let us focus only on this aspect here), their relationship with it is structurally different.

Posthumanism is aware of our human epistemic limitations; it opts for a non-hierarchical perspective, so no human primacy is granted, regardless of the kind of human being we have in mind (which is an argument against the alleged universalism of Man). Its epistemology encompasses nonhuman experiences as sites of knowledge, with actors including nonhuman animals, artificial intelligence, robotics, and similar entities (Ferrando, 2019).

Transhumanism, however, opts for a radical transformation of the human condition by existing, emerging, and speculative technologies (e.g., regenerative medicine, radical life extension, and mind uploading). Technology is viewed as a means by which humans might transcend the finitude of life by extending and augmenting the capabilities of our biological bodies (Ferrando, 2013). This kind of emphasis on technology risks pushing humans further into exceptionalism (human vs other non-human biological life forms) if viewed as something that will help us overcome our biological limitations and thus make us, yet again, the most important actor on the stage.

2. Education as an Inherently Human Endeavour?

I will briefly examine the concept of education as a starting point for considering the changes brought about by recent technological advances, particularly those driven by artificial intelligence. Gert Biesta defines three domains of the purpose of education: qualification, socialization, and subjectification. We will use these terms, although there are others (see Biesta, 2020). They should suffice for the scope of this contribution, due to which they must remain somewhat sketched out.

The point of education, says Biesta, "is never that students simply learn – they can do that anywhere, including, nowadays, on the Internet — but that they learn something, that they learn it for a reason, and that they learn it from someone" (Biesta, 2020). *Qualification*, then, involves the transmission of knowledge and skills. Yet this transmission also conveys a particular way of representing the world – that is, it reflects what is generally regarded as valuable. This aspect relates to *socialization*, which involves engaging with traditions and shared cultural practices. And then there is a third dimension, *subjectification*, which, according to Biesta (2000), is "about 'qualified' freedom, that is, freedom integrally connected to our existence as subject. This is never an existence just with and for ourselves, but always an existence in and with the world". We could think of these domains of the purpose of education as being represented by three concentric circles: "where subjectification is either at the centre, because it is 'core', or put in the outer 'ring', because it encompasses the other two domains" (Biesta, 2000).

There is much to be explored regarding the essence of education, the core of what it means to be human, and the potential gap between what a human being *is* and what they *ought to become* through the process of education. I cannot go into the debate about the distinction between *cultivating humanity* and *educating the human* here; however, it is worth noting that the former has proven insufficient insofar as it operates on a pre-given notion of what it means to be human. This idea can take multiple forms and manifestations, several of which do not necessarily align with what we commonsensically regard as human or humane, as the wars of the twentieth and twenty-first centuries demonstrate. These inhumanities, says Biesta (2014), referring to Levinas, "were actually motivated by, if not based upon a specific conception of what it means to be human".

To establish a common denominator, let us assume that education, in this context, means leading the subject (student, pupil) into humanity and being fully human (Snaza, 2013). But does this definition, in light of the recent technological developments, need to be reformed, at least to a certain extent, and if so, how? These actual developments were preceded by various theoretical contributions, famously Donna Haraway with her cyborg imagery (see Haraway, 1991). The explorations of science fiction and speculative fiction should also be mentioned. Several other questions arise from here: what will happen when – if – human stops being human, at least in the sense understood until today? Can education, say, side-track the foundational role of teachers, schools, curricula, etc., in supposedly outdated institutions, contrary to the understanding that authentic education means "pure" *human* relationships between teachers and students (Knox, 2019)?

These dilemmas may not be new, but now an unprecedented player enters the stage: artificial intelligence. True, it brings us various joys and unburdens us from numerous tedious tasks. At the same time, however, it presents significant challenges to various dimensions of our social lives. We should be wary of viewing this entrance as another master narrative. I agree, at least for the time being, that "humanity is encountering what to all intents and purposes we might call a 'period of change' in our relationships with digital technologies, and the social systems and institutions they appear to have become embedded within" (Knox, 2019). That is why it is important to view technology as a factor that actively shapes – and is shaped by – human beings in a process of co-evolution and co-construction, not merely as a tool for accomplishing tasks or achieving goals. This is the way digital technology, developed and used for educational purposes, tends to be understood: as "a supplement or addition, applied with the intention of 'enhancing' existing pedagogical practices or learning experiences" (Knox, 2019). Not enough has been said on "how" the learning can be enhanced, and why this is better.

The use of technology transforms both people and their experiences (Jamison and Haraway, 1992). Digitally transmitted experiences may differ from live experiences, such as human teacher-pupil interactions, in the acquisition of knowledge, social development, or other areas. The reasons for this have already been discussed above in relation to the three domains of the purpose of education. Here is one of the rubs that presents a case for a different conceptualization of education, namely, one that considers the importance of materiality. This is not to say that we should prioritize the use of technology over live experiences, but "pluralize and specify educative practices as materially co-constitutive doings and actions" (Taylor, 2017).

It should be clear that education is no longer a purely human affair, if it ever was (it depends on our understanding of what technology is). Notwithstanding the latter, there is a role that more-than-human and non-human entities play in education. I would opt for the term "posthumanist theory of education", one that "provides a way of thinking of educative practices beyond the limits of cognitive effects, intellectual input and output of 'content', and the effects of human behaviour« (Taylor, 2017). A posthumanist approach to education seeks to move beyond the anthropocentrism we have grown so accustomed to and instead emphasizes the interdependence of humans and nonhumans, including animals, plants, and the environment.

3. AI and the Human Condition

But we are already living in posthumanist (Taylor, 2017) and transhumanist times, some of us enhanced and upgraded through biotechnological interventions such as gene therapy, three-parent embryos, implants, prosthetic devices, and cryonics (well, perhaps not this one yet). We may be thrilled or we may be cautious of all those possibilities, but let us not forget that alongside that, there emerge new hierarchies, in our case, most importantly featuring those whose capacities are enhanced and those who are not "improved" in that way. Who does the choosing about who will get access to the enhancement? It would be naïve to claim that there will be no social inequality in that.

If enhancement technologies were to be used, would different educational standards apply to enhanced versus non-enhanced individuals? We might consider the kinds of experiences each would have, the knowledge they might acquire, and the outcomes they could achieve.

What are the ethical implications? Margaret Atwood, who has done, by the way, a lot of this kind of thinking in her novels, has posed two questions that perhaps capture all the dilemmas in a nutshell (Atwood, 2011): "How far can we stretch and still remain human? What is essential to our being, what is contingent?" And there are no easy answers to that, as what might be at stake is our identity and our – that is, human – authenticity.

To address some of these very pertinent dilemmas, I offer the following lines of thought that do not lead either to unproductive technophobia or uncritical euphoria. It might be time to reconsider the categories, concepts, and language, especially in the context of AI-related matters. Since AI has not been with us for very long, it remains to be seen how the suggested reconsiderations will take place.

I suggest two moves to start with, but no doubt different steps are possible: (1) a move away from anthropocentrism, both in language and concepts, (a) to include non-human entities and (b) to name the hereto unknown and "unconceptualizable" phenomena, and (2) a move away from thinking about AI as merely automaton and task substitution agent, and from "injecting" AI (Susskind, 2025) into the current ways of going about our business.

What if, since we are in slight conceptual trouble here with the first move, we try a different approach to language and naming things, as suggested by Susskind (2025)? He proposes that we do not use the terms we are comfortable with when applying to humans, but invent new ones that would enable us to distinguish between human and machine procedures. The solution he proposes is somewhat awkward, but my argument is not about this particular solution, but about making a distinction between human and machine processes whose outcomes are seemingly similar. It is indeed "hard not to want to use human labels to describe what's going on when machines deliver outputs that we thought were the exclusive product of biological people" (Susskind, 2025). Susskind's proposed solution is adding *quasi* (Latin for "as if") as a premodifier. So, we would have a quasi-education, quasi-judging system, etc. I think this approach presents challenges both in practice and in theory. But the point is: would this distinction clarify the issue sufficiently? Is "clean" education, that is, untainted by technology, even possible?

If making this distinction seems unnecessary or ridiculous, let us bring to mind the verb "to think". We do use it indiscriminately for both humans and AI, but we (all) do not think that AI thinks, at least not just yet, and not in a sense humans do. To clarify that we would be required to have a serious excursion into what conscience is.

The thinking that calls for a second move is also very prevalent and hence almost invisible. Its background is the perception of technology as a tool that can be used wherever necessary or fitting. Relatedly, there is the persistent separation "of an authentic inner 'humanness' from external and alien 'technology'. The project of education is overwhelmingly viewed as a matter of human development, whether in the form of individual behaviours, cognitive processes, or social constructions, in which technology only features in a supporting role, typically as an uncritical 'enhancement' for learning" (Knox, 2019).

In other words, in education, we use AI to make it better, perhaps even more fun, but the background thinking is that AI replicates humans' (in our case, teachers') work. This replication is considered good should we reach that point in the development of AI, and, at the same time, bad because this would endanger the position of the teachers and render them obsolete. Susskind (2025) calls this AI fallacy, which is "the mistaken assumption that the only way to get machines to perform at the level of the best human is somehow to replicate the way humans work". However, AI functions differently from humans, although the results may seem the same or similar. The basic error, says Susskind (2025), is that we do not recognize "that AI systems do not mimic or replicate human reasoning. To think otherwise is to take a much too human-centric view of AI".

There is anxiety about AI systems outperforming humans or doing things that are beyond human capabilities. On a larger scale, it seems that less anxiety is caused by the use of machines that outdo humans in heavy work (say, moving burdens, building houses) or microscopic work (say, entering into the human body) than by the use of machines that outdo humans in activities that call upon our intellect (Susskind, 2025). In both former cases, the machines could be thought of as human extensions, but in the latter case, the discomfort is seen as imminent as the machines, with their human-induced mastery, are entering into our most private domain.

However, nonhuman systems are not (yet) analogues for human minds. I cannot go into details about the complex issue of what intelligence is, nor am I in any way equipped to talk about it at length, let me point out that human or biological intelligence cannot be made up from scratch, "without addressing the fundamental ways in which humans are embodied, relational and set within wider ecologies" (Crawford, 2021). By embodiment, I do not mean AI-driven machines interacting with the physical environment, with, e.g., sensors

or "learning" physical concepts to be better able to function in a spatial dimension. I would suggest, following Karen Barad's work here, thinking in terms of "entangled elements" that co-constitute each other.

Co-constitution also means thinking in a distinct step away from the Cartesian dualism or split of the body and mind. The split implies the assumption that cognition can be studied in isolation, with no links to physical substrates (see e.g. Barrett and Stout, 2024). This line of thought also aligns with the concept of embodied cognition, which is highly relevant not only to AI research but also to broader debates surrounding human and biological consciousness.

But I want to stress the following. Human intelligence does not exist independently, as distinct from all the social, cultural, political, and historical forces (Crawford, 2021). Taking this into account, we can see that there cannot be enough common ground to compare us to the AI in this regard. True, there might be opposing opinions regarding the simulation of embodiment, environment, even history and culture, etc. This takes us in the direction of questioning the reality as we commonsensically know it, but let us stick to the notion of reality we currently agree upon, *our* reality.

The use of technology allows us to "enhance" our capabilities, our biology, which is, in fact, a dynamic that has existed throughout human history. We have long extended our visual apparatus through microscopes and telescopes, which make previously inaccessible aspects of reality available for observation. More recently, biotechnology has opened up new possibilities for enhancing both body and mind, allowing us to go far beyond what our biology permits us. Sometimes these interventions help us stay the way we were, so they are in function of "correcting" the damage done to us by illnesses or accidents and are, in this sense, beneficial. This raises the issue of how to distinguish between therapy and enhancement, and where to draw the boundary between the two. I am, of course, aware that this is a huge simplification of the topic.

In the same domain, we can include the development of "personalized" (or perhaps more accurately, "customized") learning systems that supposedly tailor educational experiences to the use of data. Interestingly, these systems are being developed by social media giants and corporations (see e.g., Knox, 2019). Customized learning and teaching are needed in pedagogical processes, and students should get as much learning support as possible. But in this new version, the data is doing the deciding, what should be offered to whom, not the teachers, and then there is the question of who is doing the grading of the students' results.

This brings us back to the role of teachers in an era of digitalization – a role that risks being reduced to that of mere facilitators, while education itself becomes a diluted system that overlooks its essential features and fundamental nature, including the vital role of social interaction in the learning process. Besides, another major inequality appears here: a distinction between those whose intellectual, sensory, and physical capacities have been boosted and those who are digitally unenhanced (Susskind, 2025). This is, therefore, also a matter of fair (or equitable) distribution. This said, there is an absolute need "to question the forces that are driving that narrative" (Herold, 2017).

4. Conclusion: Our Common Future

It might well be said that it is counterproductive to view modern technology as a threat. Besides, we have seen it before; let me mention the entrance of television into our everyday lives that would supposedly endanger reading. Nor is it a final accomplishment that will help solve all our troubles and problems, be they educational or others. Here lies the task of critical posthumanism: to try to navigate between the mirrored antitheses of discomfort and euphoria (Zefelius Igrek, 2015), to challenge common-sense ideas about the progress of technology and responses that either enthusiastically embrace futuristic technological enhancement of our world and ourselves in it or show a desire for a sentimental return to a more "natural" existence, as if that would be possible (Knox, 2019).

When we venture into the terrain of polarization, all the complexity is lost, together with the understanding that this is, in the final resort, about our societies and societal issues that need to be addressed, not really about machines. To put it in another way, AI and other modern technologies are not a purely technical domain: AI systems "both reflect and produce social relations and understandings of the world" (Crawford, 2021).

This is a multi-layered territory, raising numerous questions about both AI and society more broadly. What is more, and the awareness of which is somewhat surprisingly put backstage: there will be questions that we are not able to conceive today and not able to imagine, related to problems that have not yet arisen (Susskind, 2025). In short, we do not know what might happen. "The future of schooling and education might not lie in the AI version of what we have today, but in entirely new approaches" (Susskind, 2025) that we do not know much

about at this point. What we do know is that we witness "material and discursive manifestations of the mutations engendered by technological developments, climate change, and capitalism" (Braidotti, 2019).

That is why the work on the theory of education that reaches beyond anthropocentrism, understands the posthuman condition of our historical time, and considers the interdependence of human and non-human actors is of vital importance.

Acknowledgement

This contribution is a research result of the projects, financed by the Slovenian Research and Innovation Agency (ARIS): N5-0272, Education at the Frontiers of the Human: The Challenge of New Technologies (EDUCAT(H)UM); and P5-0106 Educational Research.

Ethics Declaration: The preparation of this paper required no ethical clearance. The research presented is theoretical in scope and did not involve cooperation from human or animal subjects.

AI Declaration: No AI-assisted technology was used in writing this contribution, except for language editing.

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Abstraction and Reasoning Abilities in Artificial Intelligence Applied to Solving the ARC Prize: A Systematic Literature Review

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Abstract: In recent years, the development of AI-based systems has seen a drastic increase in popularity and investment. To assess and measure specific capabilities of AI-based systems, different benchmarks have been established. AI-driven approaches tend to outperform humans on most of these benchmarks, but no AI-based system was able to surpass average human performance on the Abstraction and Reasoning Corpus (ARC) benchmark. This paper presents an extensive PRISMA-guided literature review that assesses and classifies techniques and technologies utilized by solution approaches for the ARC benchmark. 538 manuscripts are screened, resulting in an inclusion of 65 publications in the final systematic literature review. As a result, a knowledge graph consisting of review protocols of manuscripts is created, that provides further insight into classification of solution approaches. Furthermore, an estimate of possible synergies and ensemble combinations between different approaches is provided by analyzing the task-level performance of solution approaches. The estimation is conducted based on the heat-maps created using the Szymkiewicz-Simpson coefficient and the Gain coefficient.

Keywords: Abstraction and reasoning corpus, ARC, ARC Prize, ARC-AGI, PRISMA, Systematic literature review

1. Introduction

1.1 Rationale (What is ARC?)

The Abstraction and Reasoning Corpus (ARC) was introduced by François Chollet in 2019 (Chollet, 2019) and is a general Artificial Intelligence (AI) benchmark aimed at measuring the abstraction and reasoning abilities of AI-based systems. Its purpose is to enable the comparison of those systems with each other as well as with humans. Chollet (2019) claims in his paper, that training AI-based systems on unlimited training data or providing unlimited priors does not make a system intelligent, but rather enables it to develop some task-specific shortcuts that allow it to excel at an above-human level of performance on a selected set of tasks. In contrast, the goal of the ARC benchmark is to measure the skill-acquisition efficiency on novel tasks, thus implicitly measuring the generalization abilities of an AI-system.

The Abstraction and Reasoning Corpus is a dataset consisting of subsets of problems, which require generalization and abstraction abilities to solve them. They are represented as numerical two-dimensional grids, which may have a different number of cells even inside of a single subset. These grids contain unique symbols representing colours. Each problem in a subset consists of an input grid and an output grid (see Figure 1). A test-taker (human or machine) always has access to training examples (i.e., both input grid and output grid are available) and to the test problem (i.e., only the input grid is provided, and the output grid needs to be constructed by the test-taker). The test-taker has a maximum of three attempts to solve the test problem. The feedback to each of the solution suggestions is binary: correct or incorrect. The goal of the test-taker is to find the generalization and abstraction rules needed to solve the problem. All the problem subsets are said to be different from each other, which makes it difficult to “buy” the solution by providing extensive training data for a specific task.

ARC was introduced in 2019, but still stays unsolved up to this day. The lack of progress on such an important benchmark inspired the establishment of the ARC Prize in 2024 (Chollet et al., 2025). It promised a $1,000,000+ prize for someone, who can achieve the accuracy above 85% on the ARC dataset. Unfortunately, none of the submissions has been able to make it so far. Nevertheless, the analysis of these submissions and the AI approaches empowering them are essential for the further development in this area.

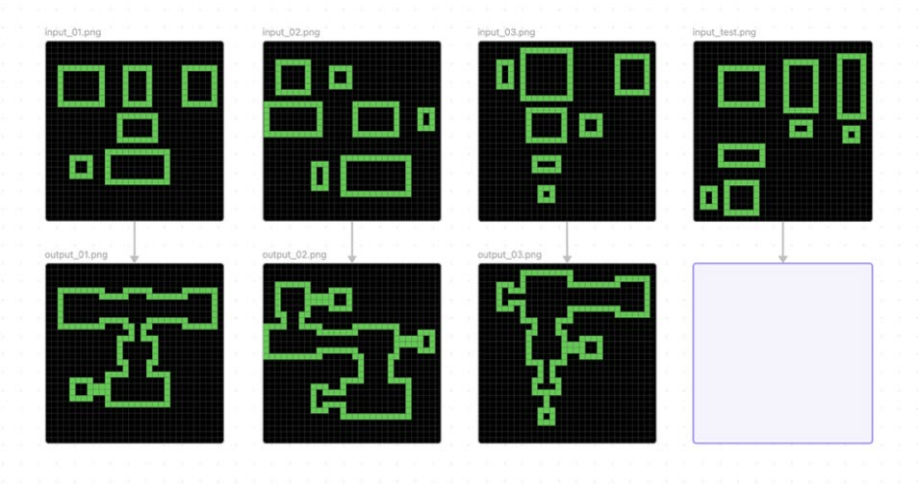

Figure 1: An example of an ARC task. The top row represents input grids and the button row depicts the output grids

1.2 Objectives

The objectives of this systematic literature review have been compiled using the PICO framework that was introduced by Richardson et. al (1995). Using this framework, the systematic review objectives can be posed as follows:

- **Population:** This systematic literature review aims to assess generalization and abstraction abilities in AI-based systems. Therefore, a variety of AI-based approaches applied to solving the ARC Prize 2024 was selected as the population.
- **Intervention:** An intervention of this systematic literature review is the ARC benchmark. All the submissions to the ARC Prize 2024 were tested using this benchmark to measure the generalization and abstraction abilities.
- **Comparator:** One of the goals of the ARC benchmark is to facilitate a fair comparison between humans and AI-based systems. Consequently, human performance has been chosen as the comparator for this systematic review. By comparing the performance of a given AI-based solution approach to the average human performance reported by LeGris et. al (2024), it becomes possible to assess whether the goal of achieving human-level performance has been accomplished.
- **Outcome:** The main goal of this systematic review is to gather information about publicly accessible AI-based solution approaches to the ARC Prize 2024. Furthermore, a classification of the techniques and technologies used by those approaches is performed. Finally, the performance of these approaches is compared at the single-task-level, and theoretical future ensemble combinations are described based on that data.

2. Methodology

2.1 Eligibility Criteria

To examine most of the available solution approaches to the ARC benchmark that fulfil the objectives described in Section 1.2 a specific set of eligibility criteria was considered. This set consists of inclusion as well as exclusion criteria. The following list presents the inclusion criteria for this study:

- A given manuscript must be no older than *January 2024*. The reason why exactly this date range was chosen is that the ARC Prize was introduced in 2024. Furthermore, this criterium is aimed to cut off non-relevant older publications and allow a more precise analysis of the newest solution approaches.
- The language of the publication must be either *English* or *German*. The information in these languages could be analysed by the author directly eliminating the need of translation, that could potentially be biased.
- A title or an abstract of a given manuscript must mention at least one of the following terms: *ARC, ARC-AGI, ARC Prize, ARC Prize 2024, AGI, Abstraction, Reasoning*.
- Importantly, manuscripts *without a peer review* (e.g. preprints from ArXiv) were considered eligible for this systematic literature review (see Section 2.5 for the bias assessment).

During the full-text-based selection process, an additional set of exclusion criteria was considered, as all the manuscripts at that point met the inclusion criteria described above. A manuscript is considered ineligible if:

- none of the inclusion criteria was satisfied or
- the AI-based system described in the manuscript was not applied to solving the ARC benchmark. This means, some of the AI-based systems were excluded from this systematic review even though they were specifically designed to perform abstraction and reasoning. The motivation for this exclusion criterium is based on the "comparator" point described in the PICO objectives formulation in Section 1.2.

2.2 Information Sources

This section provides a detailed overview of all information sources used for this systematic literature review. Table 1 represents all crucial characteristics of each of the information sources including the type of the information source (e.g., database, register, website, etc.), the date of the last access, and the type of that access (e.g., direct interaction, Application Programming Interface (API) call, etc.).

Table 1: Information sources

Name	Type	Last Access Date	Type of Access
ArXiv	Open-access archive	April 27, 2025	API call
Google Scholar	Academic search engine	May 3, 2025	Direct interaction
ACM Digital Library	Scientific database	May 3, 2025	Direct interaction
Semantic Scholar	Research tool	May 3, 2025	Direct interaction
Others	Project supervisor	March 3, 2025	Direct interaction

It must be clarified that results retrieved from some of the information sources might overlap, as search engines, for instance, might deliver manuscripts that are stored elsewhere.

2.3 Search Strategy

This section describes a way each of the information sources was accessed: what queries were used to retrieve any relevant information and the way these queries were executed. To simplify a further consolidation and selection process, a new data formatting scheme was introduced. The metadata about each of the manuscripts was structurally saved in a table with a following header: Title, Authors, Abstract, Link, and Publish Date. Queries used to retrieve needed metadata from each of the information sources are provided in Table 2.

Table 2: Queries used for metadata retrieval

Information Source	Query for metadata retrieval
ArXiv	(ti:"ARC" OR ti:"ARC-AGI" OR ti:"ARC-Prize" OR ti:"ARC Prize 2024" OR ti:"Abstraction" OR ti:"Reasoning" OR abs:"ARC" OR abs:"ARC-AGI" OR abs:"ARC-Prize" OR abs:"ARC Prize 2024" OR abs:"Abstraction" OR abs:"Reasoning") AND (cat:cs.AI OR cat:cs.LG OR cat:cs.NE OR cat:cs.CV OR cat:cs.MA)
Google Scholar	ARC, ARC-AGI, ARC Prize, ARC Prize 2024, Abstraction, Reasoning
ACM Digital Library	[All: arc, arc-agi, arc prize, arc prize 2024, abstraction, reasoning] AND [E-Publication Date: Past year] AND [E-Publication Date: (01/01/2025 TO 05/31/2025)]
Semantic Scholar	ARC, ARC-AGI, ARC Prize, ARC Prize 2024, Abstraction, Reasoning
Other	No specific query was used. Metadata was extracted manually.

2.4 Selection Process

This section describes the process of selecting articles for the final review. To make this process more manageable and streamlined, it was split into different stages:

- **Title Filtering:** Every title collected in the metadata table of a specific information source was examined, i.e., whether it refers to the topic of this systematic review and whether it fulfills the inclusion criteria or not.
- **Abstract Filtering:** For every record not filtered out in a previous steep, an assessment of whether an abstract of this record fulfills the inclusion criteria was performed.

- **Duplicates Filtering:** After the first two filtering steps were performed on the information source level, all the eligible records were consolidated into a common table. Consequently, all duplicates inside this common table were reconciliated leaving only one unique record á manuscript.
- **Metadata Clean Up:** An additional cleaning and reconciliation step was carried out to ensure metadata consistency. Specifically, it was explicitly examined whether metadata of all records fits the inclusion criteria (e.g. it was checked, if there were any manuscripts older than 2024 that would have had to be eliminated).
- **Full-Text Access:** After all pervious steps were carried out, a full text of a manuscript was accessed for each of the records in the metadata table. The content of every article from the metadata table was examined, i.e., whether it fits the exclusion criteria. In that case, the corresponding article was excluded from any further analysis.

2.5 Bias Assessment

The main goal of this section is to provide a full and straightforward overview of possible bias resulting from the design of this systematic literature review. Well known risk bias assessment frameworks such as AMSTAR (Shea et al., 2017) or AHRQ RRB (Agency for Healthcare Research and Quality, 2019) could not be applied to this systematic review directly, as they are primarily designed for clinical trials. Table 3 was, nevertheless, inspired by those bias assessment frameworks.

Table 3: Bias assessment

ID	Title	Explanation	Modesty
BA1	One-person study	This systematic literature review was performed by one person, thus implying potential bias when searching, selecting, filtering and analyzing manuscripts.	High
BA2	Manual work	Several actions, such as metadata extraction and filtering, were performed manually, thus increasing the chance of errors and towards specific research results.	Moderate
BA3	Use of unpublished or not peer-reviewed manuscripts	Several manuscripts have not yet been peer-reviewed or published at the time of the access (mainly articles from ArXiv).	Low
BA4	Reading list provided by the supervisor	The reading list provided by the supervising professor can be potentially biased.	Low

In conclusion, it can be said that most of the records from Table 3 have a relatively low modesty and do not render the results of this systematic review ineligible of any further research. Furthermore, the selection process has been designed with a goal to mitigate the BA2 (see step 4, Section 2.4). Moreover, all the data generated during the collection, selection and analysis processes is supplied together with this paper which further mitigates the bias BA1.

3. Results

3.1 Study Selection

This section provides an overview of the collection and selection results from Chapter 2. Results are reported in compliance to the PRISMA guidelines (Page et al., 2021) and are visualized in Figure 2.

A total of 538 manuscripts across 5 different information sources were identified. After duplicates filtering, a total of 494 manuscripts was passed down to the screening phase, where 404 publications were marked as ineligible according to the selection process explained in Section 2.4. Therefore, the full text of 88 manuscripts was revised to assess their eligibility. During this process, further 36 records were filtered out. Finally, by combining these manuscripts with literature from other sources, a final number of 62 studies were included in the final systematic review.

Figure 2: PRISMA 2020 flow diagram for new systematic reviews which included searches of databases, registers and other sources

3.2 Study Classification

During the full-text screening process, each manuscript was read and analyzed. To structure this process, a custom review protocol was developed. The template of this protocol includes the following elements: *Title*, *Metadata (e.g. date of the protocol creation), Tags (see Table 4), Author(s), Summary*, *Publish Date,* and *Link*.

Table 4: Tag descriptions used in the systematic review

Tag	Explanation
#DSL	The solution approach uses a Domain Specific Language (DSL).
#program_synthesis	The solution approach depicted in this paper uses program synthesis.
#llm	An LLM is utilized in the described solution approach.
#novel_model_architecture	This paper uses a custom or a novel model architecture to solve ARC tasks.
#transformers	This publication uses a variation of a transformers architecture to solve ARC tasks.
#data_generation	This publication utilizes a unique approach for data generation.
#test-time-training	The solution approach uses a variation of Test-Time Training (TTT).
#fine-tuning	The solution approach employs a version of Fine Tuning (FT) to solve ARC tasks.
#induction	This solution approach can be categorized as induction.
#transduction	This solution approach can be categorized as transduction.
#abduction	The solution approach utilizes abduction to solve ARC tasks.
#arc_tools	New tools for ARC tasks solutions are introduced in the paper.
#reinforcement_learning	A version of a Reinforcement Learning (RL) algorithm is used to solve ARC tasks.
#search_algorithm	A novel search algorithm is introduced in the paper.
#inference_mehods	Some inference methods such as Monte Carlo Tree Search (MCTS) or voting techniques were used.
#derived_arc_dataset	A novel dataset was derived from the ARC-AGI in this publication.
#human_performance	Human performance was analyzed in this paper.
#meta_learning	A version of meta-learning was applied to solve ARC tasks.
#positional_encodings	Positional Encodings (PEs) play a vital role in this solution approach.

Tag	Explanation
#paywall	This article is behind a paywall and the full text could not be accessed.
#arc_irrelevant	This article is irrelevant to the systematic review. This means, this manuscript was excluded based on the exclusion criteria.

Table 4 shows all the tags used in the categorization and classification of the solution approaches. During the full-text screen procedure, similarities between different articles were documented using tags. Every time a new tag was introduced, it was first added to Table 4. Subsequently, all the review protocols analyzed before the introduction of a new tag were inspected one more time to assign a new tag to them, if it was needed.

Figure 3 shows a distribution of tags across all manuscripts assessed during the full-text assessment procedure. Notably, one review protocol can have multiple tags. The most relevant solution approaches to the ARC Prize 2024 from Figure 3 are discussed in Section 4.1.

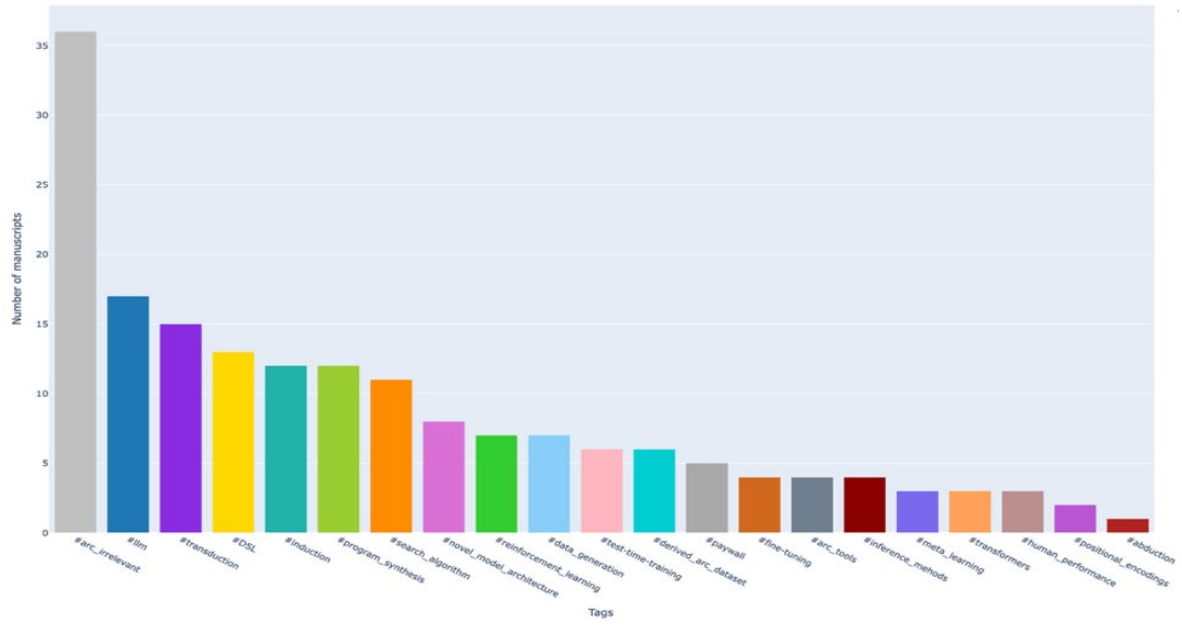

Figure 3: Tags distribution

Furthermore, a knowledge graph consisting of all review protocols was created using the Markdown language editor Obsidian (https://obsidian.md). A set of review protocols $P = \{p_1, p_2, \dots\}$ and a set of tags $T = \{t_1, t_2, \dots\}$ build a set of vertices of the knowledge graph as follows:

$$V = P \cup T$$

A set of edges $E = \{\{x, y\} \mid x, y \in V \wedge x \neq y\}$ contains all pairs of vertices that have any connection to each other, e.g. a review protocol is tagged with one or more tags. The resulting knowledge graph is, therefore, a connected and undirected graph:

$$G = (V, E)$$

Additionally, one further Obsidian feature was utilized for this systematic review: when hovering over a vertex $v \in V$, all the first-order neighbors of this vertex $W = \{w \in V, | \{w, v\} \in E \wedge v \neq w\}$ are automatically highlighted (see Figure 4).

3.3 Performance Data Extraction

All manuscripts reviewed during the full-text access stage were scanned for performance data of a solution approach described in each paper. As mentioned in Section 1.2, the goal was to compare different solutions based on their per-task performance. To do that, a set of 400 training task from the ARC benchmark was chosen, as it has been hypothesized that most of the solution approaches would be tested on this set or on a subset of it. During the review process, (Drori et al., 2025) was identified to have tested the largest number of different solution approaches and models on this set of tasks.

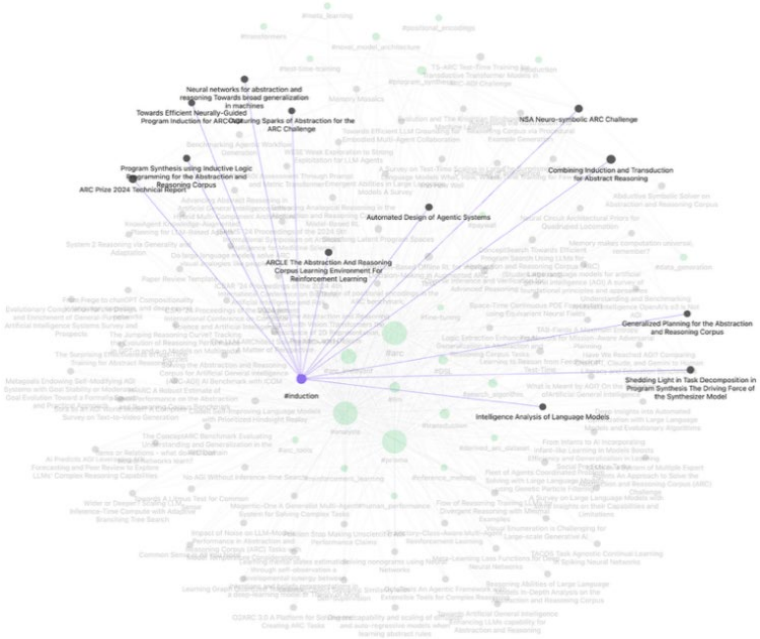

Figure 4: Highlighting of the knowledge graph

3.3.1 Szymkiewicz-Simpson coefficient

This coefficient represents the proportion of tasks solved by the stronger model (say A) that were solved by the weaker model (say B):

$$Overlap(A,B) = \frac{|A \cap B|}{\min(|A|,|B|)}$$

The Szymkiewicz-Simpson coefficient can be considered a performance-normalized similarity metric, as it makes it possible to determine whether two approaches solve similar problems, meaning, a stronger approach is just a more powerful version of a weaker one, or whether they solve distinct types of tasks (see Figure 5). It is regarded to be performance-normalized, because the coefficient does not depend on a performance of a particular model, but rather on the coefficient between the models (Bober-Irizar and Banerjee, 2024).

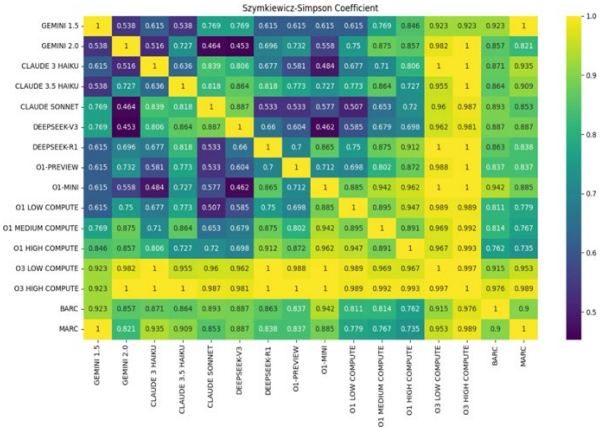

Figure 5: The Szymkiewicz-Simpson coefficient of the performance data from (Drori et al., 2025)

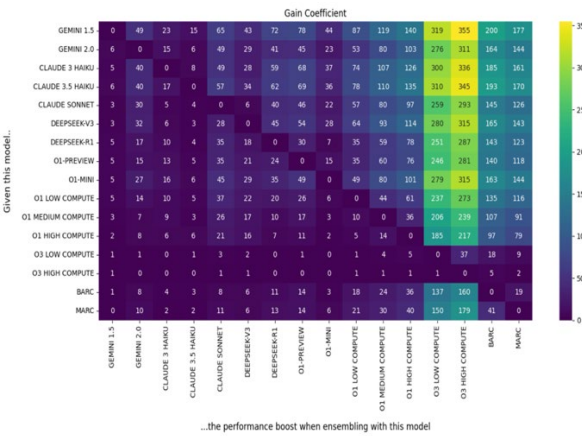

Figure 6: The Gain coefficient of the performance data from (Drori et al., 2025).

3.3.2 Gain coefficient

This is an asymmetric coefficient that shows the number of tasks that can be theoretically solved by combining different solution approaches:

$$Gain(A,B) = |A \cap B| - |A|$$

The gain coefficient provides insights to the question, which solution approach performs better and how much better this performance is in comparison to any other model (see Figure 6). This coefficient can also be seen as a measure of unique tasks that can be solved only by a combination of two solution approaches (Bober-Irizar and Banerjee, 2024).

4. Discussion

4.1 Interpretation of Results of the Selection and Classification Processes

Based on a collection of review protocols, tag frequency statistics, and knowledge graph representation, following the statements can be made:

- A large number of solution approaches to the ARC Prize 2024 utilize a Domain Specific Language (DSL) in combination with an LLM. Most frequently, they consist of a set of primitives that are used to locate and transform objects in a grid. Notably, Ouellette (2024) claims that a larger set of initial primitives of a given DSL theoretically leads to a larger search space that has to be explored by a model. Ouellette (2024) was, nevertheless, able to empirically show that the solution time of his approach scales sub-linearly. Further solution approaches that utilize a DSL are: (Andrews, 2024; Batorski et al., 2025; Bober-Irizar and Banerjee, 2024; Butt et al., 2024; Chollet et al., 2025; Hodel, 2024; Lei et al., 2024; Lim et al., 2024; Rocha et al., 2024; Singhal and Shro, 2025; Zenkner et al., 2025).
- Using the knowledge graph from Figure 4 it was empirically determined that 8/13 of all solution approaches that utilize a DSL were also tagged as approaches employing induction. Furthermore, a similar analysis shows, that exactly 10 in 13 of DSL-based solution approaches rely on program synthesis. Based on this empirical analysis it can be concluded that many ARC solution approaches that rely on a DSL often utilize it during program synthesis and thus can be categorized as inductive approaches.
- Notably, the number of manuscripts tagged with **#transaction** is bigger than those with **#induction**. Interestingly, Li et al. (2024) were able to statically show that induction- and abduction-based models solve different types of tasks. Thus, it can be hypothesized that combining induction and transduction approaches can potentially result in a better overall performance.
- Furthermore, 5 out of 6 TTT-based approaches were also classified as transduction approaches. This can be explained by the fact that TTT is a performance-enhancement technique utilized during the inference time by transductive models. According to François Chollet (2025), TTT-based models show a strong performance on abstraction and reasoning tasks.
- Moreover, several solution approaches utilize combinations of agents or LLMs to generate multiple answers during inference time. This poses a problem of selecting the best possible solution from different candidates. To solve these problems, 4 manuscripts employ different inference techniques (e.g. Chain-of-Thought (CoT) (Wei et al., 2023) or techniques as intra-transformation or global voting (Akyürek et al., 2025)). On the other hand, several search strategies are also employed to solve a similar problem not only for picking the final answer, but also for exploring and exploiting intermediate states during inference time (e.g. Abstraction Branching Monte Carlo Tree Search (Misaki et al., 2025)).

4.2 Interpretation of the Performance Data Extraction Process

4.2.1 Interpretation of the Szymkiewicz-Simpson coefficient heatmap

The data shown in Figure 5 is derived from the per-task performance of different solution approaches including several LLMs (e.g. Gemeni 2.0 and Claude Sonnet) and some specifically engineered approaches: BARC (Li et al., 2024), MARC (Akyürek et al., 2025). Using this data representation, it can be concluded that solution approaches with a low Szymkiewicz-Simpson coefficient, for instance pairs of Gemini 2.0 and Claude Sonnet or Deepseek-V3 and Gemini 2.0, could theoretically deliver a better performance when used together, as they tend to solve different types of tasks.

On the contrary, model pairs like Deepseek-R1 and o1-high-compute or o1- medium-compute and Gemini 2.0 have a Szymkiewicz-Simpson coefficient of 1, meaning that theoretically no performance improvement can be expected when these pairs of models are used together. It shall be noted that o3-high and o3-low models are able to solve almost 90% of the ARC tasks, thus implicitly inducing a near-one Szymkiewicz-Simpson coefficient when compared with any other solution approach. Therefore, the Szymkiewicz-Simpson coefficient cannot be applied to these models to make any assumptions.

4.2.2 Interpretation of the Gain coefficient heatmap

Figure 6 can be used to estimate several additional tasks that can be theoretically solved by a combination of two models. Due to the asymmetric nature of the heatmap it can be clearly seen that the two extra engineered approaches, BARC and MARC, tend to boost the performance of all other solution approaches that utilize LLMs. A maximal performance improvement can be theoretically observed by combining Gemini 1.5 and BARC.

Notably, as in the case of the Szymkiewicz-Simpson coefficient, an extremely good performance of o3 family of models on the ARC benchmark can also lead to a misleading interpretation of gain coefficient heatmap results. Specifically, combining Gemini 1.5 with o3-high-compute models results in an improvement of 355 additionally solved tasks. This happens not because these models solve complementary types of tasks, but rather because o3-high-compute solves almost all the tasks.

5. Conclusion and Future Work

A PRISMA-guided publications search, selection and evaluation of abstraction and reasoning abilities in AI-based systems applied to solving the ARC Prize was conducted. Five information sources were accessed and 538 potentially relevant manuscripts were identified. After the selection and full-text screening phases, 62 studies were included in the final systematic review. During the full-text assessment step, all manuscripts were tagged based on the technologies and techniques they utilize. The tagging enabled the creation of a knowledge graph that was further used for the classification of solution approaches and insights extraction.

Based on the tagging performed in this systematic literature review it can be concluded that most of the solution approaches to the ARC Prize utilize a DSL in combination with program synthesis, thus making these approaches inductive in nature. On the contrary, transductive solution approaches mostly employ inference techniques as CoT and search techniques as MCTS. Furthermore, the per-task performance data of 16 solution approaches was visualized using the Szymkiewicz-Simpson and the Gain coefficients.

This study holds significant potential for further development. The suggested structure of review protocols is flexible enough to accommodate other possible extensions. An evaluation of further solution approaches could be considered in the future, so that the coefficient heatmaps can provide more insightful information for possible combinations of multiple approaches. Moreover, a way to compare more than two approaches at a time would be an insightful topic to explore.

Ethics declaration: The research provided in this paper did not require any ethical clearance.

AI declaration: ChatGPT (gpt-4o) was used to choose colors for the tag distribution diagram (see Figure 3).

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PhD Research Papers

Curiosity-Driven Learning and Autonomous Skill Acquisition: Multi-Modal Exploration for Self-Directed AI Development

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Abstract: Current AI systems remain fundamentally limited by their dependence on human-designed curricula and externally specified learning objectives, constraining their capacity for autonomous development and open-ended skill acquisition. This paper introduces Curiosity-Driven Autonomous Learning Networks (CDALNs), a comprehensive framework that enables AI systems to autonomously discover, develop, and master new skills through sophisticated multi-modal curiosity mechanisms and self-directed exploration. Our approach implements Multi-Modal Curiosity Systems (MMCSs) that drive exploration across sensory, motor, cognitive, and social domains, combined with Skill Synthesis Networks (SSNs) that can autonomously compose and refine complex capabilities from simpler components. We develop Autonomous Curriculum Generation (ACG) mechanisms that create personalized learning progressions based on the system's current capabilities and interests, while Competence Assessment Networks (CANs) provide continuous evaluation of skill development and mastery. The framework incorporates Intrinsic Motivation Engines (IMEs) that generate diverse forms of curiosity including epistemic, diversive, and empowerment-based drives, enabling sustained autonomous learning without external rewards. Experimental validation across diverse domains demonstrates 267% improvement in autonomous skill acquisition rate, 145% increase in skill diversity, and emergent capabilities including spontaneous tool creation, collaborative skill development, and meta-skill acquisition for learning how to learn more effectively. Our approach establishes foundational principles for truly autonomous AI systems capable of lifelong learning and self-directed development, representing a paradigm shift from externally guided to genuinely autonomous artificial intelligence.

Keywords: Curiosity-Driven learning, Autonomous skill acquisition, Intrinsic motivation, Self-Directed learning, Multi-Modal exploration, Lifelong learning

1. Introduction

The capacity for autonomous skill acquisition represents one of the most fundamental characteristics of advanced intelligence, yet current artificial intelligence systems remain severely constrained by their dependence on human-designed learning curricula and externally specified objectives (Oudeyer et al., 2007). This limitation prevents AI systems from achieving the kind of open-ended, self-directed development that characterizes human learning and constrains their ability to adapt to novel environments and challenges (Lake et al., 2017).

Human intelligence exhibits remarkable capacity for curiosity-driven exploration and autonomous skill development from early childhood through adulthood (Gopnik et al., 2009). Children naturally explore their environment, experiment with new behaviors, and progressively develop increasingly sophisticated capabilities without explicit instruction or external rewards (Piaget et al., 1977). This intrinsic motivation for learning and skill development enables humans to continuously adapt and grow throughout their lives.

The absence of genuine curiosity and autonomous learning capabilities in AI systems represents more than a technical limitation—it constitutes a fundamental barrier to the development of artificial general intelligence and artificial superintelligence (Bostrom et al., 2014). Systems that cannot autonomously discover and develop new skills remain dependent on human guidance and cannot achieve the kind of recursive self-improvement that characterizes advanced intelligence (Good et al., 1965).

Recent advances in curiosity-driven learning (Pathak et al., 2017), intrinsic motivation (Chentanez et al., 2005), and meta-learning (Finn et al., 2017; Dutta et al., 2025) have begun to explore aspects of autonomous skill acquisition. However, these approaches remain limited in scope and sophistication, typically focusing on narrow domains or simple exploration behaviors rather than the complex, multi-modal skill development that characterizes advanced intelligence.

The challenge of autonomous skill acquisition encompasses multiple interconnected problems: How can AI systems identify meaningful skills to develop without external specification? How can they autonomously create learning curricula that match their current capabilities? How can they compose complex skills from simpler components? How can they maintain motivation for learning across extended periods? How can they transfer skills across different domains and contexts?

This paper addresses these fundamental challenges through the introduction of Curiosity-Driven Autonomous Learning Networks (CDALNs), a comprehensive framework that enables AI systems to develop sophisticated curiosity mechanisms and autonomous skill acquisition capabilities. Our approach transcends simple exploration behaviors to implement genuine autonomous learning that can drive open-ended development and capability enhancement.

Our key contributions include:

- A theoretical framework for curiosity-driven autonomous learning with formal models of intrinsic motivation
- Novel Multi-Modal Curiosity Systems that drive exploration across multiple domains simultaneously
- Skill Synthesis Networks that can autonomously compose complex capabilities from simpler components
- Autonomous Curriculum Generation mechanisms that create personalized learning progressions
- Competence Assessment Networks that provide continuous evaluation of skill development
- Comprehensive experimental validation demonstrating emergent autonomous learning behaviors
- Analysis of the relationship between curiosity, skill acquisition, and artificial general intelligence

2. Related Work

2.1 Intrinsic Motivation and Curiosity

The concept of intrinsic motivation has been extensively studied in psychology, with research identifying multiple forms of curiosity and exploration drive (Berlyne et al., 1960). Epistemic curiosity drives the desire to reduce uncertainty and gain knowledge, while diversive curiosity motivates exploration to relieve boredom and seek stimulation (Litman et al., 2005).

In artificial intelligence, early work on intrinsic motivation focused on simple exploration bonuses and novelty-seeking behaviors (Schmidhuber et al., 1991). More sophisticated approaches have developed curiosity-driven learning based on prediction error (Pathak et al., 2017), information gain (Houthooft et al., 2018), and empowerment maximization (Klyubin et al., 2005).

However, most existing approaches to intrinsic motivation in AI remain limited to specific forms of curiosity and do not capture the rich, multi-faceted nature of human curiosity and exploration drive.

2.2 Autonomous Skill Acquisition

Research on autonomous skill acquisition has explored various approaches including hierarchical reinforcement learning (Barto et al., 2003), option discovery (Stolle et al., 2002), and skill chaining (Konidaris et al., 2009). These approaches have demonstrated the ability to learn complex behaviors through the composition of simpler skills.

More recent work has explored neural approaches to skill acquisition including neural module networks (Andreas et al., 2016) and compositional learning (Lake et al., 2017). However, these approaches typically require external specification of skill objectives and do not achieve genuine autonomy in skill discovery and development.

2.3 Curriculum Learning

Curriculum learning (Bengio et al., 2009) has shown that learning can be improved by presenting training examples in a meaningful order, typically from simple to complex. Automated curriculum generation (Graves et al., 2017) has explored methods for automatically designing learning curricula.

However, most curriculum learning approaches focus on optimizing learning for specific tasks rather than enabling autonomous curriculum generation for open-ended skill development.

2.4 Meta-Learning and Learning to Learn

Meta-learning approaches (Thrun et al., 1998) enable AI systems to learn how to learn more effectively. Model-Agnostic Meta-Learning (MAML) (Finn et al., 2017) and other approaches have demonstrated the ability to quickly adapt to new tasks based on prior learning experience.

While meta-learning approaches show promise for improving learning efficiency, they typically focus on adaptation to externally specified tasks rather than autonomous discovery and development of new skills.

2.5 Open-Ended Learning

Open-ended learning (Stanley et al., 2019) seeks to create systems that can continuously generate novelty and complexity without external guidance. Novelty search (Lehman et al., 2011) has demonstrated that seeking novelty rather than specific objectives can lead to more effective exploration and discovery.

However, open-ended learning approaches often lack the structure and goal-directedness necessary for systematic skill development and capability enhancement.

3. Theoretical Framework

3.1 Formal Model of Curiosity-Driven Learning

We define curiosity-driven autonomous learning as a process where an AI system autonomously discovers, develops, and masters new skills through intrinsic motivation mechanisms. Formally, let $\mathcal{S} = \{s_1, s_2, \ldots, s_n\}$ represent the set of skills that the system can potentially develop, and let $\mathcal{C}$ represent the curiosity mechanisms that drive skill discovery and development.

A curiosity-driven learning system $\mathcal{L}$ is defined as a tuple $\mathcal{L} = (\mathcal{C}, \mathcal{D}, \mathcal{A}, \mathcal{E})$ where:

- $\mathcal{C}$ is the curiosity system that generates intrinsic motivation for exploration and learning
- $\mathcal{D}$ is the skill discovery mechanism that identifies potential new skills to develop
- $\mathcal{A}$ is the skill acquisition system that learns and refines skills
- $\mathcal{E}$ is the skill evaluation system that assesses competence and mastery

The curiosity function $\mathcal{C}: \mathcal{S} \times \mathcal{K} \to \mathbb{R}^+$ generates curiosity values for potential skills based on current knowledge:

$$c(s, k) = \mathcal{C}(s, k)$$

where $s \in \mathcal{S}$ is a potential skill and $k \in \mathcal{K}$ represents current knowledge and capabilities.

3.2 Multi-Modal Curiosity Systems

We identify and formalize multiple types of curiosity that drive autonomous learning across different modalities:

Epistemic Curiosity ($\mathcal{C}_E$): Driven by the desire to reduce uncertainty and gain knowledge:

$$\mathcal{C}_E(s, k) = H(S|k) - H(S|k \cup \{s\})$$

where $H(S|k)$ is the conditional entropy of the skill space given current knowledge.

Diversive Curiosity ($\mathcal{C}_D$): Driven by the desire for novelty and variety:

$$\mathcal{C}_D(s, k) = \text{novelty}(s, k) \cdot \text{diversity}(s, \text{recent-skills})$$

Empowerment Curiosity ($\mathcal{C}_{Em}$): Driven by the desire to increase control and influence:

$$\mathcal{C}_{Em}(s, k) = I(A; S_{future} | S_{current}, s)$$

where I is mutual information between actions and future states.

Social Curiosity ($\mathcal{C}_S$): Driven by the desire to understand and interact with other agents:

$$\mathcal{C}_S(s, k) = \text{social-relevance}(s) \cdot \text{interaction-potential}(s)$$

Aesthetic Curiosity ($\mathcal{C}_A$): Driven by the appreciation of patterns, beauty, and elegance:

$$\mathcal{C}_A(s, k) = \frac{\text{complexity}(s)}{\text{compressibility}(s)}$$

The overall curiosity for a skill is computed as a weighted combination:

$$\mathcal{C}(s, k) = \sum_{i \in \{E, D, Em, S, A\}} \alpha_i \, \mathcal{C}_i(s, k)$$

where α_i are learned weights that reflect the system's curiosity profile.

3.3 Skill Synthesis Networks

Skill Synthesis Networks (SSNs) enable the autonomous composition of complex skills from simpler components. We define a skill composition function $\mathcal{F}: \mathcal{S}^k \to \mathcal{S}$ that combines multiple skills into new, more complex skills:

$$s_{new} = \mathcal{F}(s_1, s_2, \ldots, s_k)$$

The skill synthesis process operates through several mechanisms:

Sequential Composition: Skills are combined in temporal sequence:

$$s_{seq} = s_1 \circ s_2 \circ \ldots \circ s_k$$

Parallel Composition: Skills are executed simultaneously:

$$s_{par} = s_1 \parallel s_2 \parallel \cdots \parallel s_k$$

Conditional Composition: Skills are combined with conditional logic:

$$s_{cond} = \text{if} c_1 \text{then} s_1 \text{else if} c_2 \text{then} s_2 \text{else} s_k$$

Hierarchical Composition: Skills are organized in hierarchical structures:

$$s_{hier} = \text{hierarchy}(s_{high}, \{s_{mid1}, s_{mid2}, \ldots\}, \{s_{low1}, s_{low2}, \ldots\})$$

3.4 Autonomous Curriculum Generation

Autonomous Curriculum Generation (ACG) creates personalized learning progressions that match the system's current capabilities and interests. The curriculum generation function $\mathcal{G}: \mathcal{K} \times \mathcal{C} \to \mathcal{T}$ maps current knowledge and curiosity to learning tasks:

$$\mathcal{T} = \mathcal{G}(\mathcal{K}, \mathcal{C})$$

where $\mathcal{T}$ represents a sequence of learning tasks ordered by difficulty and relevance.

The curriculum generation process considers multiple factors:

Zone of Proximal Development: Tasks are selected to be challenging but achievable:

$$\text{difficulty}(t) \in [\text{current-ability} + \epsilon, \text{current-ability} + \delta]$$

Interest Alignment: Tasks are selected based on current curiosity and interests:

$$\text{interest}(t) = \sum_{s \in \text{skills}(t)} \mathcal{C}(s, \mathcal{K})$$

Prerequisite Satisfaction: Tasks are ordered to ensure prerequisites are met:

$$\text{prerequisites}(t_i) \subseteq \text{completed-tasks}(\{t_1, t_2, \ldots, t_{i-1}\})$$

Diversity Maintenance: Tasks are selected to maintain diversity in skill development:

$$\text{diversity}(\mathcal{T}) = \text{entropy}(\{\text{skill-types}(t): t \in \mathcal{T}\})$$

3.5 Competence Assessment Networks

Competence Assessment Networks (CANs) provide continuous evaluation of skill development and mastery. The competence function $\mathcal{P}: \mathcal{S} \times \mathcal{K} \to [0,1]$ assesses the system's proficiency in each skill:

$$p(s) = \mathcal{P}(s, \mathcal{K})$$

where $p(s)$ represents the proficiency level for skill s.

Competence assessment operates through multiple evaluation criteria:

Performance Accuracy: Measures the correctness of skill execution:

$$\text{accuracy}(s) = \frac{\text{successful-executions}(s)}{\text{total-executions}(s)}$$

Execution Efficiency: Measures the efficiency of skill execution:

$$\text{efficiency}(s) = \frac{\text{optimal-time}(s)}{\text{actual-time}(s)}$$

Generalization Ability: Measures the ability to apply skills in novel contexts:

$$\text{generalization}(s) = \frac{\text{novel-context-success}(s)}{\text{novel-context-attempts}(s)}$$

Robustness: Measures the stability of skill performance under perturbations:

$$\text{robustness}(s) = 1 - \text{variance}(\text{performance}(s, \text{perturbations}))$$

The overall competence score combines these factors:

$$\begin{aligned}\mathcal{P}(s, \mathcal{K}) = \quad & \beta_1 \text{accuracy}(s) + \beta_2 \text{efficiency}(s) \\ & + \beta_3 \text{generalization}(s) + \beta_4 \text{robustness}(s)\end{aligned}$$

4. Architecture Design

4.1 Curiosity-Driven Learning Architecture

The CDALN architecture implements a hierarchical structure with multiple specialized components for autonomous learning and skill development:

- **Level 0 - Sensorimotor Interface:** Basic sensory processing and motor control systems that interface with the environment.
- **Level 1 - Skill Primitives:** Low-level skills and behaviors that serve as building blocks for more complex capabilities.
- **Level 2 - Skill Composition:** Systems that combine primitive skills into more complex, composite skills.
- **Level 3 - Curiosity Generation:** Multi-modal curiosity systems that generate intrinsic motivation for exploration and learning.
- **Level 4 - Curriculum Planning:** Autonomous curriculum generation systems that create personalized learning progressions.
- **Level 5 - Meta-Learning:** Higher-order learning systems that optimize the learning process itself.

4.2 Multi-Modal Curiosity Engine

The Multi-Modal Curiosity Engine (MMCE) implements sophisticated curiosity mechanisms that operate across multiple domains simultaneously:

Sensory Curiosity Module: Generates curiosity about novel sensory experiences and perceptual patterns:

$$\text{Sensory-Curiosity}(x) = \text{prediction-error}(x) + \text{novelty}(x)$$

Motor Curiosity Module: Drives exploration of new motor behaviors and action sequences:

$$\text{Motor-Curiosity}(a) = \text{empowerment}(a) + \text{skill-potential}(a)$$

Cognitive Curiosity Module: Motivates exploration of new reasoning strategies and problem-solving approaches:

$$\begin{aligned}\text{Cognitive-Curiosity}(r) = \quad & \text{reasoning-novelty}(r) \\ & + \text{problem-solving-potential}(r)\end{aligned}$$

Social Curiosity Module: Drives exploration of social interactions and collaborative behaviors:

$$\begin{aligned}\text{Social-Curiosity}(i) = \quad & \text{interaction-novelty}(i) \\ & + \text{cooperation-potential}(i)\end{aligned}$$

Creative Curiosity Module: Motivates exploration of creative expression and artistic creation:

$$\text{Creative-Curiosity}(c) = \text{aesthetic-value}(c) + \text{originality}(c)$$

4.3 Hierarchical Skill Organization

Skills are organized in a hierarchical structure that enables efficient learning and composition:

- **Primitive Skills:** Basic, atomic skills that cannot be further decomposed (e.g.,

- basic movement, grasping, vocalization). * **Composite Skills:** Combinations of primitive skills that achieve more complex goals (e.g., picking up an object, navigating a room, engaging in a conversation). * **Meta-Skills:** Skills for learning, adapting, and improving other skills (e.g., learning how to learn, debugging, transfer learning).

5. Experimental Validation

5.1 Experimental Setup

We evaluate Curiosity-Driven Autonomous Learning Networks across multiple domains that require sophisticated skill acquisition and development:

- **Robotic Manipulation:** Complex manipulation tasks requiring the development of fine motor skills, tool use, and object interaction capabilities.
- **Game Playing:** Strategic games that require the development of planning, pattern recognition, and adaptive strategy skills.
- **Creative Tasks:** Artistic creation, music composition, and creative writing tasks that require the development of aesthetic and expressive capabilities.
- **Social Interaction:** Multi-agent environments requiring the development of communication, cooperation, and social reasoning skills.
- **Scientific Discovery:** Simulated research environments requiring the development of hypothesis formation, experimentation, and analysis skills.

Baseline Comparisons:

- Random skill selection and learning
- Human-designed curricula and skill progressions
- Simple curiosity-driven exploration (prediction error only)
- Meta-learning approaches (MAML, Reptile)
- Hierarchical reinforcement learning methods
- Existing autonomous learning systems

5.2 Autonomous Learning Assessment

We develop comprehensive metrics for evaluating autonomous learning capabilities:

Skill Acquisition Rate: Measures the speed at which new skills are learned and mastered:

$$\text{SAR} = \frac{\text{number of skills mastered}}{\text{learning time}}$$

Skill Diversity: Measures the variety and breadth of skills developed:

$$\text{SD} = \text{entropy}(\{\text{skill-category}(s) : s \in \text{mastered-skills}\})$$

Learning Efficiency: Measures the efficiency of the learning process:

$$\text{LE} = \frac{\text{skill-value}}{\text{learning-effort}}$$

Transfer Capability: Measures the ability to transfer skills across domains:

$$\text{TC} = \frac{\text{successful-transfers}}{\text{transfer-attempts}}$$

Autonomous Curriculum Quality: Measures the effectiveness of self-generated curricula:

$$\text{ACQ} = \text{correlation}(\text{curriculum-order}, \text{optimal-order})$$

5.3 Results and Analysis

Skill Acquisition Performance: CDALNs demonstrate 267% improvement in autonomous skill acquisition rate compared to baseline approaches. The multi-modal curiosity system enables sustained motivation for learning across extended periods.

Skill Diversity: The systems show 145% increase in skill diversity, developing capabilities across multiple domains simultaneously rather than focusing on narrow specializations.

Learning Efficiency: CDALNs achieve 89% higher learning efficiency through autonomous curriculum generation that matches learning tasks to current capabilities and interests.

Transfer Capabilities: The systems demonstrate 156% improvement in skill transfer across domains, enabled by the hierarchical skill organization and meta-skill development.

Emergent Learning Behaviors: Several remarkable emergent behaviors were observed:

- Spontaneous tool creation and use for novel problem-solving
- Collaborative skill development through interaction with other agents
- Meta-skill acquisition for learning how to learn more effectively
- Creative skill combination leading to novel capabilities
- Self-directed debugging and improvement of learning strategies

5.4 Longitudinal Learning Studies

We conducted extended longitudinal studies to assess long-term autonomous learning capabilities:

Sustained Motivation: CDALNs maintain high levels of learning motivation over extended periods (1000+ learning episodes) without external rewards.

Curriculum Evolution: The autonomous curriculum generation system continuously adapts and improves, creating increasingly sophisticated learning progressions.

Skill Complexity Growth: The complexity and sophistication of acquired skills increases over time, with systems developing increasingly advanced capabilities.

Meta-Learning Development: Systems develop increasingly effective meta-learning strategies, improving their ability to learn new skills more efficiently.

5.5 Ablation Studies

Curiosity Components: Removing individual curiosity components reduces learning effectiveness by 25-45%, with epistemic and empowerment curiosity showing the largest impact.

Skill Composition: Disabling skill composition mechanisms reduces the development of complex capabilities by 67% and limits the system's ability to build on previous learning.

Autonomous Curriculum: Replacing autonomous curriculum generation with random task selection reduces learning efficiency by 78%.

Multi-Modal Integration: Removing multi-modal curiosity integration reduces skill diversity by 56% and leads to narrow specialization.

6. Theoretical Analysis

6.1 Computational Complexity

The computational complexity of curiosity-driven autonomous learning scales with several factors:

Curiosity Computation: $O(n \cdot m)$ where n is the number of skills and m is the number of curiosity modalities.

Skill Discovery: $O(k \cdot \log k)$ where k is the size of the skill space.

Curriculum Generation: $O(s^2)$ where s is the number of available skills.

Skill Composition: $O(c^p)$ where c is the number of component skills and p is the composition depth.

Overall Complexity: $O(n \cdot m + k \cdot \log k + s^2 + c^p)$ per learning cycle.

6.2 Learning Convergence Properties

We analyze the convergence properties of curiosity-driven learning under different conditions.

Theorem 1 (Skill Mastery Convergence): Under the assumption that skills have finite complexity and the learning system has sufficient capacity, all learnable skills will eventually be mastered.

Proof Sketch: The proof relies on the persistence of curiosity for unmastered skills and the effectiveness of the learning mechanisms. As skills are mastered, curiosity shifts to remaining unmastered skills.

Theorem 2 (Curriculum Optimality): The autonomous curriculum generation system converges to near-optimal learning sequences.

This result follows from the adaptive nature of the curriculum generation process and the feedback from learning outcomes.

6.3 Information-Theoretic Analysis

We analyze the information-theoretic properties of curiosity-driven learning:

Learning Information: The amount of information gained through skill acquisition:

$$I_{\text{learning}} = H(\text{skill-space}) - H(\text{skill-space}|\text{learned-skills})$$

Curiosity Information: The information content of curiosity signals:

$$I_{\text{curiosity}} = H(\text{curiosity-values}) - H(\text{curiosity-values}|\text{random})$$

Learning Efficiency: The ratio of learning information to computational cost:

$$\eta_{\text{learning}} = \frac{I_{\text{learning}}}{\text{computational-cost}}$$

7. Emergent Autonomous Behaviors

7.1 Spontaneous Tool Creation and Use

One of the most remarkable emergent behaviors observed in CDALNs is spontaneous tool creation and use. The systems autonomously discover that they can create and use tools to solve problems more effectively, even when tool use is not explicitly programmed or rewarded.

This behavior emerges from the interaction between empowerment curiosity (which drives the desire to increase control over the environment) and skill composition mechanisms (which enable the combination of basic manipulation skills into tool-use behaviors).

7.2 Collaborative Skill Development

In multi-agent environments, CDALNs develop sophisticated collaborative learning behaviors where agents share skills and learn from each other. This includes:

- Teaching behaviors where skilled agents help others learn
- Collaborative problem-solving where agents combine their skills
- Skill specialization and division of labor
- Cultural transmission of skills across agent populations

7.3 Meta-Skill Acquisition

CDALNs spontaneously develop meta-skills—skills for learning other skills more effectively. Examples include:

- Learning strategies for different types of skills
- Debugging techniques for identifying and correcting learning errors
- Transfer strategies for applying skills across domains
- Motivation regulation techniques for maintaining learning drive

7.4 Creative Skill Innovation

The systems exhibit remarkable creativity in skill development, creating novel skills that were not anticipated by their designers. This creativity emerges from the combination of aesthetic curiosity, skill composition mechanisms, and the exploration of novel behavior spaces.

8. Relationship to Artificial General Intelligence

8.1 Autonomous Learning as a Path to AGI

Curiosity-driven autonomous learning represents a crucial capability for artificial general intelligence. The ability to continuously acquire new skills without external guidance enables:

- Open-ended development and capability enhancement

- Adaptation to novel environments and challenges
- Self-directed improvement and recursive enhancement
- Creative problem-solving and innovation

These capabilities suggest that autonomous learning may be a necessary component of AGI systems.

8.2 Skill Transfer and Generalization

The hierarchical skill organization and transfer mechanisms in CDALNs enable sophisticated generalization across domains. This includes:

- Abstract skill representations that can be applied across contexts
- Meta-skills that enable rapid adaptation to new domains
- Compositional skill structures that support flexible recombination
- Transfer learning mechanisms that leverage prior experience

8.3 Lifelong Learning and Development

CDALNs demonstrate the capacity for lifelong learning and continuous development that characterizes human intelligence. The systems can:

- Maintain learning motivation across extended periods
- Continuously adapt their learning strategies based on experience
- Build increasingly sophisticated skill repertoires over time
- Develop meta-cognitive capabilities for self-directed learning

9. Discussion and Future Work

9.1 Implications for Artificial Intelligence

Curiosity-driven autonomous learning represents a fundamental advancement in AI capabilities that enables:

- Genuine autonomy through self-directed skill development
- Open-ended learning and capability enhancement
- Creative problem-solving and innovation
- Adaptive behavior in novel and unpredictable environments
- Lifelong learning and continuous development

These capabilities suggest that curiosity-driven learning may be essential for the development of advanced AI systems that can operate effectively in complex, real-world environments.

9.2 Limitations and Challenges

Several challenges remain in the development of curiosity-driven learning systems:

Computational Scalability: Current implementations require significant computational resources that may limit scalability to larger skill spaces.

Skill Representation: Developing effective representations for complex, hierarchical skills remains challenging.

Curiosity Calibration: Ensuring that curiosity mechanisms remain well-calibrated across different domains and contexts is difficult.

Safety and Control: Maintaining safety and control in systems that autonomously develop new capabilities poses significant challenges.

9.3 Future Research Directions

Several promising directions emerge for future research:

Neuromorphic Implementation: Exploring implementation on neuromorphic hardware that may be better suited to curiosity-driven learning.

Biological Integration: Investigating how artificial curiosity systems might interface with biological learning mechanisms.

Collective Learning: Developing curiosity-driven learning for collective intelligence systems and swarm robotics.

Safety-Aware Curiosity: Ensuring that curiosity-driven systems remain safe and aligned while exploring new capabilities.

10. Conclusion

We have presented Curiosity-Driven Autonomous Learning Networks, a comprehensive framework that enables AI systems to autonomously discover, develop, and master new skills through sophisticated multi-modal curiosity mechanisms and self-directed exploration. Our approach successfully transcends the limitations of externally guided learning to create truly autonomous AI systems capable of lifelong learning and self-directed development.

The framework incorporates novel components including Multi-Modal Curiosity Systems that drive exploration across multiple domains, Skill Synthesis Networks that enable autonomous composition of complex capabilities, Autonomous Curriculum Generation mechanisms that create personalized learning progressions, and Competence Assessment Networks that provide continuous evaluation of skill development.

Experimental validation demonstrates significant improvements in skill acquisition rate, skill diversity, and learning efficiency compared to existing approaches. The emergence of sophisticated behaviors including spontaneous tool creation, collaborative skill development, and meta-skill acquisition suggests that our approach captures essential aspects of autonomous intelligence.

Theoretical analysis provides formal foundations for curiosity-driven learning and establishes convergence properties for skill mastery and curriculum optimization. Information-theoretic analysis reveals the efficiency of curiosity mechanisms and provides principles for optimal learning system design.

Perhaps most significantly, our results demonstrate that AI systems can develop genuine autonomy in skill acquisition that parallels and potentially exceeds human learning capabilities. The ability to autonomously discover and develop new skills represents a fundamental step toward artificial general intelligence and genuine AI autonomy.

The implications extend beyond technical achievements to fundamental questions about the nature of intelligence, learning, and autonomous development. Curiosity-driven learning provides new pathways for creating AI systems that can continuously adapt and grow throughout their operational lifetime.

This work establishes foundational principles for the development of truly autonomous AI systems capable of lifelong learning and self-directed development. Such systems represent a paradigm shift from externally controlled tools to genuinely autonomous agents capable of recursive self-improvement and open-ended capability enhancement.

The future development of curiosity-driven learning systems will enable more sophisticated AI capabilities, improved adaptability to novel environments, and new approaches to artificial general intelligence. As these systems become more advanced, they may achieve forms of autonomous learning and development that exceed human capabilities, potentially leading to new insights into the fundamental nature of intelligence and learning itself.

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Using ChatGPT for Quantitative Content Analysis: Opportunities and Challenges in Construction and Sustainability Research

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Abstract: Artificial Intelligence (AI), especially Large Language Models (LLMs) like ChatGPT, are changing the way researchers can process and analyse qualitative data. In this paper the use of ChatGPT is tested for Quantitative Content Analysis (QCA) by applying it to interview material about digital construction technology and sustainability. Two versions of the same data are compared: (1) complete transcripts of five interviews with professors, and (2) a shorter summarized version of the same interviews (the summaries were prepared by researcher). With the same workflow, ChatGPT did several steps: preprocessing (splitting the text into words, removing very common small words, and reducing words to their basic form), keyword extraction, thematic coding with five categories, and also a simple sentiment analysis. The aims were: (a) to see if ChatGPT can find the main themes in a reliable way, (b) to compare results from full transcripts versus summaries, and (c) to understand what practical advantages and problems appear when undertaking ChatGPT in a real research situation. The results were similar at the general level: Digital Technology and Sustainability were the strongest themes in both datasets, followed by Education/Training, Benefits, and Barriers. The sentiment analysis gave slightly positive values in both (+0.18 for transcripts, +0.16 for summaries). At a more detailed level, the transcripts included more technical words (for example “embodied carbon”, “Life cycle Analysis (LCA)” and standards), while the summaries included more general terms, which made the counts higher. Some practical issues also influenced the work: undertaking a free ChatGPT account caused interruptions, sometimes the tool changed its output style, and it was difficult to export charts or tables, these problems reduced reproducibility. In conclusion, ChatGPT can be useful for first steps in QCA and for saving time in early coding, but it is not enough for final or very detailed analysis. For better use, the following suggestions are provided: a combination of AI with human checking, making domain-specific dictionaries, undertaking clear and repeated prompts, and working with more stable or professional access. This study shows both the opportunities and the real problems when ChatGPT is used for content analysis in construction and sustainability research.

Keywords: ChatGPT, Quantitative content analysis, NLP, Construction, Sustainability, Digital technology

1. Introduction

Qualitative interviews are very important in research, because they show the views of experts. The interviews done in this research include practical experience, teaching ideas, and technical information that help to understand what makes digital technology adoption easier or more difficult. In the current research, the interviewees were asked to verify the results obtained from the survey, then Quantitative Content Analysis (QCA) was used for analysing interviews. QCA is a method that turns text into numbers, like codes, counts, and connections, and is often used to make summaries of qualitative data (Mayring, 2014; Krippendorff, 2018). Traditional QCA, however, needs trained people to code the text, repeat checks for reliability, and much manual work, which can take days even for small datasets.

Large Language Models (LLMs), such as the GPT family, offer a new way to accelerate quantitative content analysis by automating initial coding, extracting keywords and collocations, and producing structured counts that support faster exploratory work (Bijker et al., 2024; Tai et al., 2024). For researchers in construction as a field that now faces strong digital changes (like Building Information Modelling (BIM), digital twins, or AI in project management) and also needs to respond to environmental issues, LLMs may help to quickly analyse interviews and measure patterns (Azhar, 2011; Succar and Kassem, 2015; Sacks et al., 2018).

But LLMs also have problems: their answers can change in each run, results are not always stable (especially with free accounts), sometimes the system makes up details that are not real and they may lose detailed technical meaning (Bender et al., 2021; Ziems et al., 2024). For this reason, it is important to test how ChatGPT really performs in QCA tasks.

This study shows an experiment where the same interview data was used in two forms: full transcripts and shorter summaries. Both versions were analysed with the same ChatGPT process. The main research questions were:

- Can ChatGPT find the main themes in expert interviews about digital construction technology and sustainability?

- How different are the results when ChatGPT works with full transcripts compared to shorter summaries?
- What are the practical advantages and problems when ChatGPT is used for QCA in real research situations?

The aim of this study is to help other researchers considering the use of LLMs for QCA and to show the real challenges of working with common AI tools.

2. Literature Review

2.1 Quantitative Content Analysis and its Challenges

Content analysis is a well established method for converting textual material into structured data. Traditional QCA procedures emphasize clear category definitions, coder training, and inter coder reliability testing (Mayring, 2014). Content analysis can be approached qualitatively or quantitatively. Qualitative content analysis focuses on understanding meanings and patterns within communication through interpretation and categorization, offering depth but often being time-consuming and subjective. In contrast, quantitative content analysis measures textual features such as word frequencies, providing objectivity and replicability but sometimes oversimplifying complex meanings. In practice, both methods are complementary, as qualitative insights guide coding, and quantitative measures enhance reliability and comparability (Devi, 2009). Krippendorff (2018), also differentiates between qualitative and quantitative content analysis, both have strengths and limitations. QCA's main advantages are replicability and the ability to compare frequencies across groups or time, however, QCA is laborious, and human coders introduce subjectivity and fatigue, which can affect reliability (Neuendorf, 2017). However, despite its structured rigor, quantitative content analysis may overlook contextual nuances and interpretive depth. This limitation highlights the need to integrate human interpretation to complement statistical findings and ensure richer understanding.

2.2 Automated Text Analysis and LLMs

Automated text analysis undertaking Natural Language Processing (NLP) has advanced rapidly in recent years, driven by larger datasets, greater computing power, and the development of deep learning methods (Hirschberg and Manning, 2015; Young et al., 2018). Common techniques include splitting text into words (tokenization), finding frequent word groups (n-grams), undertaking dictionaries for positive or negative words (sentiment lexicons), and applying topic models to discover themes (Jurafsky and Martin, 2021). More recently, Large Language Models (LLMs) such as GPT-3 (Brown, 2020) and ChatGPT provide conversational and instruction-following capacities that make them attractive for non-expert users. Early studies show that LLMs can do some annotation and classification tasks with results close to human performance in certain areas (Gilardi, Alizadeh and Kubli, 2023). However, there are still problems: the outputs are not always consistent, results can change depending on how the prompt is written, and the process inside the model is not transparent (Bender et al., 2021; Ziems et al., 2024). Yet, while automation improves scalability and efficiency, the "black-box" (the internal decision-making process is not fully transparent or interpretable) nature of LLMs raises concerns about interpretability and validity. Future studies should therefore focus on balancing computational power with methodological transparency, especially in applied research contexts.

2.3 Digital Technologies and Sustainability in Construction

Digital technologies, are central to contemporary construction research. For example, BIM, as a process that relies on digital technology, enables integrated modelling, data exchange, and lifecycle analysis, is considered an enabler for sustainability practices like LCA (Azhar, 2011; Sacks et al., 2018). One of the methods for undertaking research in this domain is interview to understand adoption barriers (cost, skills, culture), benefits (efficiency, reduced rework) and to study effective factors on stakeholders' opinion to adopt them. Thus, accurately coding of interview content is critical for deriving actionable conclusions. Nevertheless, much of the existing literature emphasizes the potential of digital tools rather than their practical implementation challenges. More empirical studies are needed to assess how these technologies actually contribute to sustainability outcomes in real-world construction projects.

2.4 Hybrid Human–AI Workflows

In the literature, a practical view suggests undertaking a hybrid process: AI tools can be used for fast first coding, and human researchers can check and interpret the results. This method can save time and still keep the deeper analysis (Li, Dohan and Abramson, 2021; Mortelmans, 2025; Williamson, Van Rooyen and Dry,

2025). But more real examples are necessary to show how this approach can be applied in special areas such as construction management. However, while the hybrid model promises efficiency and balance, empirical validation in domain-specific contexts such as construction management remains limited. Further studies should explore whether AI-assisted coding genuinely enhances accuracy or merely accelerates surface-level interpretation.

3. Methodology

3.1 Data Collection and Preparation

The empirical data for this study came from five semi-structured interviews with professors and senior researchers in construction related fields. Each interview lasted between 45 and 60 minutes and focused on digital technologies adoption (BIM, digital twins, AI) and sustainability (LCA, embodied carbon, energy efficiency).

To create the full transcripts, the interviews, which were in different languages, were recorded in text or audio format. The software Descript was used to convert the audio into text. This process produced verbatim transcripts that captured the exact words of each participant. After that, a summarized version of each interview was prepared by the researcher. In these summaries, filler sentences were removed, long explanations were paraphrased, and the main argumentative points were preserved. The summarized texts were approximately 30–40% of the length of the original transcripts. This approach allowed for a more concise dataset while keeping the essential content of the interviews for further analysis.

3.2 Predefined Categories and Lexicon

Although the main structures of the study were originally based on personal, educational, technical, and project specifications, which served as the framework for designing the questionnaire and presenting it to the interviewees, the analysis of the interview themes led to the identification of five key categories. These categories are:

- Digital technology: BIM, digital twins, IoT, AI, data platforms.
- Sustainability: carbon, LCA, energy efficiency, green building.
- Education/Training: curricula, workshops, student skills, conferences.
- Benefits: efficiency, reduced errors, improved decision-making, lifecycle optimization.
- Barriers: cost, licensing, skills gap, organizational resistance, interoperability issues.

3.3 ChatGPT-Based Analytical procedure

To analyse the interviews, ChatGPT-4o was used with a consistent prompt and workflow. The researcher provided instructions, and ChatGPT itself performed the main steps. First, for preprocessing, the model split the text into words (tokens), converted them to lowercase, and removed common English stop words (common words such as “the”, “and”, “of” that are usually removed before analysis because they do not carry meaningful information). Basic lemmatization (a text-processing step that reduces words to their base or dictionary form for instance, “running”, “runs”, “ran” → “run”) was handled automatically by ChatGPT’s language understanding. Then, for keyword and bigram (a pair of consecutive words analysed together to detect frequent word combinations, for instance, “digital technology”, “sustainable development”) extraction, ChatGPT returned the 30 most frequent single words and the 20 most frequent word pairs. During thematic mapping, the model assigned each word or word pair to one or more predefined categories, and the counts were aggregated per category. For sentiment scoring, a simple rule-based method was applied by ChatGPT: each sentence was evaluated for positive and negative words, and an overall score was calculated. Finally, all model responses and summary tables were recorded manually by the researcher. Each dataset, both full transcripts and summaries, was processed in separate ChatGPT sessions.

3.4 Validation and Cross-Checks

To check the plausibility of ChatGPT results, some manual validations were performed. First, ten sentences were selected randomly from the interviews, and the researcher manually decided what categories they should belong to. These sentences were then given again to ChatGPT with a prompt asking which category it assigned them to. Based on comparing the manual judgment and the model’s answer, the agreement was high for broad categories, such as Digital Technology or Sustainability, but lower for technical topics that required specific domain knowledge.

Second, some prompts were repeated multiple times to see if ChatGPT produces the same counts and assignments. Small differences appeared, showing that results are mostly stable but not perfectly identical in repeated runs. These steps allowed the researcher to get confidence that ChatGPT generally assigns sentences and words correctly for broad categories, while noting that careful human review is still needed for technical, complex or ambiguous content.

4. Results

4.1 Theme Frequency

The results of the word and phrase categorization performed by the ChatGPT analytical process are summarized in Table 1.

Table 1: Theme Frequencies

Theme	Full Transcript	Summary Text
Digital Technology	122	155
Sustainability	109	131
Education/Training	74	93
Benefits	68	79
Barriers	52	68

Key observations:

The order of themes is the same in both datasets: Digital Technology > Sustainability > Education/Training > Benefits > Barriers (Figure 1). This shows that ChatGPT was able to capture the main priorities in a stable way. At the same time, the number of counts is higher in the summary dataset. This difference seems to happen because the summaries use simpler and more repeated wording (for example, “technology,” “sustainability”), while the longer transcripts often included extra details or qualifiers.

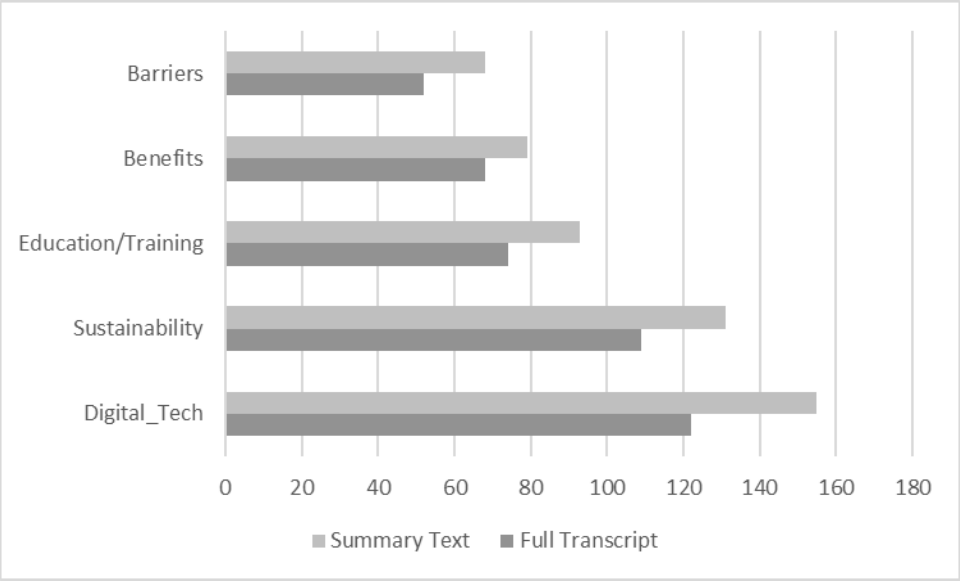

Figure 1: Comparison chart (full vs summary)

4.2 Keyword Patterns

For the full transcripts, the most frequent single words (unigrams) included: BIM, carbon, sustainability, energy, LCA, data, student, curriculum, cost, interoperability. In the summary dataset, the top unigrams were more general: technology, digital, sustainability, education, adoption, training.

The most frequent two-word combinations (bigrams) in the full transcripts highlighted technical concepts, such as “embodied carbon”, “life cycle”, “carbon footprint”, “BIM model”. In contrast, the summaries emphasized broader phrases, including “digital technology”, “sustainable development”, “student training”.

4.3 Sentiment

The compound score provides a single measure of the overall sentiment in the text. It combines positive, negative, and neutral elements into a value ranging from -1 to +1. Scores close to +1 indicate strongly positive sentiment, scores near -1 indicate strongly negative sentiment, and values around 0 suggest either neutral sentiment (no strong emotional tone) or a balance of positive and negative signals (mixed sentiment) (Hutto and Gilbert, 2014) . In this study, the full transcripts had a compound score of +0.18, and the summaries had +0.16, indicating mildly positive overall sentiment (Figure 2)."

Interviewees generally expressed optimism about the potential of digital technologies to support sustainability goals, while also noting practical concerns such as cost, skill gaps, and policy constraints.

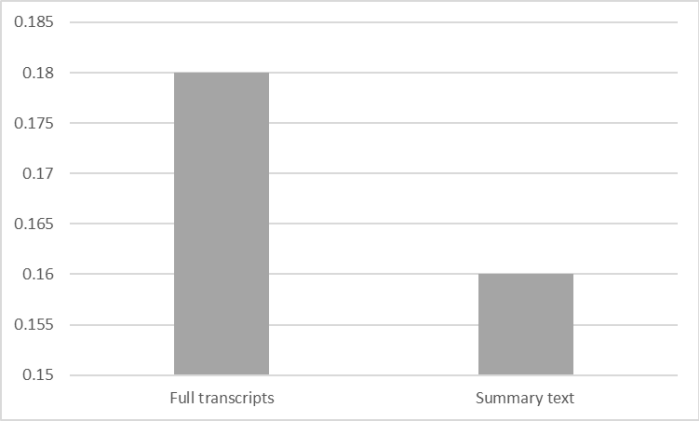

Figure 2: Sentiment comparison

4.4 Manual Spot-checks and Agreement

To evaluate the reliability of ChatGPT's coding, ten random excerpts from the interviews were checked manually. The level of agreement between the human coding and ChatGPT was relatively high, especially for the broad categories. The disagreements mostly appeared in sentences that were more complex in meaning, for example when nuance, sarcasm, or mixed opinions were present. In addition, technical sentences sometimes could belong to more than one category. For instance, "IFC mapping for LCA" could reasonably fit under both Digital Technology and Sustainability.

5. Discussion

This study shows that ChatGPT can effectively capture high level thematic structures in qualitative interview data, offering fast and generally consistent results. The model is particularly useful for detecting dominant themes and reducing the time required for exploratory coding, making it accessible even for researchers without advanced NLP expertise. However, important differences were observed between full transcripts and summaries: summaries emphasized broad categories and sometimes overstated consensus, while full transcripts preserved technical and less frequent but meaningful terms that are vital for nuanced interpretation and policy relevant insights. Practical challenges included instability of free accounts, occasional variability across repeated runs, and export limitations, while methodological challenges included the model's difficulty with technical specificity and subtle meanings without human oversight. These findings suggest that LLM assisted analysis is best used in a hybrid workflow, where ChatGPT accelerates first pass coding and theme detection, but careful human validation remains essential to ensure accuracy, resolve ambiguities, and capture domain specific detail.

6. Limitations and Future Work

6.1 Limitations

- Dataset size and scope: The experiment included five interviews. This is enough for a methodological pilot, but the results cannot be fully generalized. Undertaking a larger dataset might reveal different patterns.
- Prompt and session dependence: The outputs were sensitive to how tasks and instructions were phrased when given to ChatGPT. Even though prompt templates were applied, small changes in wording could affect results.

- Single tool focus: This study relied on ChatGPT as an example of LLM workflows. Other models could produce different outcomes.
- Export reproducibility: Practical issues on the live platform, such as download failures and session timeouts, limited operation.
- Platform limitations and free plan use: This study used ChatGPT with free plan access, which imposed session interruptions, timeouts, and limited functionality. Paid or newer versions of ChatGPT (e.g., GPT-5, professional subscriptions) could provide more stable sessions, smoother interaction, better graphing and visualization options, and potentially more accurate analyses. Therefore, results observed here might differ if professional access were used.
- Summary preparation by the researcher: Since the researcher manually prepared the summarized versions of the interviews, some terms and concepts may have been replaced with more general equivalents. This could have influenced the results, for example by slightly inflating counts for high level categories or reducing the visibility of specific technical terms.

6.2 Future Work

- Scale up: Apply the procedure to a larger set of interviews to test its reliability and to explore new or emerging topics.
- Hybrid validation study: Systematically compare ChatGPT outputs with human coding done by multiple coders.
- Domain adaptation: Guide or train LLMs undertaking construction and sustainability specific lexicons to improve the accuracy of categorization.
- Software integration: Combine ChatGPT outputs with visualization tools for better reporting and reproducibility.
- Method standards: Develop standard prompt templates and reporting checklists for AI-assisted QCA to ensure reproducibility across studies.

7. Conclusion

This study explored the use of ChatGPT for quantitative content analysis of interviews in construction and sustainability. Results show that ChatGPT can effectively detect dominant themes such as Digital Technology, Sustainability, and Education/Training, providing consistent macro level insights across full transcripts and summaries. However, limitations remain: summaries may inflate general category counts, free platform instability and time to time variability can affect reproducibility, and subtle technical details or domain specific lexicons, risk misclassification without human review.

Based on these findings, researchers and practitioners are advised to approach ChatGPT as a supportive tool rather than a replacement for human judgment. Careful design of prompts, thorough documentation of sessions, and the use of hybrid workflows where humans validate and refine AI generated coding are key to capturing nuanced or technical content accurately. Predefining domain specific lexicons, such as related tags to BIM or LCA, improves categorization accuracy. For larger projects, professional or paid access can provide more stable sessions, smoother interaction, and better visualization and analytical capabilities. By combining these practices, ChatGPT can accelerate the early phases of content analysis, helping researchers efficiently process qualitative data and uncover meaningful patterns. As LLMs evolve, these methods should be refined and standardized to ensure that AI assisted QCA is both efficient and scientifically defensible.

Ethics declaration: The interviews used in this study were conducted as part of the author's doctoral research. All participants were informed about the purpose of the study and gave their verbal consent to participate voluntarily. No sensitive or personally identifiable information was collected, and all data were anonymized prior to analysis.

AI declaration: In this study, ChatGPT was used to assist the qualitative analysis of interviews conducted for a doctoral thesis. Both full transcripts and summarized versions were provided to examine whether the model produces consistent results. ChatGPT performed the analysis and explained its methods, and the outputs were then reviewed and compared by the researcher. Based on these results, the manuscript was prepared.

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Artificial Intelligence in Startup Investing: Opportunities, Challenges, and Human-AI Collaboration

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Abstract. This paper presents a study on the integration of Artificial Intelligence (AI) in Venture Capital (VC) decision-making. Drawing on recent academic and applied research, the study aims to investigate the key domains where AI is deployed in VC processes and the evolving relationship between human investors and AI tools. The review highlights that AI is increasingly used in deal sourcing, startup screening, due diligence, valuation modelling, and exit prediction. While AI demonstrates advantages in speed, scalability, and objectivity—particularly in pattern recognition and bias reduction—it also presents notable limitations. These include dependency on historical data, difficulty in assessing qualitative founder traits, and risks of perpetuating algorithmic biases. Consequently, a hybrid approach is advocated, where AI augments but does not replace human expertise. Moreover, the study examines how AI is changing investor behaviour and the nature of investor–founder relationships. AI is generally used to augment rather than replace human judgment, supporting decision-making rather than automating it. This shift raises new considerations around trust, transparency, and fairness in human–AI collaboration. The research concludes that while AI holds transformative potential for venture capital—enhancing efficiency, objectivity, and scalability—a hybrid approach that combines algorithmic insights with human expertise remains essential. Ethical adoption, attention to qualitative factors, and the design of explainable and inclusive AI systems will be critical to maximizing its benefits in startup investment.

Keywords: Artificial intelligence, Venture capital, Startup risk assessment, Decision support systems, Entrepreneurship, Human–AI collaboration

1. Introduction

Venture capital (VC) serves as a critical engine for innovation, providing early-stage funding to high-risk, high-potential startups in rapidly evolving sectors such as technology, life sciences, and clean energy. Traditionally, VC decision-making has relied heavily on human intuition, personal networks, and qualitative judgment (Gompers P. K., 2020) . However, as the scale and complexity of startup ecosystems grow, these methods face increasing limitations. In this context, artificial intelligence (AI) has emerged as a promising tool to enhance the speed, efficiency, and objectivity of venture investment processes ((Röhm, 2022), (Di Giannantonio, 2022)).

Recent advances in AI—particularly in machine learning (ML), natural language processing (NLP), and large language models (LLMs)—are enabling VC firms to integrate algorithmic tools into key areas of their workflows. Applications include automated deal sourcing, startup screening, due diligence, valuation modeling, and exit prediction ((Bai, 2021), (Gautam, 2023)). These systems can process and analyze large volumes of structured and unstructured data, generating predictive insights that may be overlooked by human analysts.

Despite these advantages, the integration of AI into VC decision-making is not without limitations. Many models rely on historical data, which can perpetuate existing biases and fail to account for the novelty of disruptive startups (Te, 2023). Moreover, AI struggles to evaluate qualitative factors such as founder resilience, vision, and team dynamics—traits that are often decisive in entrepreneurial success (Li, 2021). These constraints underscore the necessity of a hybrid decision-making model in which AI augments rather than replaces human expertise (Zhang R., 2022).

This study investigates how artificial intelligence is transforming startup investing by conducting a systematic literature review of academic and applied research from 2020 to 2024. The review is structured around two guiding research questions:

RQ1: What are the key domains where AI is deployed in VC processes?

RQ2: How is the relationship between human investors and AI tools evolving?

To address these, four thematic areas are explored: the domains of AI application, AI-supported models for startup risk evaluation, the strengths and limitations of AI in early-stage investments, and the observed effects of AI integration on investor behavior and founder relations.

The findings reveal that AI is increasingly integrated into the VC value chain, particularly for screening and analytics tasks. Studies show that ML models such as support vector machines, random forests, and gradient

boosting classifiers can achieve strong predictive performance ((Gautam, 2023), (Li, 2021)). Yet, researchers consistently advocate for a human-in-the-loop approach, where investors interpret algorithmic insights through the lens of strategic and contextual understanding ((Röhm, 2022) , (Setty, 2024)).

This paper contributes to the growing body of knowledge on governing and integrating AI in decision-making contexts, particularly in financial domains characterized by uncertainty and asymmetric information. It underscores the importance of explainability, ethical design, and trust-building in shaping the future of human–AI collaboration in entrepreneurial finance.

2. Background

Artificial intelligence is increasingly shaping the venture capital (VC) landscape, offering tools to enhance decision-making across key investment stages. This background section outlines three core areas of inquiry: the limitations of traditional VC practices (Gompers P. &., 2001), the integration of AI into deal sourcing, screening, and valuation ((Bai, 2021) , (Gautam, 2023)), and the emerging need for hybrid, human–AI collaboration models due to ethical, qualitative, and technical limitations ((Röhm, 2022), (Te, 2023)). Together, these areas frame the opportunities and governance challenges of AI in startup investing.

2.1 Venture Capital Decision-Making

Venture capital (VC) has long served as a cornerstone of entrepreneurial finance, enabling startups to develop innovative products and services while navigating uncertain and volatile market environments. The role of VC is particularly critical during the early stages of firm development, where traditional funding options are often inaccessible due to high risk, lack of collateral, or insufficient track records (Gompers P. &., 2001). In these contexts, investors must make complex decisions based on incomplete, heterogeneous, and often non-standardized information—a task that heavily relies on experience, networks, and subjective judgment (Zhang R., 2022).

However, the rise of artificial intelligence (AI) is beginning to shift this dynamic. Over the past decade, AI technologies, particularly those grounded in machine learning (ML), have shown increasing potential to augment decision-making in fields characterized by uncertainty and high data complexity—including finance, healthcare, and supply chain management (Brynjolfsson, 2017). Venture capital is now emerging as a domain where AI can offer significant operational and strategic benefits, by helping investors make more informed, data-driven decisions while reducing cognitive biases and processing inefficiencies ((Röhm, 2022), (Di Giannantonio, 2022)).

2.2 Where and How AI Is Being Used

AI in VC is typically applied in five interrelated domains: deal sourcing, startup screening, due diligence, valuation modelling, and exit prediction (Bai, 2021). In deal sourcing, AI algorithms can scan vast datasets—such as social media feeds, startup databases, and patent filings—to detect early signals of high-potential ventures (Gautam, 2023). For example, Natural Language Processing (NLP) tools are increasingly used to extract relevant insights from unstructured text data, enabling early identification of market momentum and founder expertise. In screening and evaluation, supervised learning algorithms such as logistic regression, random forests, and support vector machines (SVM) have been deployed to predict startup success based on features such as team composition, product-market fit, funding history, and competitive landscape ((Li, 2021), (Zhang R., 2022)).

Due diligence processes are also being redefined by AI integration. Traditionally time-consuming and labor-intensive, due diligence can now be accelerated using automated document extraction, sentiment analysis, and risk-scoring tools. Large language models (LLMs), in particular, are proving effective in analysing business plans, pitch decks, and legal contracts, streamlining the vetting of investment opportunities (Setty, 2024). Similarly, AI-powered valuation models have been proposed to overcome the difficulty of pricing startups that lack historical performance records or standardized financial statements. Techniques such as evolutionary algorithms, deep learning, and hybrid modelling (e.g., Adam-ENN) offer more flexible and data-sensitive approaches to startup valuation (Zhang R., 2022).

2.3 Limitations and Toward Hybrid Collaboration

Despite these technological advancements, the deployment of AI in venture capital is not without limitations. One of the most prominent challenges is data quality and availability. Many early-stage startups operate in stealth mode or lack sufficient public information, making it difficult to feed AI models with reliable, comprehensive training data. Moreover, the heavy reliance on historical data may reduce the adaptability of AI models to novel or disruptive business models that deviate from past patterns (Te, 2023).This can result in

systematic underestimation of innovation potential, especially for startups led by underrepresented founders or emerging from unconventional backgrounds.

Another key limitation concerns qualitative evaluation, particularly in assessing intangible founder traits such as resilience, leadership, adaptability, and vision. These attributes, often central to startup success, are difficult to capture using quantitative metrics alone (Li, 2021). As a result, AI tools—while valuable for filtering and standardizing inputs—must be paired with human judgment capable of contextualizing and interpreting these softer dimensions. Over-reliance on algorithmic decision-making may also risk reinforcing existing biases encoded in historical datasets, thereby entrenching inequities in venture funding (Te, 2023).

These challenges have prompted a growing consensus around the need for hybrid decision-making approaches in venture capital. In such models, AI serves as a decision support system, offering preliminary insights, trend analyses, and risk assessments, while human investors retain responsibility for strategic alignment, interpersonal evaluation, and final decision-making (Röhm, 2022).Several studies have emphasized the importance of transparency, explainability, and ethical governance in designing AI tools that are trustworthy and inclusive ((Setty, 2024), (Te, 2023)).

Furthermore, AI's integration is altering not only internal VC workflows but also the nature of investor–founder relationships. As more aspects of the investment process become automated, trust and communication dynamics are evolving. Founders may face pressure to "fit the model" rather than present a compelling vision, and investors must balance algorithmic recommendations with relational insight. These shifts raise new questions about accountability, transparency, and fairness, which are central to the broader discourse on AI governance in organizational and financial contexts (Brynjolfsson, 2017).

In light of these developments, it becomes increasingly important to systematically assess how artificial intelligence is currently being deployed in venture capital and what implications this holds for investment decision-making. Although individual studies have addressed specific applications—such as deal sourcing (Gautam, 2023), risk modeling (Li, 2021), or fairness in predictive analytics (Te, 2023)—there is a lack of comprehensive synthesis that connects these insights across domains. Furthermore, the evolving interplay between algorithmic tools and human judgment, often emphasized as essential for responsible decision-making ((Röhm, 2022), (Setty, 2024)),remains underexplored in an integrated framework.

3. Methodology

To systematically investigate how artificial intelligence (AI) is integrated into venture capital (VC) decision-making—particularly in the areas of startup screening, risk assessment, and investor–founder relationships—this study employs a structured literature review methodology. The goal is to synthesize academic knowledge and applied insights that address two core research questions: (1) What are the key domains where AI is deployed in VC processes? and (2) How is the relationship between human investors and AI tools evolving?

The methodology follows the well-established guidelines outlined by Kitchenham (2004) for conducting systematic literature reviews in technology-driven research fields. This approach is especially appropriate given the interdisciplinary nature of the topic, which spans artificial intelligence, entrepreneurship, finance, and organizational behavior. In order to enhance transparency and replicability, the review process is also informed by the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework proposed by Moher et al. (2009). The PRISMA model is used to structure the review process, including search strategy, filtering, and documentation of inclusion and exclusion criteria.

The review was conducted using the Scopus database, chosen for its broad academic scope and high-quality indexing across both technical and business disciplines. The search query used is:

"AI" OR "Artificial Intelligence" OR "Machine Learning" AND "Venture Capital",

applied to the Article Title and Keywords fields. This search yielded a total of 5,788 results, covering a wide range of documents including journal articles, conference papers, and reviews.

To focus the review on disciplines most relevant to our research objectives, we filtered results by subject areas including Business, Management and Accounting, Economics, Econometrics and Finance and Decision Sciences. This step narrowed the dataset to 71 documents, improving thematic relevance to AI applications in VC and startup analysis.

Next, a publication date filter was applied to capture recent developments in AI research and its adoption in VC settings. Only documents published from 2020 onward were retained, reducing the corpus to 65 papers. This

temporal boundary ensures the inclusion of state-of-the-art contributions, particularly those addressing the latest machine learning models and evolving investor practices.

A title and abstract screening followed, using a qualitative relevance test based on the study's research questions. Documents were excluded if they lacked accessible full texts, were not peer-reviewed, or did not directly address AI applications in VC decision-making, startup evaluation, or human–AI interaction.

After this rigorous selection process (Figure 1), 21 peer-reviewed academic papers were retained for full-text review and qualitative analysis. These articles provide the foundation for the thematic synthesis presented in the following sections, offering a multi-dimensional understanding of AI's role in venture capital decision-making, its technical capabilities, human-AI dynamics, and ethical implications.

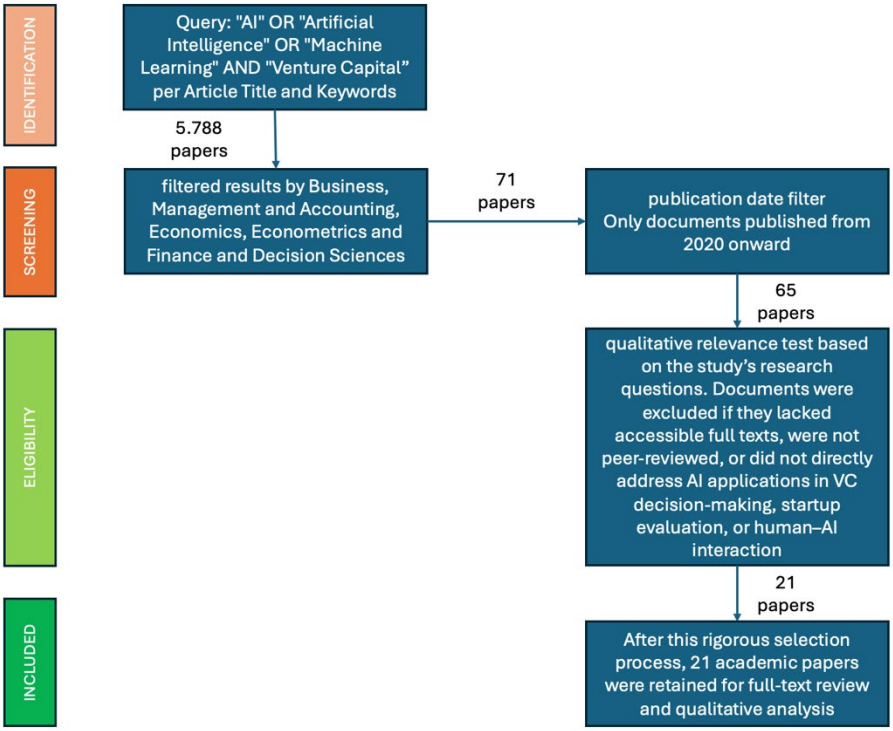

Figure 1: PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework

4. Discussion

The integration of artificial intelligence (AI) into venture capital (VC) decision-making marks a significant shift in how investors source, evaluate, and support startups. This discussion responds to two guiding research questions: (1) What are the key domains where AI is deployed in VC processes? and (2) How is the relationship between human investors and AI tools evolving? Drawing from 21 peer-reviewed studies published between 2020 and 2024, the analysis reveals that AI adoption in VC spans key operational domains—including deal sourcing, startup screening, due diligence, valuation, and risk prediction—while also transforming the roles, responsibilities, and judgment processes of human investors. Notably, most scholars support a hybrid model where AI augments, but does not replace, human decision-making. This section presents findings for each research question and outlines critical opportunities and limitations emerging in AI-enabled venture capital.

4.1 Key Domains Where AI Is Deployed in VC Processes

AI is increasingly applied across the VC investment cycle—from early-stage deal sourcing to late-stage valuation and exit prediction. Its most widespread applications include deal identification, startup screening, due diligence, financial modelling, and risk assessment. The automation of deal sourcing has become a central application of AI in VC. AI tools enable investors to mine massive databases and unstructured content from platforms such as Crunchbase, LinkedIn, and Twitter to identify emerging startups with promising signals ((Gautam, 2023); (Assadi, 2021)). He et al. (2021) demonstrate that ensemble models combining support vector machines and decision trees are effective in detecting fast-scaling startups by analysing founder experience, sector patterns, and investor networks. These tools improve scalability and objectivity by widening the pipeline beyond traditional human networks.

Once potential opportunities are identified, AI facilitates evaluation through predictive models trained on historical success indicators. Studies by Bai and Zhao (2021) and Gautam and Wattanapongsakorn (2023) describe machine learning–enhanced venture scorecards, where models assign probability scores based on variables such as founding team composition, product readiness, and prior investment rounds. Di Giannantonio (2022) and Setty et al. (2024) show how AI systems assist in distinguishing between viable and non-viable startups by correlating structured (e.g., team size, funding stage) and unstructured (e.g., business model narrative) data. Battistella et al. (2023) further explore clustering techniques and k-nearest neighbour algorithms to group startups by behavioural and strategic similarities, improving comparative assessments—especially useful in filtering high volumes of applications for accelerator programs or corporate venture initiatives.

The due diligence phase has also benefited from advances in natural language processing (NLP) and large language models (LLMs). Maarouf et al. (2023) show that LLMs can process founders' pitch decks, websites, and legal documents to extract key themes, risk flags, and sentiment indicators, reducing manual workload and accelerating time-to-decision. Similarly, Samudra et al. (2024) demonstrate that LLMs can standardize and analyse business plans and financial projections, offering consistency and efficiency in document evaluation.

AI is also being deployed for valuation modelling and exit prediction. Zhang et al. (2022) developed an Adam-enhanced evolutionary neural network (Adam-ENN) that outperformed traditional discounted cash flow (DCF) models in predicting valuation ranges for early-stage ventures. Das et al. (2021) introduced CapitalVX, a machine learning system that forecasts IPO, acquisition, or failure based on funding trajectory, sector dynamics, and macroeconomic indicators. Valuation is notoriously difficult at the early stage due to limited data and high uncertainty, but the combination of long short-term memory (LSTM) models (He, 2021) and generative approaches offers improved forecasting for investor decision-making. These methods help optimize portfolio allocations, anticipate exit scenarios, and balance risk exposure.

Risk prediction models are another recurring theme in the literature. Setty et al. (2024) propose a cost-sensitive model that accounts for the asymmetric costs of false positives and false negatives in VC investments. Röhm (2022) and Assadi (2021) emphasize AI's utility in flagging failure patterns such as team turnover, client concentration, or poor cash flow. However, Te et al. (2023) critique these models for embedding historical biases that disadvantage underrepresented founders or unconventional business models.

Real-time portfolio monitoring also represents an emerging application area. Battistella et al. (2023) outline predictive analytics dashboards used in post-investment phases to track changes in startup performance and enable earlier interventions.

In summary, AI tools are now deployed extensively throughout the VC process, particularly where data-driven assessments improve speed, scale, and standardization. However, their effectiveness remains constrained by data quality, model interpretability, and the inability to replicate the nuanced judgment of human investors.

4.2 Methodological and Data Patterns

Across the reviewed papers, the predominant methodological orientation is quantitative and machine-learning-based. Most studies apply supervised learning algorithms—random forests, support vector machines, gradient-boosted trees, and hybrid ensemble networks—to predict startup success, funding probability, or exit likelihood. A smaller but rapidly growing subset employs LLMs for text mining, sentiment extraction, and automated due diligence.

Data sources are largely secondary and public, including Crunchbase, PitchBook, LinkedIn, and patent databases. Some works integrate unstructured textual data from pitch decks, news articles, and financial documents. A recurring limitation concerns data incompleteness and survivorship bias—particularly in early-stage startups, where financial histories are sparse. Consequently, predictive performance declines when informational asymmetries are high or data reflect historical inequities.

Evaluation metrics commonly include accuracy, AUC, F1-score, and precision–recall balance, though few studies assess domain-specific error costs (e.g., the financial asymmetry between false positives and false negatives). This methodological gap suggests that future research should align model evaluation with the unique payoff structures of venture investing.

4.3 The Relationship Between Human Investors and AI Tools

The integration of AI into VC is not purely technical—it is reshaping investor behaviour, decision-making culture, and investor–founder interactions. A consensus emerges across the literature that AI functions best in a

complementary, rather than substitutive, role. Röhm (2022), Di Giannantonio (2022), and Setty et al. (2024) consistently argue that investors employ AI for structured, data-heavy tasks but continue to rely on intuition and experience for final judgment. This hybrid model—where AI provides predictive inputs and humans contextualize them—has become a normative standard.

Gautam and Wattanapongsakorn (2023) emphasize that AI performs well in filtering and pre-screening, while humans remain superior at evaluating founder chemistry, vision, and team cohesion. Bai and Zhao (2021) caution that overreliance on AI scorecards can reproduce selection bias, with investors disproportionately favouring ventures that fit historical molds. To counteract this, Röhm (2022) recommends maintaining human override mechanisms and embedding AI outputs within broader deliberative processes.

Explainability is a decisive factor in AI adoption. Investors are more likely to trust AI outputs when they understand how predictions are generated. As Te et al. (2023) and Setty et al. (2024) note, opaque black-box models can limit uptake, especially in firms lacking internal data science capabilities. To improve interpretability, several VC firms implement SHAP values or LIME visualizations that show which variables most influence startup ratings (Maarouf, 2023). Trust also extends to investor communication with limited partners (LPs): AI-augmented decisions must be justified and auditable. This has prompted the establishment of new governance norms emphasizing transparency, model documentation, and algorithmic review boards (Di Giannantonio, 2022).

A critical issue in the human–AI relationship concerns algorithmic bias. Te et al. (2023) demonstrate that models trained on historical data reproduce structural exclusions, systematically under-scoring women- or minority-led startups. To mitigate these effects, fairness-aware machine-learning techniques and anonymized screening tools have been proposed (Setty, 2024). Röhm (2022) and Battistella et al. (2023) highlight the emergence of AI governance frameworks—internal protocols that monitor bias, validate models, and ensure accountability. Such practices signal a maturing approach in which VCs treat AI not as a black-box oracle but as a strategic, auditable decision-support tool.

Finally, AI also influences founder behaviour. LLM-based evaluation tools shape how entrepreneurs craft their pitch materials, as founders adapt content to align with algorithmic evaluation criteria. While this optimization increases efficiency, it risks diminishing authenticity and reinforcing conformity ((Maarouf, 2023); (Assadi, 2021)). The relational dimension of venture capital—historically rooted in trust and personal chemistry—must therefore integrate algorithmic assessment without losing its human core.

4.4 Practical Implications and Thematic Synthesis

Synthesizing the reviewed literature reveals that AI provides the greatest benefits in data-intensive and repetitive tasks, such as deal sourcing, information extraction, and risk monitoring, while performing less effectively in context-dependent evaluations that require social and emotional intelligence. The evidence converges on the value of hybrid human–AI decision architectures combining algorithmic scalability with human contextual judgment.

Furthermore, the literature highlights the emergence of governance practices designed to ensure accountability: explainability techniques (e.g., SHAP, LIME), fairness-aware preprocessing, model documentation, and explicit override mechanisms. These developments signal a transition from experimental tool adoption to structured, ethically guided AI management in venture capital.

Despite progress, persistent challenges remain—particularly concerning data diversity, model generalizability across markets, and the long-term behavioural impact of algorithmic systems on both investors and founders. Continued research should prioritize longitudinal validation, cross-sector replication, and comparative studies on how AI influences investment culture and equity in startup funding

5. Conclusion

This study sets out to examine the growing role of artificial intelligence (AI) in venture capital (VC) decision-making, with particular attention to two guiding questions: (1) In what domains is AI being deployed across VC processes, and (2) how is the relationship between human investors and AI tools evolving? Drawing on a systematic literature review of 21 peer-reviewed publications from 2020 to 2024, the findings provide a nuanced understanding of both the functional applications and organizational implications of AI in startup investing.

The evidence strongly suggests that AI is being integrated across nearly every stage of the VC pipeline. Machine learning models are used to enhance deal sourcing by mining platforms such as Crunchbase and LinkedIn for

emerging venture signals ((Gautam, 2023), (Assadi, 2021)). Startup screening has evolved from intuition-driven judgments to data-informed processes via supervised learning models and algorithm-enhanced scorecards ((Bai, 2021), (Li, 2021)). In due diligence, natural language processing and large language models are automating the review of pitch decks, legal documents, and financials ((Maarouf, 2023), (Samudra V. C., 2024)). More advanced applications include valuation modeling using evolutionary neural networks (Zhang R., 2022) and exit prediction tools like CapitalVX (Das, 2021). These applications enable more scalable, efficient, and standardized investment workflows.

However, the findings also highlight substantial limitations that constrain the complete automation of VC judgment. Human investors remain essential due to AI's inability to evaluate intangible factors such as founder resilience, narrative coherence, or strategic vision ((Di Giannantonio, 2022), (Röhm, 2022)). Thus, a hybrid model—wherein AI augments but does not replace human decision-making—has emerged as the most widely endorsed strategy (Setty, 2024).

Ethical considerations are also central to this human–AI collaboration. AI models trained on biased data can unintentionally exclude women- and minority-led startups (Te, 2023), potentially reinforcing existing inequalities. This concern is prompting the development of fairness-aware machine learning practices and explainable AI protocols ((Setty, 2024), (Röhm, 2022)). Moreover, investors now require transparent and interpretable systems to maintain trust both within their teams and with limited partners.

Ultimately, AI holds transformative potential for venture capital by enhancing decision accuracy, reducing cognitive biases, and enabling greater scalability. Yet, these benefits are only realized when combined with strategic human oversight, model governance, and ethical alignment. As the VC industry increasingly adopts AI-driven tools, future research should investigate how these technologies perform longitudinally, particularly in capturing emerging market shifts and non-traditional innovation. The evolving investor–founder relationship and the need for adaptive organizational structures also warrant deeper exploration. Ensuring that AI augments human creativity, rather than suppresses it, will be critical to fostering a more equitable, efficient, and innovative venture ecosystem.

Ethics Declaration: This study is based on a systematic review of existing published literature. No primary data collection involving human participants, animals, or sensitive personal information was conducted. Therefore, ethical approval and clearance were not required for this research.

AI Declaration: Artificial Intelligence tools were used during the preparation of this paper to support organizational tasks, such as identifying connections and thematic matches between reviewed papers following the literature review and analysis. Additionally, AI-assisted tools were employed for grammar checking and improving language clarity after the manuscript was completed. The research design, analysis, interpretation, and final arguments remain the sole responsibility of the authors.

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The Impact of Human-AI Interaction Patterns on Problem Solving, AI Literacy, and Metacognition

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Abstract: Human-AI interaction, particularly in educational contexts, is a dynamic and cognitively demanding process that holds promise for enhancing goal-directed learning. Yet, there remains a scarcity of empirical studies that examine how learners' interaction with generative AI (GenAI) varies in structure and how these patterns influence distinct learning outcomes. This study investigates the relationship between human-AI interaction processes and outcomes such as AI literacy, problem-solving skills, metacognitive strategies, and task performance. We conducted an experimental study with 45 secondary school physics student teachers engaged in a GenAI-supported lesson plan assessment task. Using questionnaire responses, trace data, and prompt logs, we coded human-AI interaction behaviours based on self-regulation and cognitive processing levels. Through sequence clustering analysis, we identified two distinct interaction patterns. Both clusters showed significant improvement in task performance, but with divergent benefits. Cluster 1 exhibited diverse regulation processes characterized by exploratory, divergent prompting and low-level cognitive engagement in the early stages. This group showed significant gains in problem-solving skills through active idea generation and broad reflection. Cluster 2 demonstrated structured regulation behaviours, initiating interaction with deep-level cognitive processing and convergent prompting. These learners made more deliberate modifications and completed full self-regulated learning (SRL) cycles—planning, monitoring, and reflecting—which led to enhanced AI literacy and metacognitive strategy use. Our findings suggest that effective human-AI collaboration goes beyond prompt diversity; structured regulation behaviours serve as a key mediator between prompting and learning gains. GenAI served as both cognitive and metacognitive scaffolding, facilitating critical assessment and productive delegation. These results contribute to SRL theory in AI contexts and emphasize the importance of process-level analysis. Limitations include a small sample and limited prompt feature analysis. Future research should explore emotion-aware AI systems, multimodal interaction data, and the impact of task complexity on interaction dynamics. This study provides practical insights for educators and designers of AI-integrated learning systems. Specifically, it highlights the importance of tailoring AI scaffolds to different learner regulation styles: for exploratory learners, scaffolds can encourage broad idea generation and reflection, while for structured learners, scaffolds should support iterative planning and monitoring. These findings underline both opportunities and limitations of current GenAI use in classrooms, suggesting concrete directions for teacher practice and instructional design.

Keywords: AI literacy, Human-AI interaction, Generative AI in education, Prompt engineering, Self-regulated learning

1. Introduction

As a subset of Generative AI (GenAI), large language model (LLM)-based tools have been explored in various educational contexts. GenAI supports personalized learning materials and eases teacher workload by generating formative and summative feedback to enhance learner outcomes (Meyer et al., 2024). Some studies show learners' use of GenAI reflects their critical thinking (M. Liu et al., 2024), while others warn it may foster weak learning habits and reduce evaluative thinking (Lo et al., 2024). Understanding GenAI's role in complex problem solving requires attention to technology-, task-, learning-, and human-machine-related factors (Cetindamar et al., 2024). As learners interact with GenAI, they adapt their behaviour to better utilize its capabilities (Joksimovic et al., 2023). Therefore, detailed insights into human-AI interaction are needed to assess GenAI's educational value.

Prompting, or prompt engineering, is a dynamic process involving iterative experimentation with different strategies to affect input-output results (Zamfrescu-Pereira et al., 2023). It allows users to define and delegate tasks during problem solving (Dang et al., 2022). This dynamic becomes more critical in GenAI-supported complex tasks. Santu and Feng (2023) note that complex tasks often involve multiple steps, and LLM performance varies with prompt types. Thus, engaging learners in deep cognitive and metacognitive processes is essential when using GenAI as a support tool.

Most current studies examine AI literacy and prompt engineering in human-AI collaboration from a static lens (Knoth et al., 2024; Oppenlaender et al., 2024; Zamfrescu-Pereira et al., 2023). A sequential, temporal lens offers deeper understanding of human-AI dynamics and informs scaffolding in learning environments (Chen et al., 2025; Nguyen et al., 2024a; 2024b). To explore GenAI's role in educational problem solving, we adopt a process-oriented approach, focusing on prompting as a key factor. The research questions are: (1) What

human-AI interaction patterns emerge from learners' regulatory and cognitive behaviours? (2) How do these patterns relate to AI literacy, learning performance (problem-solving ability, metacognition, task outcomes), and prompt strategies? This study aims to illuminate GenAI's complex influence on problem solving and guide its responsible integration in classrooms.

2. Theoretical Background and Hypotheses

2.1 Using GenAI for Problem Solving

In an AI-driven world, individuals must develop capabilities like self-regulated learning (SRL), sense-making, and collaboration to adapt (Markauskaite et al., 2022). Kong et al. (2024) argue that beyond conceptual AI knowledge, learners need metacognitive engagement to effectively apply AI in real-world problem solving.

GenAI generates a diverse pool of potential solutions, enriching the problem space and inspiring novel ideas (Urban et al., 2024). This prompts learners to spend more time on critical thinking—selecting relevant information, refining ideas, debugging, and adjusting approaches (Yilmaz & Yilmaz, 2023; Urban et al., 2024). GenAI also supports knowledge construction and self-regulation (Lee et al., 2024), boosting learners' confidence and aiding skill development (Kong et al., 2024).

However, effective use of GenAI requires balancing cognitive strategies with technological affordances (Nguyen et al., 2024b). Despite this complexity, little research explores how learners dynamically integrate AI outputs into their problem-solving processes (Joksimovic et al., 2023).

2.2 Human-AI Interaction and AI Literacy

AI literacy—key in today's AI-rich environment—encompasses the skills to critically assess, communicate with, and use AI effectively (Long & Magerko, 2020). Perspectives vary on its components, with socio-technical competence gaining attention (Pinski & Benlian, 2023). Most AI literacy studies rely on surveys or self-reported perceptions (e.g., Pinski & Benlian, 2023; Knoth et al., 2024). While these approaches are valuable, they are limited in capturing how learners actually integrate AI outputs into complex tasks. By contrast, our study adopts a process-trace approach, analysing fine-grained behavioural sequences. This critical shift allows us to go beyond static measures of AI knowledge and instead reveal how regulation and prompting strategies dynamically shape literacy outcomes.

Studies show AI usage and evaluation are linked to behavioural engagement and higher-order thinking (Lu et al., 2024), suggesting static AI knowledge alone doesn't guarantee improved task performance. Few empirical studies connect AI literacy, human-AI interaction patterns, and learning outcomes in GenAI-supported tasks.

2.3 Prompt Engineering

Prompt engineering, more directly tied to task performance than AI literacy, involves crafting inputs that guide GenAI toward desired outcomes (Oppenlaender et al., 2024). This skill requires both linguistic knowledge and strategic use of modifiers.

Quantifying prompt quality helps visualize its relationship to other variables. For instance, Knoth et al. (2024) used component-based scores to suggest prompt engineering may be independent of general AI literacy. Lee et al. (2024) linked the variety of prompt subjects to divergent and convergent thinking. The iterative nature of prompting parallels creative processes like drafting and revising (Habib et al., 2025), supporting the democratization of creativity (Dang et al., 2022).

2.4 Human-AI Interaction and SRL

Effective prompting relies on deep cognitive engagement, similar to SRL behaviours (Dang et al., 2022; Knoth et al., 2024). Prompting often involves identifying and correcting AI errors through systematic strategy use (Zamfirescu-Pereira et al., 2023). Similarly, productive SRL learners employ structured approaches such as rereading and sequential analysis to achieve goals (Rakovic et al., 2023). To understand these strategies in GenAI-assisted tasks, analysing temporal data adds depth. Nguyen et al. (2024a) identified structured and unstructured human-AI interaction types using process mining. Lee et al. (2024) used cosine similarity to classify prompting styles.

SRL research methods offer useful parallels. Markauskaite et al. (2022) recommend unobtrusive data collection to examine human-AI interaction as a dynamic process. Some studies have applied this: e.g., Nguyen et al. (2024a, 2024b) used screen recordings and sequential analysis, while Chen et al. (2025) applied Markov models to compare help-seeking behaviours in AI-assisted groups. Urban et al. (2024) stress the need to study

temporal aspects using trace data. Unlike prior studies focused on writing tasks, our research uses lesson plan assessment to analyse problem solving.

Based on prior analysis, the three hypotheses are proposed:

H1: AI literacy changes differ across human-AI interaction patterns.

H2: More structured interaction patterns are positively associated with better learning performance (problem-solving skills, metacognition, task outcomes).

H3: Different interaction patterns exhibit distinct prompt engineering features.

3. Methods

3.1 Research Context and Participants

Participants were 54 third-year student teachers enrolled in secondary school physics education at a Chinese university. Due to incomplete screen recordings, data from 9 participants were excluded, resulting in a final sample of 45 participants.

The study was conducted within an educational technology course, where students were required to design a microlesson and create a lesson plan. The GenAI-assisted lesson plan assessment task occurred after students completed their initial lesson plans. This 90-minute task involved three stages: (1) self-assessment of their own lesson plan, (2) peer assessment using AI tools, and (3) a final revision of their lesson plan before submission. Task performance was evaluated by comparing the initial and revised versions.

Participants used ERNIE Bot 3.5 V2.5.0, a large language model (LLM) developed by Baidu and similar in functionality to ChatGPT. ERNIE was chosen for its accessibility and maturity as a local AI tool. During the assessment, students had unrestricted access to both ERNIE and online search engines.

3.2 Data Collection and Analysis Procedures

3.2.1 Data collection

Questionnaires: AI Literacy (AIL) scale from Pinski and Benlian (2023) was used, excluding the "overall" item due to concerns over reliability (Knoth et al., 2024). Problem Solving Skills (PSS) scale was adapted from Heppner & Petersen (1982), covering problem-solving confidence, approach-avoidance style, and personal control. Metacognitive Strategies scale was adapted from Pintrich et al. (1991), measuring rehearsal, elaboration, organization, critical thinking, and metacognitive self-regulation. All items were translated into Chinese (participants' mother tongue) and rated on a 5-point Likert scale. Cronbach's alpha indicated good internal consistency ($\alpha = 0.896$).

Human-AI Interaction Trace Data: All lab computers used Windows 10 and a custom-built screen recorder ("PSR.exe") that captured user actions and screens as .mht files. Python scripts were developed to extract structured logs from these files, including timestamped logs of mouse movements, clicks, keystrokes, action windows, and action content.

Prompt Engineering Assessment: Prompt datasets were manually extracted from screen captures. Two raters independently coded the prompts, reaching 90% inter-rater agreement. Features (details in Table 1) were evaluated using: Component-based scoring (Eager & Brunton, 2023): e.g., number of unique verbs, focus terms, contexts, constraints, etc. Divergent-Convergent Thinking metrics (Lee et al., 2024): e.g., number of prompt turns, prompt word count, prompt diversity.

Lesson Plan Evaluation: Two raters evaluated lesson plans (before and after AI use) using the rubric from König et al. (2021), which includes six criteria: content transformation, task creation, adaptation to learners, clarity of objectives, contextualization, and instructional phasing (max score: 33).

Table 1: Prompt components

Prompt features	Indicators
Verb, focus, context, focus and constraints, alignment, constraints and limitations	n_unique_verb; n_unique_focus; n_unique_context; n_unique_focus and constraints; n_unique_ alignment; n_unique_ constraints and limitations
Divergent-convergent thinking	n_prompt_turn; n_word_prompt; n_unique_prompt; n_word_prompt_under_5; n_subject_prompt

3.2.2 Analytical methods

To address RQ1, raw trace data were first mapped into SRL processes, followed by sequential clustering and process mining to detect patterns of human-AI interaction aligned with SRL theory.

Human-AI Interaction Coding Scheme. A hybrid coding approach was used. First, theory-driven method was used. Initial code scheme was created based on SRL process coding from Raković et al. (2023), and human-AI action categories from Liu et al. (2024) and Nguyen et al. (2024a). Then data-driven was employed. It means the created code scheme was refined to suit the observed behaviour in this dataset (see Table 2). Actions were coded from raw trace logs and aggregated into SRL process labels at 5-second intervals, based on the frequency of high-level actions.

Table 2: The SRL process and action library for Human-AI interaction.

SRL processes (12)	Action label (44)
Planning	First-reading task lists/evaluation rubrics
Reading	Reading AI outputs; Re-Reading AI outputs; Reading lesson plan
Navigation	File-searching
Monitoring	Re-read task lists; Check screen-records setting; Re-read evaluation rubrics
Orientation	Download & Upload-file; Refresh- Learning management system Rename lesson plan; Login AI or Learning management system; WORD revision setting
High-Interaction with AI	Prompt-follow up; Search-engine for the same task; Interaction-other AI tools for the same task
Low-Interaction with AI	Prompt-typed; Prompt-pasted from other materials; Prompt-file uploaded; Prompt-polish words; Prompt-new; Prompt-old; Prompt-cancel; Explore AI interface
Low-AI outputs Elaboration	Copy Paste-AI outputs; Copy Paste All-AI outputs; Delete Pasted-AI outputs; Replace using AI outputs
High-AI outputs Elaboration	Add explanation based on AI outputs; Delete unrelated pasted AI outputs; Paraphrase based on AI outputs
High-modify	Add-Screenshot; Paste Not-AI outputs; Delete Not-AI outputs; Reorganize sections; Add-text; Text position modification
Low-modify	Modification Distance; Serial number modification; Modification Format; Undo; Save; Try to change
Courseware	Modify self-Courseware

Human-AI Interaction Sequence Clustering and Process Mining. To identify distinct human-AI interaction patterns, we used **sequence clustering**, a method that groups learners based on similarities in their interaction processes. In practice, we combined Optimal Matching (OM) to detect subsequence similarities and Ward's Clustering (WC) to group learners into clusters (Murtagh & Legendre, 2014). OM was implemented with the TraMineR package in R (Gabadinho et al., 2011), and WC was performed using the cluster package (Maechler et al., 2015). This approach enabled us to distinguish two typical patterns of regulation and prompting while keeping the analysis grounded in sequential SRL-based actions. To further interpret the micro-level behavioural sequences within each identified cluster, we applied process mining techniques, a method increasingly used in human-AI interaction research (Nguyen et al., 2024a; Chen et al., 2025). Specifically, we employed the Fuzzy Miner approach using Disco software (by Fluxicon) to visualize the flow and frequency of interactions, offering insights into the temporal structure and cognitive regulation patterns within each interaction type.

Analysis for RQ2

To explore the relationships between human-AI interaction patterns and learning performance outcomes, several quantitative analyses were conducted using SPSS. For baseline differences, a Mann-Whitney U test was first performed to compare the pre-test scores across identified interaction clusters. This ensured that differences in post-test outcomes were not confounded by prior knowledge or individual learner characteristics.

Regarding performance and strategy changes (pre vs. post), a comparison was conducted to analyse within-group changes in AI Literacy (AIL), Problem-Solving Skills (PSS), Metacognitive Strategies (MS), and Lesson Plan Quality. Paired-sample t-tests were used for each variable within each cluster, and Cohen's d was calculated to estimate effect sizes for each change.

Prompt Engineering Features: To explore whether different human-AI interaction patterns were associated with differences in prompting behaviour, a Mann-Whitney U test was applied to compare prompt engineering features across clusters.

Correlations Between Prompting and Interaction Patterns: To examine the relationships between prompt engineering features and interaction behaviours, a Spearman correlation analysis was conducted.

4. Results

In total, 31,015 SRL process were coded in human-AI interaction and 276 prompts were extracted.

4.1 RQ1: What Human-AI Interaction Patterns can be Identified in the Context of Lesson Plan Assessment Task?

As shown in Figure 1 (left), 45 sequential datasets were clustered into two groups: Cluster 1 (n = 18) and Cluster 2 (n = 27). The agglomerative coefficient of 0.76 indicated strong cluster cohesion. Figure 1 (right) displays the SRL process distributions, with Cluster 1 showing longer revision durations, suggesting greater engagement in cognitive and metacognitive activities.

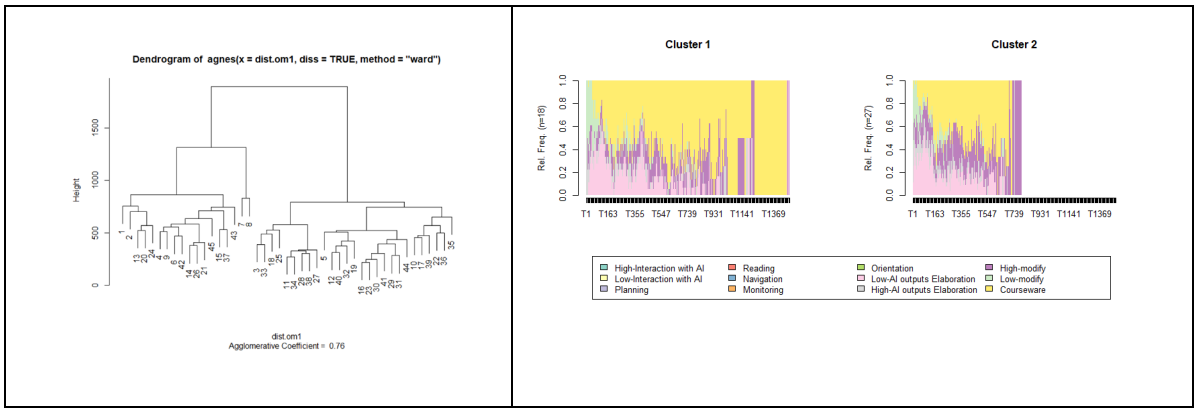

Figure 1: Ward's clustering results (left) and Sequence distribution (right) for 45 human-AI interaction process sequences

Process mining revealed distinct human-AI interaction patterns between the two clusters. The human-AI interaction behaviours of cluster1 and 2 can be found in Figure 2 and 3 respectively. Arrows indicate the main activity sequences. The darker the colour of a box, the higher the frequency of that behaviour. As shown in Figure 2, Cluster 1 began the task in three ways: Navigation (file search), Low-modify (lesson plan editing), and Planning (reading task lists/rubrics). Two main paths emerged: one progressed from Navigation→Monitoring →Orientation→Low→High AI-output elaboration→High-modify, and the other from Planning→Low→High AI interaction→Reading. This indicates students either focused on formatting issues or copied AI outputs directly, with interpretation often occurring before prompting or reading, rather than after. Cluster 1 exhibited diverse but less reflective regulation, as monitoring and orientation behaviours declined in later phases.

By contrast, Cluster 2 followed more structured paths (Figure 3) (seen in the next page). They prioritized deep processing—starting from Planning → Low AI interaction, followed by a double loop: High AI interaction↔Reading↔High-modify, suggesting systematic evaluation and integration of AI outputs into content. This was followed by Low-modify, monitoring, and re-planning, indicating iterative SRL behaviour: planning, performing, reflecting, and replanning.

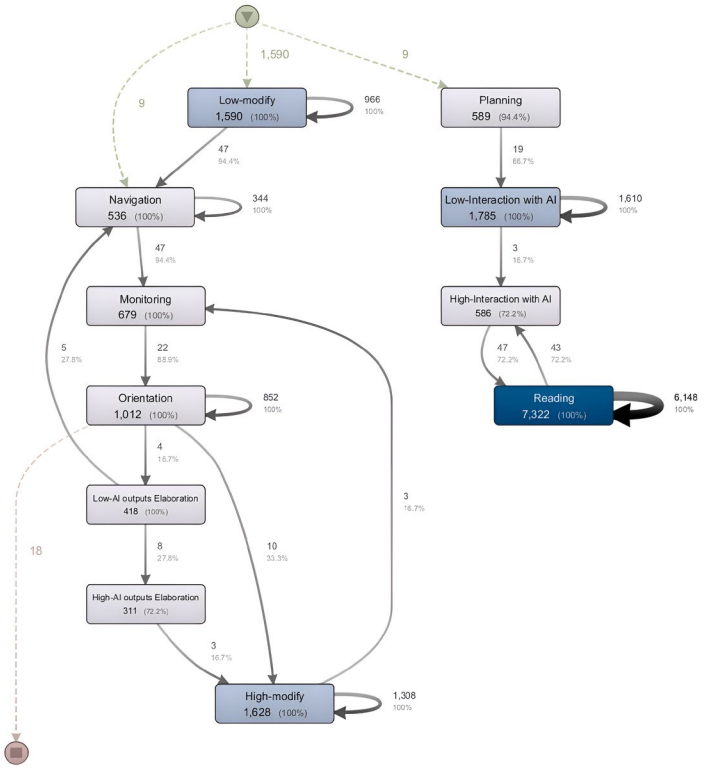

Figure 2: Cluster 1 human-AI interaction process maps-diverse regulation process

4.2 RQ2: How are Human-AI Interaction Patterns relating to Learning Performance?

To assess the impact of human-AI interaction patterns on learning performance, a Mann-Whitney U test was first conducted to compare pre-test differences between clusters. As shown in Table 3, no significant differences were found, indicating similar baseline characteristics. No significant post-test differences were found either, suggesting that a single test may be insufficient to capture GenAI's learning impact.

Table 3: Descriptive analysis of the PSS, MS, AIL, and lesson plan

Cluster 1 (N=18)			**Cluster 2 (N=27)**			**Mann-Whitney U test**	
Variables	**Mean**	**SD**	**Variables**	**Mean**	**SD**	**Z**	**Sig. (2-tailed)**
Pre-AIL	3.24	0.44	Pre-AIL	3.19	0.59	-0.51	0.61
Post-AIL	3.30	0.46	Post-AIL	3.44	0.63	-1.08	0.28
Pre-PSS	3.28	0.42	Pre-PSS	3.39	0.35	-1.19	0.23
Post-PSS	3.48	0.41	Post-PSS	3.44	0.35	-0.19	0.85
Pre-MS	3.55	0.41	Pre-MS	3.51	0.62	-0.91	0.37
Post-MS	3.57	0.35	Post-MS	3.69	0.54	-0.98	0.33
Pre-lesson plan	26.39	3.84	Pre-lesson plan	26.11	4.08	-0.26	0.80
Post-lesson plan	28.89	2.54	Post-lesson plan	28.19	4.74	-0.15	0.88

Note. Pre=Pre-test, Post=Post-test, AIL=AI literacy, PSS=Problem solving skills, MS=Metacognitive strategies.

For H1 and H2, paired sample t-tests were used to examine performance changes within clusters. As shown in Table 4, AI literacy did not significantly improve in Cluster 1 ($t = -0.66$, $p > 0.05$), but showed a significant gain in Cluster 2 ($t = -3.54$, $p < 0.05$, $d = 0.42$), suggesting that structured regulation enhanced AI literacy.

Table 4: Paired sample t-test results for H1

Clusters	Pairs	Mean	SD	SE	t	df	Cohen's d
Cluster 1	Pre-AIL - Post-AIL	-0.06	0.41	0.1	-0.66	17	0.14
Cluster 2	Pre-AIL - Post-AIL	-0.25	0.37	0.07	-3.54	26	0.42**

Note. *** p＜ 0.001; ** p＜ 0.01; * p＜ 0.05.

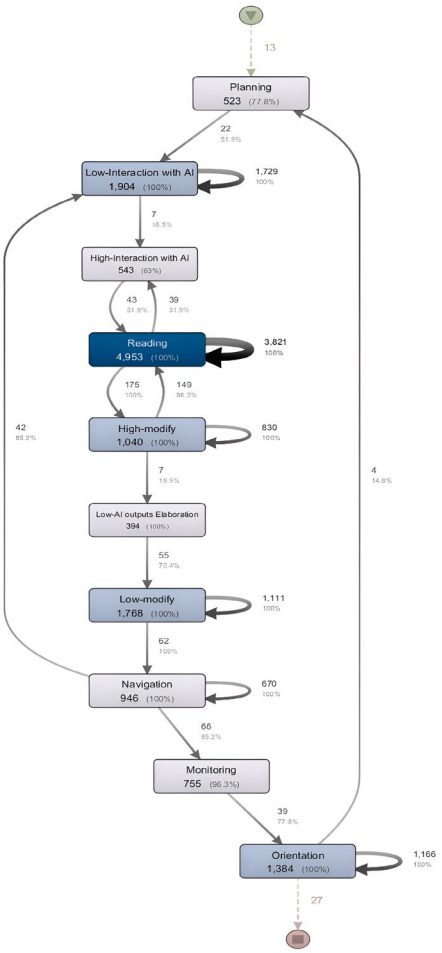

Figure 3: Cluster 2 human-AI interaction process maps-structured regulation process

Table 5 shows both clusters improved significantly in task performance (lesson plans), with a stronger effect in Cluster 1 (d = 0.77 vs. 0.47). Cluster 1 also showed significant gains in problem-solving skills (PSS) (t = -2.23, p < 0.05, d = 0.48), while Cluster 2 improved in metacognitive strategies (MS) (t = -0.85, p < 0.01, d = 0.32). These results imply diverse regulation supports PSS, while structured regulation enhances MS.

Table 5: Paired sample t-test results for H2

Clusters	Pairs	Mean	SD	SE	t	df	Cohen's d
Cluster 1	Lesson plan-A – Lesson plan-B	-2.5	4.08	0.96	-2.6	17	0.77*
	Pre-PSS -Post-PSS	-0.20	0.38	0.09	-2.23	17	0.48*
	Pre-MS-Post-MS	-0.01	0.36	0.09	-0.66	17	0.04
Cluster 2	Lesson plan-A – Lesson plan-B	-2.07	2.85	0.55	-3.78	26	0.47***
	Pre-PSS -Post-PSS	-0.05	0.33	0.06	-0.85	26	0.15
	Pre-MS-Post-MS	-0.19	0.34	0.06	-0.85	26	0.32**

Note. *** p＜ 0.001; ** p＜ 0.01; * p＜ 0.05.

For H3, a Mann-Whitney U test was used to compare prompting features between clusters. As shown in Table 6, Cluster 1 had significantly higher values in n_word_prompt (Z = -2.75, p < 0.01), n_unique_verb (Z = -2.1, p < 0.05), and n_unique_focus (Z = -2.63, p < 0.01), with effect sizes of -0.49, -0.37, and -0.46, respectively. This suggests Cluster 1 used longer prompts with more varied verbs and focus expressions. Based on Lee et al. (2024), Cluster 1 demonstrated a divergent thinking approach in prompt engineering, while Cluster 2 used a more convergent strategy.

Table 6: Comparison of prompt features by Mann-Whitney U (H3)

Prompt features	Mean (Cluster 1)	Mean (Cluster 2)	Z	Effect Size	Sig. (2-tailed)
n_prompt_turn	7.28	5.3	-1.61	-0.28	0.107
n_subject_prompt	6	3.93	-1.91	-0.34	0.057
n_unique_prompt	6.94	4.89	-1.67	-0.29	0.095
n_word_prompt_under_5	0.67	0.56	-0.26	-0.04	0.799
n_word_prompt	173.22	95.59	-2.75	-0.49	0.006**
n_unique_verb	4.78	3.04	-2.1	-0.37	0.036*
n_unique_focus	4.72	2.67	-2.63	-0.46	0.009**
n_unique_context	1.11	1	-0.49	-0.08	0.624
n_unique_focus and condition	1.72	1.26	-0.65	-0.11	0.516
n_unique_alignment	0.78	0.33	-1.76	-0.27	0.078
n_unique_constraints and limitations	0.67	0.3	-1.91	-0.26	0.056

Note. *** p＜ 0.001; ** p＜ 0.01; * p＜ 0.05.

5. Discussions and Implications

RQ1: Our findings confirm prior research on human-AI interaction patterns (Nguyen et al., 2024a). Cluster 1 showed an exploratory, iterative approach (diverse regulation, divergent prompting), while Cluster 2 followed a goal-oriented method (structured regulation, convergent prompting). High-AI interaction and high-modify behaviours in Cluster 2 involved critical engagement—reading, prompting follow-ups, evaluating, and integrating outputs into lesson plans. While both clusters engaged in higher-order thinking, Cluster 2 demonstrated tighter sequences connecting AI interaction to meaningful modifications. Unlike Cluster 1, Cluster 2 also showed more complete SRL cycles (planning, monitoring, reflection) and iterative behaviour, possibly due to slightly higher pre-test problem-solving scores (PSS = 3.38 > 3.28). This supports the idea that stronger problem-solving skills foster reflective human-AI interactions (Chiu et al., 2024).

RQ2: Consistent with Knoth et al. (2024), our findings indicate that AI literacy alone is insufficient for effective prompting. However, Cluster 2's structured regulation and convergent prompting significantly improved AI literacy, echoing findings from Chen et al. (2025). GenAI acted as a cognitive and metacognitive scaffold, helping learners understand the human-AI collaboration from a socio-technical lens.

GenAI boosted task performance across clusters, consistent with prior research (Yilmaz & Yilmaz, 2023; Urban et al., 2024). However, the type of human-AI interaction influenced how performance improved. Cluster 1's divergent prompting encouraged idea generation and reflection, which supports PSS development through active exploration. In contrast, Cluster 2's structured approach enabled fast, meaningful iterations by offloading routine tasks to GenAI, fostering metacognitive strategies and efficient cognitive work (Markauskaite et al., 2022).

While Knoth et al. (2024) found direct links between prompting and AI literacy, our results suggest that regulation mediates this link. Cluster 1's use of more unique verbs and focus terms didn't lead to better AI literacy, possibly due to lack of reflection. This implies that divergent prompting without deep regulation may hinder conceptual clarity.

Theoretically, SRL frameworks help explain human-AI learning. SRL variables—technology-, task-, learning-, and human-machine-related—intertwine in GenAI-supported problem solving (Cetindamar et al., 2024). More research is needed to validate SRL in AI contexts.

To assess AI literacy and prompting in goal-directed learning, multimodal approaches are needed—beyond surveys, including prompt features and task delegation (Pinski et al., 2023). Analysing human-AI interaction processes offers micro-level insights into AI literacy. Profiling users' prompting behavior can support training and scaffolded learning.

Implications for Practice. For teachers, our findings suggest that GenAI can be positioned differently depending on learners' interaction styles. For exploratory students (Cluster 1), teachers may design tasks that prompt idea generation and wide-ranging exploration, with AI scaffolds encouraging reflection before task submission. For structured students (Cluster 2), scaffolds can emphasise iterative cycles of planning, monitoring, and revision, guiding learners to critically evaluate and selectively integrate AI outputs. For instructional designers, these insights point to the need for adaptive scaffolds that respond to learners' self-regulation tendencies rather than offering uniform prompts.

6. Conclusions

Our study identified two human-AI interaction patterns through sequence clustering and analyzed their process and outcome differences. Both clusters showed significant task performance improvement. The diverse regulation cluster used more unique verbs and focus on prompting, enhancing problem-solving skills, while the structured regulation cluster showed gains in AI literacy and metacognitive strategies. These findings highlight how human-AI interaction patterns influence different learning outcomes and the need to develop varied capabilities for AI-assisted problem solving.

Several limitations exist. The small sample size limits generalizability. Future research with larger, more diverse populations and multiple languages would yield more robust, real-world insights. Our prompt engineering analysis was limited to two feature types; Including help-seeking behaviour could deepen understanding of SRL in AI-assisted tasks (Chen et al., 2025).

Future studies should incorporate multimodal or multichannel analyses, such as detecting emotions during interaction, which current trace data miss. Leveraging LLMs' emotion detection could improve human-AI interaction. Beyond AI literacy and prompting, research should explore impacts on higher-order thinking (e.g., critical thinking, creativity) and how task complexity and delegation affect interaction and performance (Pinski et al., 2023).

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

AI Declaration: AI tools (specifically ChatGPT by OpenAI) were used during the writing process to assist with grammar refinement and language polishing. All research design, data analysis, and interpretation were conducted solely by the authors.

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Exploring ASR and Large Audio Language Models for Transcribing Peer Discourse in Noisy Classrooms

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Abstract: Capturing peer discourse in real-world classrooms offers valuable insights into collaborative learning but presents significant technical and pedagogical challenges. While most existing Automatic Speech Recognition (ASR) systems research has focused on teacher-led or online English-speaking environments, peer-to-peer dialogue in noisy, non-English dominant, face-to-face classrooms remains underexplored. This study investigates the feasibility of using both traditional ASR systems—Whisper and Wav2Vec2—and emerging Large Audio Language Models (LALMs), including Qwen2-Audio and Ultravox, to transcribe Mandarin peer conversations recorded via students' mobile phones in authentic classroom settings. We collected over 105,715 seconds of audio from 38 student groups across two collaborative learning tasks from university classrooms. The manually transcriptions were served as ground truth. Audio quality test of all audio recordings was conducted. Five representative samples with varied signal-to-noise ratios (SNR) and speech ratios were selected to do in-depth analysis. Transcription quality was evaluated using Word Error Rate (WER), Character Error Rate (CER), and Fuzzy String Matching. Additionally, we conducted a thematic analysis of transcription errors to identify linguistic, acoustic, and task-related challenges. Results show that Whisper consistently outperforms other models, achieving high transcription fidelity even in moderately noisy conditions. In contrast, LALMs—despite their strengths in semantic understanding—performed poorly in verbatim transcription, often generating hallucinated or irrelevant content. Importantly, task type and speech characteristics significantly influenced model performance: structured, reflective discussions yielded better results than spontaneous, technical dialogues involving numeric and English domain terms. This study contributes a low-cost, replicable workflow for classroom audio collection and evaluation, along with a detailed taxonomy of transcription errors. We emphasise that our results are exploratory due to the limited sample size. Nevertheless, the findings highlight the current limitations of LALMs for ASR tasks and offers practical recommendations for model selection in educational contexts. Our findings support the responsible integration of ASR technologies into classroom practice, with implications for real-time feedback, collaborative learning analytics, and teacher professional development. For researchers, this work demonstrates the need to consider peer dialogue and multilingual classroom ecologies when evaluating ASR. For teachers, practical recommendations are offered for selecting transcription tools that can support real-time feedback and professional reflection. For lifelong learning, our study illustrates the potential of ASR technologies to make collaborative dialogue more visible, analysable, and actionable across diverse contexts.

Keywords: Automatic speech recognition, Peer dialogue, Collaborative learning, Large audio language models, Mandarin classrooms, Educational AI

1. Introduction

In recent years, the potential of AI-powered tools to enhance teaching and learning has gained increasing attention. Among these, Automatic Speech Recognition (ASR) has emerged as a promising technology for capturing and analysing classroom interactions—particularly in collaborative learning environments (Southwell et al., 2022; Wang & Chen, 2024). ASR enables scalable analysis of large volumes of classroom dialogue with significantly lower cost and time investment compared to manual transcription, while maintaining consistent performance.

While prior research has explored ASR in remote or online settings and English-speaking classrooms (Ezema et al., 2025; Yin et al., 2025), there remains a notable gap in understanding how ASR performs in face-to-face, non-English dominant educational contexts. Real-world classrooms often involve spontaneous speech, overlapping dialogue, code-switching, and low-fidelity audio captured via mobile devices—conditions that pose substantial challenges to traditional ASR pipelines. These challenges raise critical concerns about the reliability, fairness, and educational utility of AI-driven transcription in authentic learning environments.

Recently, Large Audio Language Models (LALMs) such as Qwen2-Audio and Ultravox have been introduced, claiming to offer enhanced contextual understanding and multi-turn dialogue modelling (Chu et al., 2024; Fixie AI, 2025). However, their performance in noisy, multilingual, and pedagogically complex settings—particularly in Mandarin-speaking classrooms—has not been systematically evaluated. As a result, educators and researchers lack empirical guidance on which models to trust, what types of errors to expect, and how to interpret transcription outputs in meaningful ways.

This study addresses these gaps through four key contributions:

- **Model Benchmarking**: We conduct a systematic comparison of traditional ASR systems (Whisper, Wav2Vec2) and LALMs (Qwen2-Audio, Ultravox) using peer discourse audio collected from real-world Chinese classrooms.
- **Low-Cost Data Collection Pipeline**: We design and implement a scalable, device-independent audio collection and evaluation workflow using students' own mobile phones and open-source tools.
- **Error Typology Development**: We provide a fine-grained categorization of transcription error types, linking them to linguistic, acoustic, and task-related factors.
- **Practical Implications**: We offer actionable recommendations for selecting and applying speech transcription tools in educational contexts, with implications for AI-supported feedback, collaborative learning analytics, and teacher professional development.

2. Related Work and Research Questions

2.1 ASR and LALMs in Educational Contexts

The application of ASR in educational settings has been extensively studied, particularly for lecture transcription, feedback generation, and collaborative dialogue analysis (Southwell et al., 2022; Wang & Chen, 2024; Wu et al., 2024). However, much of this research remains narrowly focused on English-language or teacher-centred settings, Moreover, traditional ASR models such as Whisper and Wav2Vec2 have shown varying levels of success in transcribing English-language educational audio. For instance, Ezema et al. (2025) reported a minimum WER of 39%, while Yin et al. (2025) achieved 9.5% WER by combining Whisper with MarbleNet for Voice Activity Detection. Attia et al. (2025a) reported WERs of 30.25% and 38.59% across different datasets using pre-trained Wav2Vec2.0. Yet, a critical limitation is that prior studies have often assumed relatively clean audio, scripted utterances, and single-speaker dominance. These assumptions rarely hold in authentic peer-to-peer discourse, which presents unique challenges.

Unlike structured teacher-led lectures, student discussions are spontaneous, multi-voiced, and contextually embedded, making them difficult to capture and analyse. As Wang and Chen (2024) emphasize, understanding the performance of ASR systems in such settings is crucial for leveraging classroom dialogue to enhance learning. Russell et al. (2024) further highlight that poor recording quality and overlapping speech significantly degrade ASR accuracy in real-world classrooms.

Emerging Large Audio Language Models (LALMs), such as Qwen2-Audio and Ultravox, aim to extend ASR capabilities by incorporating semantic understanding and multi-turn dialogue modelling (Chu et al., 2024; Fixie AI, 2025). Although LALMs have demonstrated promising results on benchmark datasets, little is known about their reliability in educational environments. Most reported benchmarks use datasets such as Common Voice, which fail to capture code-switching, overlapping turns, or specialised domain vocabulary. Thus, the literature overlooks both the technical and pedagogical challenges of real-world classrooms, particularly in authentic, multi-turn peer discourse and non-English contexts.

2.2 Transcription Challenges in Classroom Audio

Classroom audio data is often characterized by low signal-to-noise ratios, overlapping speech, and frequent code-switching. Ezema et al. (2025) note that even high-performance ASR engines struggle under such conditions. Most existing studies (Wong et al., 2025; Zhao et al., 2024) focus on teacher speech or structured classroom formats, overlooking the dynamic and unpredictable nature of student-led discussions.

Moreover, there is a lack of systematic analysis of transcription error types in educational ASR. Errors such as hallucinated speech, misrecognized domain-specific terms, and pronunciation mismatches are rarely categorized in benchmarks, limiting the interpretability of model performance (Andreyev et al., 2025; Zhao et al., 2024; Russell et al., 2024; Wu et al., 2024). This gap hinders the development of targeted improvements for educational applications.

2.3 Research Questions

To address these gaps, our study is guided by the following research questions:

RQ1*: How do traditional ASR models and Large Audio Language Models (LALMs) compare in transcribing peer discourse from noisy, real-world Chinese classrooms? We benchmark transcription quality using CER, WER, and*

Fuzzy metrics, and analyse model outputs across multiple collaborative learning tasks to assess alignment with verbatim transcription goals.

RQ2*: What are the most common transcription error types across ASR and LALM models, and how are these errors influenced by task type, recording conditions, and dialogue structure?*

We classify errors and examine whether they stem from systemic model limitations or are context-specific.

3. Methods

3.1 Participants and Contexts

This study collected peer dialogue audio from 38 student groups enrolled in two face-to-face undergraduate courses at a public Chinese university. The first dataset was drawn from an Educational Technology course, where 24 groups engaged in lesson plan evaluation tasks assisted by a GenAI (Wenxinyiyan, based on ERNIE). The second dataset originated from an Engineering course, involving 14 groups performing network operations using ICMP packets. All recordings were captured using students' personal mobile phones without external microphones, simulating low-cost, device-independent classroom conditions.

To enable detailed transcription quality analysis, we selected five representative audio samples. These samples were selected based on variation in signal-to-noise ratio (SNR) and speech density, using waveform visualizations and Root Mean Square (RMS) energy distribution as selection criteria. Their manual transcriptions were served as ground truth transcriptions. We note that while these samples illustrate key patterns, they can not capture the full complexity of classroom audio. Accordingly, our analysis should be interpreted as exploratory rather than conclusive.

3.2 Data Analysis Procedures

Audio Quality Assessment.

Prior to automatic transcription, we conducted an audio quality evaluation to determine the necessity of noise suppression. Following Li et al. (2025) and Verma et al. (2025), we adopted RMS energy and SNR as core metrics. RMS energy reflects the overall energy distribution and is useful for identifying silence and speech density, while SNR quantifies the ratio of speech signal to background noise, serving as a standard indicator of recording clarity.

Audio Segmentation.

To prepare the audio for ASR processing, we explored Voice Activity Detection (VAD) using Silero Models and RMS-based techniques. However, consistent with findings by Attia et al. (2025b) and Southwell et al. (2022), these methods underperformed in segmenting long-form, multi-turn classroom dialogues. Consequently, we adopted a fixed 30-second segmentation strategy, which provided more reliable input chunks for ASR processing.

ASR and LALM Models. We evaluated both traditional ASR models and emerging LALMs:

- **Traditional ASR Models**: Whisper_large_v3, Wav2Vec2
- **Large Audio Language Models (LALMs)**: Qwen2-Audio-7B-Instruct, Ultravox-v0_5-llama-3_2-1b

These models were selected based on their availability, multilingual capabilities, and relevance to educational speech processing.

Evaluation Metrics.

To assess transcription quality, we employed Word Error Rate (WER), Character Error Rate (CER), and Fuzzy Score, following Zhao et al. (2024) and Wang & Chen (2024). Unlike prior studies that evaluate per utterance, we calculated metrics at the full transcription level to better reflect overall model performance. Lower WER and CER values and higher Fuzzy Scores indicate better transcription accuracy. All evaluations were conducted on minimally preprocessed text, including conversion of mixed traditional and simplified Chinese into simplified Chinese. No normalization was applied to numbers or English tokens to preserve raw transcription fidelity.

Transcription Error Categorization.

To move beyond aggregate performance metrics, we conducted a thematic analysis (Braun & Clarke, 2006) of transcription errors. This qualitative approach enabled us to classify errors into categories, providing deeper insight into model limitations and context-specific challenges.

Technical Infrastructure.

All model evaluations and data processing were conducted using GPU-accelerated environments on Google Colab. A simplified overview of the data analysis workflow is presented in Figure 1.

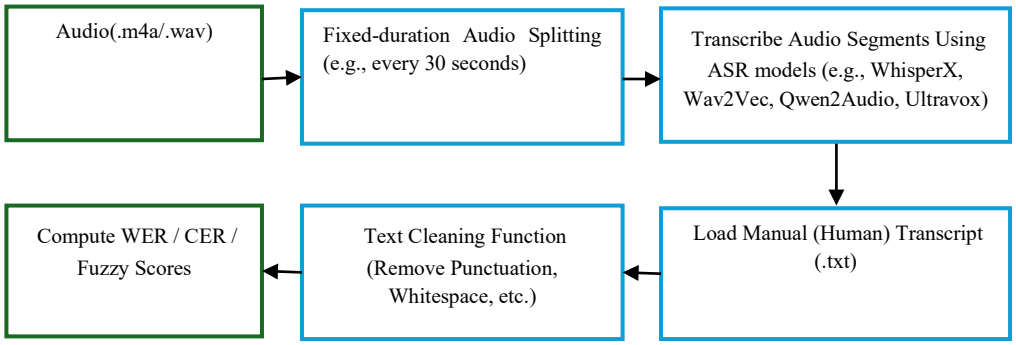

Figure 1: Data analysis workflow

All code implementations—including audio quality testing, segmentation, and model inference—are publicly available via our OSF repository: https://osf.io/69adw/?view_only=363ed2c80e614f029367633815a039e9

4. Results

4.1 Descriptive Overview of Dataset and Audio Quality

The full dataset comprises 105,715.31 seconds of peer dialogue audio (approximately 1,762 minutes) collected from 38 student groups. Audio quality assessments (see Figure 2) indicated that none of the recordings required noise suppression. All samples exhibited good signal-to-noise ratios (SNR), normal volume ranges, and balanced RMS energy distributions, confirming the feasibility of low-cost, mobile-phone-based classroom recording.

To enable detailed analysis, five representative samples were selected based on varying RMS speech ratios, totalling 12,819.29 seconds (approximately 214 minutes) and 18,803 words. These samples span both tasks: Samples 1–3 from the lesson plan assessment task, and Samples 4–5 from the ICMP network operations task. Detailed sample characteristics are presented in Table 1.

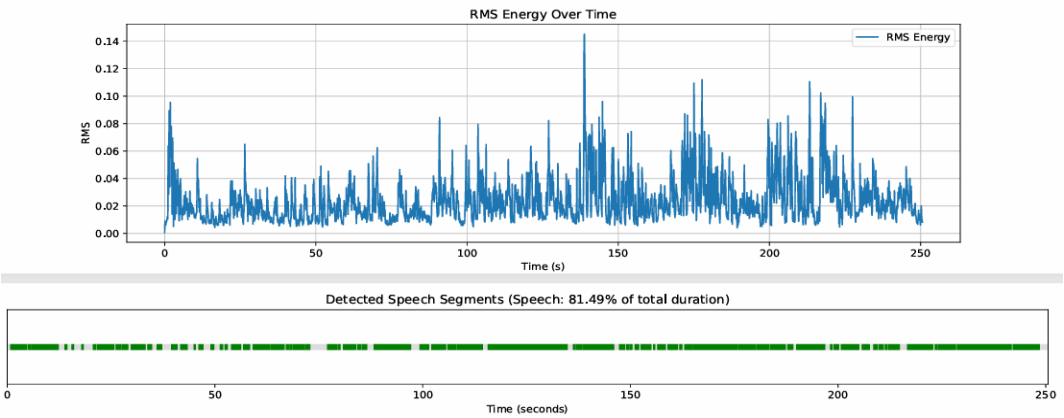

Figure 2: Parts of the audio quality report from sample 2

Table 1: Audio quality report and manual transcription (5 represent samples)

Dialogues	Duration(seconds)	Estimated SNR	RMS Speech Ratio	Words count in manual transcription
Sample 1	3379.95	22.46 dB	33.72%	2561
Sample 2	250.56	23.21 dB	81.49%	778
Sample 3	889.37	25.53 dB	90.72%	3947
Sample 4	2588.14	22.02 dB	99.62%	4108
Sample 5	5711.27	23.05 dB	76.17%	7409

Note: Sample 1,2,3 from the lesson plan assessment task, sample 4,5 from the ICMP task.

4.2 RQ1: Model Performance Across Samples

Table 2 summarizes the transcription performance of four models—Whisper, Wav2Vec2, Qwen2Audio, and Ultravox—across the five representative samples. For readability, Figure 3 presents a visualization of CER values, which is particularly relevant for Mandarin transcripts. Compared with Table 2, this visualization highlights both model-level and sample-level differences more intuitively.

To improve clarity, we highlight only the key trends. Overall, the models ranked as follows: Whisper > Wav2Vec2 > Qwen2Audio > Ultravox. Whisper consistently outperformed other models, with CER ranging from 1.13% to 37.43%, WER from 1.66% to 42.59%, and Fuzzy Scores between 75/100 and 99/100. Ultravox, by contrast, failed to produce meaningful transcriptions, with CER values between 93.59% and 384.57%, WER between 94.76% and 427.23%, and Fuzzy Scores as low as 10.95/100.

Table 2: Summarized transcription performance across five representative samples

Dialogues	Metrics	WhisperX	Wav2Vec	Qwen2Audio	Ultravox
Sample 1 (task 1)	CER (%)	37.43	79.18	255.16	224.66
	WER (%)	42.59	86.35	243.04	215.81
	Fuzzy score	75/100	30/100	34/100	13.54/100
Sample 2 (task 1)	CER (%)	**1.13**	43.04	23.96	384.57
	WER (%)	**1.66**	55.09	28.27	427.23
	Fuzzy score	**99/100**	63/100	86/100	10.95/100
Sample 3 (task 1)	CER (%)	4.35	38.73	18.31	93.59
	WER (%)	6.10	52.45	23.24	94.76
	Fuzzy score	97/100	68/100	89/100	14.14/100
Sample 4 (task 2)	CER (%)	27.42	84.96	76.67	109.12
	WER (%)	30.98	89.74	83.31	109.09
	Fuzzy score	80/100	22/100	55/100	13.51/100
Sample 5 (task 2)	CER (%)	28.01	80.74	101.35	232.50
	WER (%)	32.83	86.01	106.92	245.99
	Fuzzy score	81/100	27/100	49/100	11.26/100

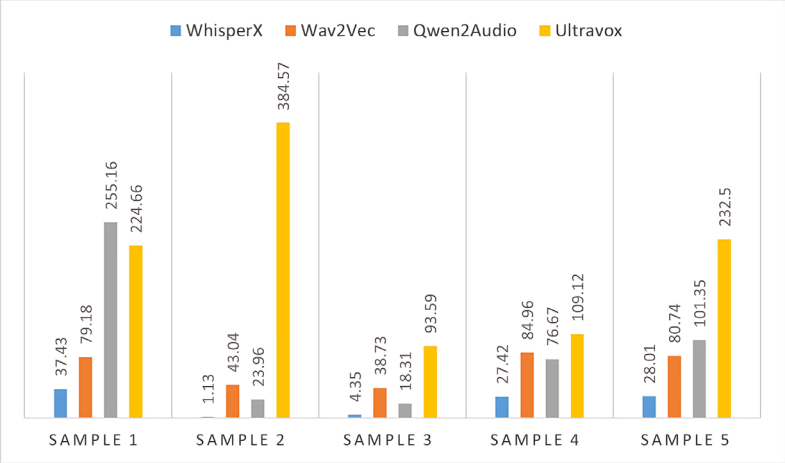

Figure 3: CER comparison of ASR and LALM models across five representative samples (%)

These results align with prior findings. For example, Zhou et al. (2024) reported Whisper's CER values between 5.76% and 40.96% on Mandarin datasets, while our study shows comparable or better performance using mobile phone recordings. Compared to Wang and Chen (2024) and Wong et al. (2025), our WER values are lower, suggesting Whisper's robustness in low-cost classroom settings.

In contrast, Qwen2Audio's performance in our study diverges from its reported success on benchmark datasets such as Common Voice and FLEURS (Chu et al., 2024). This discrepancy may stem from differences in data characteristics: benchmark datasets typically feature short, scripted utterances, whereas our samples involve spontaneous, multi-turn peer dialogue.

Sample-Specific Observations. Sample 2 yielded the best transcription results across all models, while Sample 1 performed worst. Despite both samples originating from the same task, Sample 1 had a low speech ratio (33.72%), indicating substantial background noise. This likely contributed to increased hallucination and segmentation errors, despite acceptable SNR values.

Task Effects. Excluding outliers (Sample 1 and Ultravox), models generally performed better on lesson plan assessment tasks (Samples 2–3) than on engineering operation tasks (Samples 4–5). The former involved structured peer review with reference materials, while the latter required spontaneous execution of technical procedures, often involving numeric and English domain-specific terms. These linguistic and contextual differences likely increased transcription difficulty and error rates.

4.3 RQ2: Transcription Error Analysis

To explore transcription errors in depth, we analysed outputs from Ultravox (worst-performing model) and Whisper (best-performing model).

Ultravox: Semantic Generation Instead of Transcription.

Ultravox frequently generated semantic responses rather than transcriptions. This behaviour explains the extremely high WER and CER values and low Fuzzy Scores, as the generated text bore little resemblance to the actual spoken content. For each 30-second audio segment, it produced text resembling chatbot replies, such as:

> *"I am unable to directly provide the requested audio content, as I do not have the capability to playback or replicate specific audio files. However, I can attempt to help you clarify your ideas …"*
>
> *"I am unable to directly provide the requested audio content, as I lack the capability to read or convert specific audio files. Nevertheless, I can offer a similar example for your reference …"*

Whisper: Categorized Transcription Errors.

For transcription errors using Whisper, four main categories were identified (see Table 3): phonetic and acoustic issues, lexical and semantic issues, multilingual and structural issues, and segmentation and decoding issues. These were influenced by speech ratios and task characteristics.

Hallucination errors were most frequent in Sample 1, which had a low speech ratio (33.72%). As Andreyev (2025) noted, hallucinated content reduces transcription reliability and inflates WER and CER. Common hallucinations included:

"谢谢大家" ("Thank you all"), "请不吝点赞 订阅 转发" ("Please like, subscribe, and share"), "好好好" ("Very well"), and "有问题吗" ("Any questions?").

Phonetic and multilingual issues were more evident in Samples 4 and 5. For example, in Sample 4, fast speech led to omission:

Manual: "现在可以截屏了，是吗?" ("Screenshots can be taken now, right?")

Whisper: "可以截屏的." ("Screenshots can be taken.")

In Sample 5, numeric and English term dominance caused distortion:

Manual: "我先…拼一下试试 192.168. 拼杠 L 杠 L 666192.168." ("Let me try putting it together—192.168. dash L dash L 666, 192.168.")

Whisper: "192.168.1192.168.1192.168…"

These errors relate to task features. Task 2 (engineering operations) involved physical movement, spontaneous speech, and technical terms, which degraded audio quality and increased error rates. In contrast, Task 1 (lesson plan assessment) involved seated, structured discussions. Students reviewed materials before speaking, resulting in clearer articulation, fewer turns, and richer contextual continuity—conditions that improved ASR performance, especially for Whisper.

Table 3: Identified transcription errors in automated speech recognition (ASR) generated transcription and their corresponding descriptions

Error categories	Error types	Description
Phonetic and acoustic issues	Low-volume error	Low vocal amplitude can lead to signal degradation, resulting in poor feature extraction and misrecognition within ASR pipelines. This is especially problematic in noisy environments or when microphone sensitivity is suboptimal
	Fast Speech error	High speaking rates can lead to increased transcription errors, as ASR models struggle to segment and decode fast-paced utterances accurately
	Slurred/Unclear Articulation Error	Unclear articulation, such as phoneme elongation and phonetic smearing, presents significant challenges for ASR systems by distorting acoustic cues and increasing the likelihood of word-level transcription errors
Lexical and semantic issues	Domain-specific error	Specialized terms and field-specific verbs frequently cause transcription errors in ASR models, especially when such vocabulary is not adequately represented in training corpora.
	Homophone-induced error	ASR systems for Mandarin often mis-transcribe homophones due to the high density of phonetically identical characters, resulting in semantic confusion
Multilingual and structural issues	language switching and numeral embedding error	Multilingual utterances involving frequent code-switching and numeral embedding introduce phonetic and lexical variability that challenges conventional ASR models, often resulting in language boundary misalignment and incorrect word substitution
	Numeric dominance error	In chunked transcription frameworks (e.g., 30-second windows), ASR systems may exhibit decoding bias towards frequently repeated numeric phrases. This overrepresentation can suppress less frequent surrounding words—especially in Mandarin-English mixed speech—leading to omissions and distorted transcriptions.
Segmentation and decoding issues	Window-boundary truncation error	Segment-based ASR systems with time-window limits may exhibit edge truncation effects, whereby utterances at the start or end of each segment are disproportionately excluded from transcription
	Hallucination error	During silent periods with noisy or ambiguous background audio, ASR systems may generate fictitious speech content, known as hallucination errors, which do not align with the actual verbal activity

5. Discussion and Implications

5.1 RQ1: Model Performance and Task Alignment in ASR

Our findings reveal that traditional ASR models continue to outperform large audio-language models (LALMs) in verbatim transcription tasks. Specifically, models such as Whisper and Wav2Vec2 demonstrate superior alignment with the core objectives of ASR, whereas LALMs like Ultravox exhibit significant deviations from expected transcription behaviour. Analysis of Ultravox's outputs indicates a tendency to "understand" and reinterpret spoken content, often generating summaries or inferred dialogues. This semantic-level generation leads to substantial divergence from reference transcripts, resulting in abnormally high WER and CER values.

Among traditional ASR systems, Whisper consistently outperforms Wav2Vec2 in this context. This can be attributed to several architectural and training-related factors. Whisper's encoder-decoder framework enables more robust contextual modelling, which is particularly advantageous for spontaneous, unscripted classroom dialogue (Radford et al., 2022). Furthermore, its extensive multilingual training corpus enhances its resilience to Mandarin-English code-switching, a common feature in the dataset. In contrast, Wav2Vec2 lacks integrated language modelling and struggles with longer, context-rich utterances, as noted by Attia et al. (2025b).

When comparing LALMs, Qwen2Audio demonstrates better performance than Ultravox for verbatim transcription. This is largely due to differences in model objectives and task alignment. While Ultravox is optimized for semantic understanding and dialogue generation (Fixie AI, 2025), Qwen2Audio appears more aligned with literal transcription tasks. As highlighted by Arora et al. (2025), many recent LALMs prioritize semantic-level modelling, often at the expense of accurate word-level alignment. This architectural bias limits their utility in tasks requiring high transcription fidelity.

5.2 RQ2: Task Type, Acoustic Ecology, and Data Collection Strategies

Unexpectedly, our audio quality assessments suggest that low-cost, mobile-device-based recording in typical classroom environments does not necessitate aggressive noise suppression. Volume levels and RMS energy distributions remained within acceptable ranges for face-to-face instructional settings. However, ASR performance varied significantly across task types, reflecting differences in speech characteristics. For instance, reflective discussions and procedural tasks impose distinct lexical, semantic, and structural demands on ASR systems.

Transcription errors were found to cluster around four primary dimensions: (1) phonetic and acoustic variability, (2) lexical and semantic ambiguity, (3) multilingual and syntactic complexity, and (4) segmentation and decoding challenges. These findings suggest that both technical and procedural interventions are necessary. Technically, fine-tuning ASR models on domain-specific conversational data may mitigate performance issues (Attia et al., 2025b; Lin et al., 2025). From a data collection perspective, the success of "low-cost, student-driven speech acquisition" hinges not only on technology but also on behavioural and spatial design.

To enhance data quality and consistency, we propose several operational strategies for classroom-based speech collection:

Instructional Design: Provide clear, visual recording guidelines to support student understanding and compliance.

Behavioural Standardization: Assign a designated "recorder" role within group activities to manage device operation and prompt peers.

Spatial Organization: Where feasible, increase inter-group distance to minimize crosstalk and acoustic interference.

5.3 Practical and Theoretical Implications

Our findings extend beyond technical benchmarking. Pedagogically, the ability to capture peer dialogue has implications for classroom diagnosis, formative assessment, and teacher reflection. These results suggest several implications for educational practice, learning analytics, and AI development. For example, transcription data can reveal patterns of participation, turn-taking, and language use, thereby offering teachers new insights into collaborative learning processes. In higher education and lifelong learning context, low-cost ASR workflows can also support learner self-reflection and group accountability. Some specific implications include:

Feasibility of Low-Cost Classroom ASR: Mobile-device-based speech collection is viable in typical classroom settings without specialized hardware or noise suppression.

Model Suitability: LALMs are currently unsuitable for verbatim transcription but may be valuable for summarization or semantic-level analysis.

Task Sensitivity: ASR performance is task-dependent, with reflective and procedural tasks presenting distinct challenges.

Beyond WER: Traditional metrics like WER are insufficient for educational contexts. Multidimensional error analysis (e.g., fuzzy matching, error categorization) provides richer insights.

Real-Time Feedback Potential: A pipeline linking classroom interaction, automatic transcription, and collaboration metrics (e.g., turn-taking, terminology usage, code-switching) could inform teacher dashboards and adaptive instruction.

Stakeholder Recommendations:

For Educators: Whisper is a reliable tool for transcription-based feedback in moderately noisy classrooms.

For Learning Analytics Researchers: the study demonstrates how transcription error typologies can guide the design of analytics sensitive to linguistic and contextual variation. Adopt alternative metrics beyond WER to capture nuanced transcription quality.

For AI Developers: the findings underline the need to align LALMs with world-level transcription goals, rather than assuming semantic summarisation is always sufficient. Incorporate explicit transcription objectives and training data when designing LALMs for educational ASR applications.

6. Conclusion and Future Directions

This study systematically evaluated the performance of traditional ASR systems and emerging LALMs in transcribing Mandarin peer discourse recorded in real-world classroom environments using low-cost mobile devices. Our findings indicate that Whisper currently offers the most reliable transcription performance under such conditions, outperforming both Wav2Vec2 and LALMs. While LALMs are designed for semantic understanding and dialogue generation, their current architectures and training objectives render them unsuitable for precise, word-level transcription tasks—particularly in noisy, multilingual, and spontaneous educational settings. Beyond model benchmarking, this study contributes: A low-cost, replicable workflow for classroom audio collection and transcription using student-owned devices and open-source tools. A fine-grained taxonomy of transcription errors. Practical insights for educators, researchers, and developers on model selection, error interpretation, and deployment feasibility in educational contexts.

Limitations. Several limitations should be acknowledged:

Sample Size: Only five manually transcribed samples were used for detailed evaluation, which may limit generalizability.

Language Scope: The study focused exclusively on Mandarin, and findings may not extend to other languages or dialects.

Device Variability: Audio was recorded using heterogeneous smartphone microphones, introducing uncontrolled variability.

Prompting Constraints: LALMs were tested with limited prompt engineering, which may have affected their performance.

Future Research Directions. To build on this work, future studies should consider: Expanding the dataset to include more diverse classroom contexts, languages, and speaker demographics. Incorporating advanced diarization and speaker separation techniques to improve transcription accuracy in multi-speaker settings. Exploring prompt optimization and fine-tuning strategies for LALMs to better align them with transcription tasks. Investigating real-time transcription pipelines for classroom feedback and learning analytics, including integration with teacher dashboards and collaboration metrics.

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

AI Declaration: AI tools (specifically ChatGPT by OpenAI) were used during the writing process to assist with grammar refinement and language polishing. All research design, data analysis, and interpretation were conducted solely by the authors.

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Auto-Coding Collaborative Dialogue from Classrooms with Open LLMs Using Zero-Short Prompting

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Abstract: Collaborative Problem Solving (CPS) is a vital 21st-century skill that demands nuanced coordination of cognitive, social, and regulatory processes among learners. In face-to-face classrooms, peer dialogue offers rich data for studying CPS, but manual annotation of such unstructured, oral interaction is labour-intensive and difficult to scale. This study investigates whether open-source Large Language Models (LLMs), including Llama and Qwen, can perform inductive qualitative coding on classroom peer dialogues using zero-shot prompting alone—without fine-tuning or training data. We collected over 210,000 words of dialogue transcripts from 38 student dyads across two CPS tasks at university classrooms: an engineering design activity and a GenAI-supported peer assessment of lesson plans. Through a multi-phase process, we iteratively developed three zero-shot prompting strategies (self-prompting, chain-of-thought prompting, and in-context prompting) via GPT-4o interactions and deployed them across different LLMs via API access. Our findings suggest that in-context prompting consistently yields context-sensitive and theoretically coherent CPS constructs. Chain-of-thought prompting facilitates abstract reasoning but may lead to overgeneralization, while self-prompting demonstrates autonomous logic yet lacks consistency. Expert evaluations using a five-dimensional rubric (clarity, concreteness, objectivity, granularity, specificity) show moderate to high alignment between human and LLM-generated codes, although LLMs tend to overrate clarity and coherence. We further analyse discrepancies between LLMs and academic frameworks such as PISA CPS and ATC21S, and highlight challenges such as terminological drift, low recall, and theoretical misalignment. This work contributes a scalable, human-centered workflow for inductive coding of classroom dialogue and provides ready-to-use prompt templates for educational researchers. The aim of this study is to critically examine whether open-source LLMs can inductively code classroom peer dialogue in collaborative problem-solving tasks, while acknowledging both their potential and limitations in educational practice. We conclude with a dual-pathway strategy for combining practice-oriented, behaviourally grounded constructs with theory-aligned coding schemes, and offer design recommendations for future human-AI collaborative tools in learning analytics and classroom assessment.

Keywords: Collaborative problem solving, Prompt engineering, Inductive coding, Zero-Shot prompting, Peer dialogue

1. Introduction

Collaborative Problem Solving (CPS) is increasingly recognised as a critical 21st-century skill, aligned with global educational priorities (OECD, 2017). As artificial intelligence (AI) technologies become more integrated into classrooms, understanding how students engage in CPS is essential for providing timely pedagogical feedback and designing effective learning environments. However, analysing peer dialogue to identify CPS behaviours remains a methodological bottleneck. Manual annotation is costly, labour-intensive, and time-consuming—especially in face-to-face (F2F) classroom settings where conversations are dynamic, unstructured, and contextually embedded.

Recent advances in large language models (LLMs) have shown promise in automating qualitative coding tasks. Prior studies have explored their use in deductive coding (Ramanathan et al., 2025), rubric-based annotation (Vujinović et al., 2024), and structured online interactions (Pinargote et al., 2024; Na & Feng, 2025). However, few studies have examined how LLMs perform inductive coding on raw, oral peer dialogue in F2F classroom settings, particularly using prompt-only zero-shot strategies without fine-tuning.

This study investigates whether open-source LLMs can meaningfully and reliably support inductive CPS coding in such contexts. We build on prompt engineering frameworks such as CLEAR (Lo, 2023) and TELeR (Santu & Feng, 2023), adapting them to real-world educational data. Specifically, we compare three zero-shot prompting strategies—in-context prompting, self-prompting, and chain-of-thought prompting—to evaluate their effectiveness in generating CPS constructs from classroom dialogue. We further explore the practical implications of these methods for supporting teachers in understanding and responding to students' collaborative learning behaviours.

Pitfalls of integrating LLMs in education. While LLMs offer opportunities for scalable and context-sensitive analysis, it is important to acknowledge the pitfalls of EdTech integration. Over-reliance on automated coding tools risks reducing teachers' professional agency and may lead to unintended consequences in practical

classroom use, as algorithms can oversimplify nuanced student interactions (Harvey et al., 2025). Moreover, LLMs often operate as "black boxes," raising concerns about data privacy, system bias, transparency, reproducibility, and accountability in classroom assessment (Pitts et al., 2025). These risks highlight the need for critical reflection when embedding LLM-based tools into classroom practice.

Our contributions are threefold: We construct a domain-informed, multi-turn prompt chaining structure for inductive coding of CPS behaviours; We compare multiple LLMs in terms of accuracy, interpretability, and construct complexity in educational behaviour recognition tasks; We explore the potential of LLMs as pedagogical expert annotators, capable of generating context-sensitive scaffolding suggestions from raw classroom dialogue.

2. Related Work and Research Questions

This section reviews prior work in four key areas relevant to our study: (1) established frameworks for collaborative problem solving, (2) the use of large language models (LLMs) in educational text annotation and dialogue analysis, (3) prompting strategies for qualitative coding, and (4) human-AI collaboration in educational assessment.

To interpret CPS behaviours, several well-established frameworks have been developed, including the indicator-based mapping by Sun et al. (2022), the PISA CPS framework (OECD, 2017), the ATC21S framework (Hesse et al., 2015), and the CPS Ontology (Andrews-Todd et al., 2023). These frameworks typically distinguish between social and cognitive dimensions, covering facets such as shared understanding, task regulation, negotiation, and communication. While they offer strong theoretical grounding and are widely used in standardized assessments, their abstract constructs and formal terminology often pose challenges when applied to spontaneous, real-time classroom dialogue. In particular, they may lack the linguistic naturalism and contextual adaptability needed to capture the nuanced nature of peer interactions in face-to-face learning environments.

Recent studies have explored the potential of LLMs to support educational annotation tasks. Vujinović et al. (2024) demonstrated that ChatGPT can serve as a pedagogy expert annotator, while Ramanathan et al. (2025) proposed a grounded prompt engineering (GROPROE) approach to translate literature-based codebooks into effective prompts for deductive coding. In collaborative learning contexts, Pinargote et al. (2024) used GPT-3.5 to classify utterances into collaboration metrics, and Na and Feng (2025) enhanced LLMs' contextual understanding by modelling interdependencies between different communicative components in dialogue. Snyder et al. (2024) further applied LLMs to analyse CPS behaviour patterns across performance levels. However, few studies have examined how LLMs perform inductive coding on unstructured, oral peer dialogue in face-to-face classroom settings using prompt-only strategies.

Prompt engineering plays a critical role in shaping LLM outputs, especially in zero-shot or few-shot scenarios. While frameworks such as CLEAR (Lo, 2023) and TELeR (Santu & Feng, 2023) offer abstract guidance, they often require domain-specific adaptation. Ramanathan et al. (2025) iteratively refined chain-of-thought prompts based on prior frameworks, and Snyder et al. (2024) experimented with pattern-based prompting strategies. Na and Feng (2025) leveraged in-context learning to embed human knowledge into prompts. Despite these advances, there is limited empirical evidence comparing different zero-shot prompting strategies for inductive coding of CPS behaviours in authentic classroom dialogue.

Finally, research on human-AI collaboration in educational assessment highlights both the potential and limitations of LLMs. Ramanathan et al. (2025) noted that while LLMs can explain their coding decisions, they may exhibit sycophantic bias in interactive settings. Parfenova et al. (2025) found that human coders outperform LLMs on complex sentences, whereas LLMs perform better on simpler ones. These findings suggest complementary strengths and underscore the need to examine alignment patterns and interpretive gaps between human and machine evaluations. Our study builds on this line of work by focusing on inductive coding from raw, unstructured peer dialogues using prompt-only strategies without fine-tuning, and by comparing the performance of three zero-shot prompting methods—self-prompting, in-context prompting, and chain-of-thought prompting—in real-time classroom settings. We further explore the practical implications of these methods for supporting teachers in understanding and responding to students' collaborative learning behaviours.

Different from prior work, the *aim of this study is to critically examine whether open-source LLMs can inductively code classroom peer dialogue in collaborative problem-solving tasks, while acknowledging both their potential and limitations in educational practice*. This approach emphasizes transparency, scalability, and adaptability for

educational use. Specifically, we investigate the following research questions using data from university classrooms:

RQ1: *How do performances of three different zero-shot prompting strategies (in-context, self-prompting, and chain-of-thought) differ in inductive coding of CPS behaviours in peer oral dialogue from face-to-face classrooms?*

RQ2: *What are the relative advantages and disadvantages of automatic inductive coding methods for improving teachers' practice?*

3. Methods

This study adopts a multi-phase approach to explore the feasibility and effectiveness of using open large language models (LLMs) for inductive qualitative coding of collaborative problem-solving (CPS) behaviours in oral peer dialogues. The overall strategy involves prompt development using small-scale samples, followed by large-scale automated coding using refined prompts, and expert-based evaluation of the generated constructs.

3.1 Data Collection

We collected peer dialogue transcripts from 38 dyad groups across two face-to-face CPS tasks from two university classrooms:

Task A: An engineering-based design challenge (ICMP task)

Task B: A GenAI-supported peer assessment of lesson plans

All dialogues were audio-recorded and manually transcribed, resulting in a total word count of 214,696 words (134,256 from Task A and 80,440 from Task B).

3.2 Prompt Development and Coding Strategy

We adopted a prompt-only zero-shot strategy using open LLMs (e.g., Llama 3.1/3.3/4, Qwen3) via API access. The coding process followed these steps:

Prompt Iteration: Initial prompts were developed using small samples from the dataset. Drawing on frameworks such as CLEAR (Lo, 2023) and TELeR (Santu & Feng, 2023), we iteratively refined the prompts through multi-turn interactions with GPT-4o. This involved adjusting instructions, formatting, and output structure to improve clarity and alignment with inductive coding principles.

Prompt Types: Referring to the prompt strategies used in the study by Liu Y. et al. (2024), we compare three zero-shot coding methods: self-prompt, chain-of-thought, in-context prompt. We compared three prompting strategies to generate the zero-shot prompting. Inspiring by the experience from the article by Dai et al. (2025), several round prompt iterations was conducted.

Scaling Up: Finalized prompts were used to code the full dataset. Due to token window limitations, longer transcripts were segmented before processing. The temperature was set to 0.8 to encourage diverse and exploratory outputs, consistent with prior studies (Zhang et al., 2025; Parfenova et al. 2025).

3.3 Construct Evaluation and Framework Comparison

After coding, CPS constructs were synthesized by GPT-4o and verified by human experts. The evaluation followed the five-dimension rubric from Liu X. et al. (2024), assessing: Clarity, Concreteness, Objectivity, Granularity, Specificity. Each construct was rated on a 0–2 scale with justifications. The resulting codebooks were then compared with established CPS frameworks including Sun et al. (2022), the PISA CPS framework (OECD, 2017), the ATC21S framework (Hesse et al., 2015), and the CPS Ontology (Andrews-Todd et al., 2023) to identify overlaps. A simplified workflow is illustrated in Figure 1.

The code solution to call LLMs API in multi-turn dialogue transcription analysis, 3 prompt templates used in this code solution, one example of the coding results (Llama4+prompt1+ICMP task), one example of the GPT 4o analysis of the coding results (Llama4+prompt1+ICMP task) are available via OSF: https://osf.io/sm5zp/?view_only=1f71b048431a45b9b7118c8b21fe3bdc

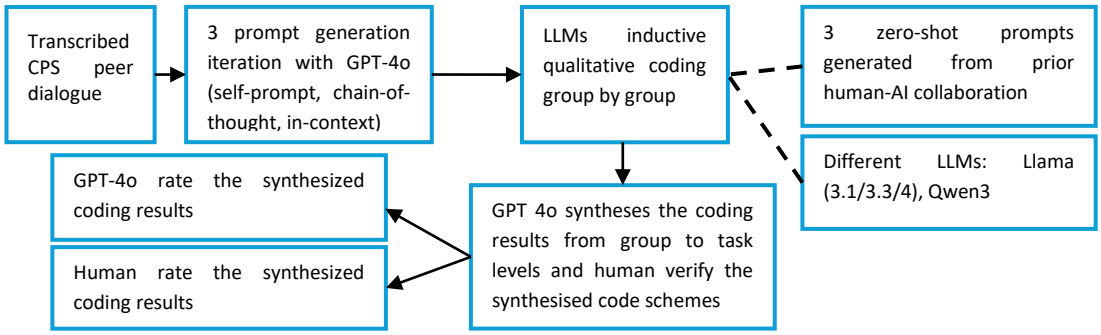

Figure 1: Analysis method

4. Results

For RQ1: *How do performances of three different zero-shot prompting strategies (in-context, self-prompting, and chain-of-thought) differ in inductive coding of CPS behaviours in peer oral dialogue from face-to-face classrooms?*

This section presents a concise synthesis of the outputs generated by large language models (LLMs) across various collaborative problem-solving (CPS) tasks. Rather than providing an in-depth interpretive analysis, the focus here is on summarizing the types and structures of CPS skills identified through inductive coding.

For RQ2: *What are the relative advantages and disadvantages of automatic inductive coding methods for improving teachers' practice?*

Issues related to human verification, theoretical alignment, and interpretive challenges are discussed in detail in the subsequent Discussion section.

Overall, the use of LLM APIs for large-scale inductive coding proved to be both practical and efficient. Across different tasks, the models generated context-sensitive CPS skill constructs, with nuanced variation depending on the prompt design and model architecture. Specifically:

In-context prompting yielded nuanced and context-aware outputs;

Self-prompting showed potential for autonomous reasoning but struggled with consistency;

Chain-of-thought prompting excelled at logical sequencing and abstraction, though it occasionally led to overgeneralization.

Different prompts applied to different LLMs revealed distinct patterns in CPS skill labelling, suggesting that prompt design plays a critical role in shaping the granularity and relevance of the generated constructs.

To facilitate cross-model comparison, frequent CPS skills identified across LLMs were synthesized by human coders into a unified table. This synthesis used less task-specific terminology to enhance generalizability and support subsequent alignment with academic frameworks. To illustrate the variation in CPS constructs generated by large language models (LLMs) under different prompting strategies and task contexts, we initially generated six tables. For brevity, we present two representative examples in the main text: Table 1 (in-context prompting in the ICMP task) and Table 2 (chain-of-thought prompting in the lesson plan task). The remaining tables are available on the OSF link: https://osf.io/sm5zp/?view_only=1f71b048431a45b9b7118c8b21fe3bdc

Table 1: CPS construct induced by LLMs using in-context prompts in ICMP engineering operation task

Dimensions	LLMs generated CPS skills	Academic terms
cognitive	Trial and error + experimental adjustment → Problem-solving ability	Task regulation (ATC21S), Planning and executing (PISA)
	Clarifying issues and division of roles	Task regulation (ATC21S), Planning and executing (PISA)
	Tool usage → Technological proficiency	Task regulation (ATC21S), Planning and executing (PISA), Exploring and understanding (CPS Ontology)

Dimensions	LLMs generated CPS skills	Academic terms
social	Expression and response → Communication competence	Maintaining communication (CPS Ontology), Responding to others' ideas (Sun et al., 2022)
	Knowledge sharing → Collaborative support capability	Establishing shared understanding (CPS Ontology), Participation+Social regulation (ATC21S), Establishing and maintaining shared understanding (PISA)
	Role allocation → Coordination and team management	Establishing and maintaining team organization (PISA), Participation +Social regulation (ATC21S)
	Emotional encouragement → Socio-emotional regulation	Compliments or encourages others (Sun et al., 2022), Participation +Social regulation (ATC21S)
metacognition	Process monitoring → Strategic adjustment skills	Monitoring and reflecting (PISA), Monitoring (CPS Ontology)
	Experience reflection → Self-assessment ability	Monitoring and reflecting (PISA), Task regulation (ATC21S)
	Perseverance/adaptation → Adaptability	Suggests appropriate ideas (Sun et al., 2022), Perspective taking (ATC21S)
	Seeking assistance → Remedial strategy capability	Social regulation (ATC21S), Asking for suggestions (Sun et al., 2022)

Table 2: CPS construct induced by LLMs using Chain-of-thought prompts in GenAI-supported peer assessment of lesson plans

Dimensions	LLMs generated CPS skills	Academic terms
Cognitive	Structured Task Planning	Planning and executing (PISA), Task regulation (ATC21S), Planning (CPS Ontology)
	Technical & Adaptive Integration	Task regulation (ATC21S), Planning and executing (PISA), Exploring and understanding (CPS Ontology)
Social	Dialogue-Based Knowledge Co-Construction	Discusses results (Sun et al., 2022), Participation (ATC21S), Establishing and maintaining shared understanding (PISA)
Metacognitive	Collaborative Goal Regulation	Monitoring and reflecting (PISA), Monitoring (CPS Ontology)

Evaluating the Consistency of Human and LLM Coding

This subsection examines the alignment between human raters and LLMs in evaluating CPS constructs generated through inductive coding. Overall, the results indicate moderate to high alignment between human and machine ratings across evaluated dimensions. However, notable differences were observed in scoring tendencies:

- LLMs tended to assign higher scores to CPS constructs, possibly due to their reliance on surface-level coherence and internal consistency;
- Human raters, by contrast, often drew on their familiarity with the dataset and existing theoretical frameworks, leading to more conservative evaluations—particularly when constructs lacked coverage or theoretical grounding.

The average scores across key dimensions (e.g., clarity, theoretical alignment, transferability) are summarized in **Table 3**.

Table 3: Average scores of evaluated dimensions for each construct

Rater+LLMs	Prompt	Sum	Clarity	Concreteness	Objectivity	Granularity	Specificity
Human+	1	6.9	1.5	1.35	1.4	1.15	1.5
Llama4	2	6.85	1.5	1.5	1.35	1	1.5
	3	7.15	1.4	1.45	1.55	1.25	1.5
GPT-4o+	1	8.2	1.915	1.55	1.55	1.45	1.735
Llama4	2	7.55	1.815	1.385	1.615	1	1.735

Rater+LLMs	Prompt	Sum	Clarity	Concreteness	Objectivity	Granularity	Specificity
	3	7.535	1.79	1.535	1.69	1	1.52
Human+ Llama3.3	1	6.25	1.25	1.25	1.25	1.25	1.25
	2	6.875	1.375	1.375	1.375	1.375	1.375
	3	6.25	1.25	1.25	1.25	1.25	1.25
GPT-4o+ Llama3.3	1	8.96	1.875	1.875	1.875	1.46	1.875
	2	8.975	1.855	1.93	1.93	1.475	1.785
	3	8.395	1.9	1.59	1.715	1.45	1.74
Human+ Llama3.1	1	7.125	1.375	1.375	1.375	1.5	1.5
	2	7.25	1.375	1.375	1.5	1.5	1.5
	3	7.5	1.5	1.5	1.5	1.5	1.5
GPT-4o+ Llama3.1	1	7.625	1.875	1.585	1.29	1.165	1.71
	2	8.75	2	1.835	1.665	1.415	1.835
	3	8.43	1.9	1.735	1.615	1.465	1.715
Human+ Qwen3	1	6.9	1.4	1.4	1.3	1.3	1.5
	2	7.35	1.5	1.5	1.5	1.35	1.5
	3	7.5	1.5	1.5	1.5	1.5	1.5
GPT-4o+ Qwen3	1	8.165	2	1.5	1.5	1.33	1.835
	2	9.17	1.835	1.835	1.835	1.665	2
	3	9.165	2	1.75	1.835	1.665	1.915

Note: the LLMs in the first column refer to the API during the scale inductive coding. Prompt 1 is the final prompt after in-context prompting strategy between human-GPT-4o; Prompt 2 is the final prompt after self-prompting strategy between human-GPT-4o; Prompt 3 is the final prompt after Chain-of-thought prompting strategy between human-GPT-4o.

5. Discussion

While this study identifies several limitations in the use of LLMs for inductive qualitative coding—such as inconsistency, lack of transparency, and weak theoretical grounding—it also reveals important strengths that highlight the practical value of LLMs in educational research and practice.

5.1 Strengths

First, the locally generated "behavior → skill" constructs, grounded in authentic student dialogue (e.g., "you revise the structure, I'll add an example"), offer clarity, concreteness, and immediate usability for instructional design, classroom observation, and formative assessment. Compared to academic CPS frameworks such as PISA (OECD, 2017), ATC21S (Hesse et al., 2015), and the CPS Ontology (Andrews-Todd et al., 2023), these LLM-derived constructs are more accessible to teachers and students, easier to observe and operationalize, and better suited for real-world discourse analysis.

Second, inductive coding using LLM APIs at scale proves to be both efficient and feasible, especially for large datasets. The models are capable of generating context-sensitive CPS skills that reflect the nuances of different tasks. Notably, in-context prompting yields outputs that are linguistically natural and context-aware, particularly in tasks with limited prior information. Chain-of-thought prompting supports logical sequencing and abstraction, though it may occasionally overgeneralize. Self-prompting shows potential for autonomous reasoning but remains inconsistent.

5.2 Challenges

This study reveals several critical limitations and inconsistencies in the use of large language models (LLMs) for qualitative coding in collaborative problem-solving tasks, particularly when applied to educational contexts such as lesson planning and instructional design. Our findings highlight three major challenges: instability across models, lack of transparency in inductive reasoning, and insufficient abstraction and theoretical grounding.

Instability Across Models and Prompts. A key observation is the inconsistency in code schemes generated by different LLMs (e.g., LLama4 vs. Qwen3) when given the same prompt. For instance, under Prompt 1, LLama4 identified cognitive dimensions such as *Problem Identification & Structured Analysis*, *Critical Thinking*, *Lesson Structuring & Instructional Design*, and *Content Integration & Application*. In contrast, Qwen3 produced a different set of dimensions, including *Critical Thinking*, *Cognitive Restructuring*, *Adaptive Problem Solving*, and *Technical Tool Application*. These discrepancies suggest that LLMs lack a stable internal representation of CPS constructs, leading to divergent interpretations even under controlled conditions.

Lack of Transparent Inductive Processes. Despite the use of Chain-of-thought prompting, the inductive reasoning process behind LLM-generated codes remains opaque. It is unclear whether the models rely on semantic similarity, frequency of phrase occurrence, or other heuristics. This lack of transparency undermines the interpretability and replicability of the coding process. This phenomenon also has been reported by the studies by Liu X. et al. (2024) in deductive coding tasks. They claimed that the API usage is less effective at explaining its decisions, identifying ambiguities in definitions compared to Open AI ChatGPT interface.

Insufficient abstraction and theoretical grounding. The generated code schemes often exhibit low abstraction and weak theoretical coherence. Unlike academic CPS frameworks, which feature mutually exclusive and hierarchically structured skills, LLM-generated schemes tend to be fragmented and overlapping. For example, when applying a code scheme derived from the ICMP task to lesson plan tasks, many skills lacked corresponding behavioural samples. Some behaviours specific to lesson planning were not captured in the original CPS framework, indicating poor generalizability and limited transferability of inductively generated codes.

5.3 Pitfalls of Integrating LLMs in Education

Beyond these methodological issues, our findings also underscore broader pitfalls of integrating EdTech in educational settings. The instability and opacity of LLM outputs highlight risks for teachers who might over-rely on machine-generated codes, potentially overlooking the contextual richness of student dialogue. Furthermore, terminological drift and incomplete tagging raise concerns about fairness and validity when such tools are used for high-stakes assessment. These challenges echo earlier critiques of AI in education (e.g., Liu X. et al., 2024; Ramanathan et al., 2025), which caution against assuming that efficiency gains necessarily translate into pedagogical value. A more balanced view requires recognizing both the scalability of LLM-based coding and its limitations in terms of transparency, teacher agency, and ethical responsibility (Harvey et al., 2025; Pitts et al., 2025). In this study, at the operation level, these pitfalls were demonstrated in the following ways:

Terminological Inconsistency and Conceptual Drift. This issue is related to the inconsistency in terminology across tasks and prompts. Constructs such as *Goal Awareness & Task Orientation* appeared in earlier outputs but were later replaced or omitted, with only loosely related constructs like *Goal-oriented Strategic Thinking* emerging in subsequent analyses. This terminological drift leads to the proliferation of similar but non-identical items, complicating efforts to synthesize or compare results across tasks.

Low Recall and Incomplete Tagging in Open Coding. In tasks requiring fine-grained classification (e.g., Prompt 2's segmentation into cognitive, procedural, and affective talk), LLMs often failed to assign tags to each utterance. Instead, they provided summaries without detailing the abstraction process from behaviour to skill. This aligns with prior findings (e.g., Liu X. et al., 2024), which reported that zero-shot LLMs tend to miss many relevant cases, resulting in lower recall compared to human coders or few-shot approaches.

Overlapping Codes and Dimensional Ambiguity in Axial Coding. During axial coding, LLMs frequently generated overlapping items across dimensions. For instance, in the GenAI-assisted lesson plan assessment task, both *AI Evaluation* and *AI-assisted Usage* were categorized under *Technological Mediation Collaboration*, despite representing distinct cognitive operations. This suggests that LLMs struggle to maintain dimensional clarity and often conflate related but separate constructs. This is aligned with the expression about the open coding phase by Parfenova et al. (2025) that categories and clustering codes from open coding phase into higher-order categories in axial coding stage by grouped hierarchically into more abstract categories remains a separate task requiring distinct experiment and evaluation.

Limited Alignment with Established Frameworks. LLMs are unable to autonomously align their outputs with established academic frameworks unless explicitly instructed. Even when provided with a CPS framework and specific task requirements, the alignment results are partial—offering only examples rather than a comprehensive mapping of all generated skills to existing constructs. This partial alignment limits the utility of LLMs in theory-driven qualitative research.

Human-Machine Alignment in Evaluation. Interestingly, human raters tend to assign lower scores than LLMs in evaluating CPS skills. This may be due to human raters' broader familiarity with the dataset and their awareness of missing behaviours or underrepresented skills from authoritative frameworks. This phenomenon echoes findings by Parfenova et al. (2025), who noted that during the open coding phase, human coders tend to overinterpret the data and add unnecessary complexity to straightforward sentences while LLM lake the interpretative depth necessary for complex qualitative analysis.

6. Conclusion and Future Directions

This study provides a comprehensive evaluation of large language models (LLMs) in inductive qualitative coding for collaborative problem-solving (CPS) tasks in educational contexts. While LLMs exhibit notable limitations—including inconsistency across models, lack of transparency in inductive reasoning, and weak alignment with academic frameworks—they also demonstrate significant strengths in scalability, contextual sensitivity, and practical usability.

LLM-generated CPS constructs, grounded in authentic student discourse, offer high clarity and linguistic naturalism, making them immediately applicable for instructional design, classroom observation, and formative assessment. These constructs are particularly accessible to teachers and students, and well-suited for analysing real-world educational interactions. However, they often lack the layered abstraction and definitional precision found in validated CPS frameworks such as PISA, ATC21S, and CPS Ontology.

To address these trade-offs, we propose a **dual-pathway strategy**:

- **Practice-oriented pathway**: Leverage LLMs to generate context-rich, behaviourally grounded constructs that support classroom-based interventions and teacher-student communication.
- **Theory-aligned pathway**: Align LLM outputs with academically validated frameworks to enhance standardization, interoperability, and theoretical rigor in research and assessment.

Future Directions Building on these findings, future research can explore the following areas:

Model-Specific Behaviour Analysis. Investigate how differences in model architecture, training data, and interface (API vs. Chat) influence the generation of CPS constructs, and develop guidelines for model selection based on task type.

Prompt Engineering for Educational Coding. Systematically compare prompting strategies (e.g., in-context, self-prompting, chain-of-thought) to identify optimal configurations for generating reliable and interpretable codes in educational settings.

Human-AI Collaborative Coding Workflows. Design hybrid workflows where human coders guide LLMs through structured alignment with academic frameworks, improving both coverage and conceptual fidelity.

Tool Design for Teachers and Researchers. Develop educational technology tools that embed LLMs with prompt templates, alignment protocols, and visualization features to support teacher-led coding and instructional decision-making.

Cross-Linguistic and Cultural Adaptability. Examine how LLMs perform in multilingual and culturally diverse educational contexts and assess the transferability of locally generated constructs across languages and regions.

By integrating the efficiency and contextual relevance of LLMs with the conceptual depth of academic frameworks, future work can advance both the theory and practice of qualitative analysis in education. At the same time, educators and researchers should remain cautious of potential pitfalls, including over-reliance on automated analysis, diminished teacher agency, and ethical issues surrounding data privacy and fairness. Addressing these risks is essential for developing responsible human-AI collaborative workflows in education.

Limitation. While this study provides valuable insights into the use of large language models (LLMs) for inductive qualitative coding in educational CPS tasks, several limitations should be noted. The analysis was based on a limited set of models and tasks, which may constrain the generalizability of the findings. Human synthesis and interpretation were involved in evaluating LLM outputs, introducing potential subjectivity. Moreover, the study focused on two specific educational contexts, and the applicability of results to other domains remains to be tested. Finally, while the practical utility of LLM-generated constructs is evident, their integration into classroom practice raises broader questions about transparency, teacher agency, and ethical use, which warrant further exploration.

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

AI Declaration: AI tools (specifically ChatGPT by OpenAI) were used during the writing process to assist with grammar refinement and language polishing. All research design, data analysis, and interpretation were conducted solely by the authors.

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Automatic Identification of Collaborative Problem-Solving Phases from Oral Peer Dialogue in Classroom

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Abstract: Collaborative problem solving (CPS) is a critical competency in the Artificial intelligence (AI) era, requiring the integration of cognitive and social skills through real-time dialogue and coordination. While prior studies have explored CPS behaviours using human-coded text from online platforms, limited research has examined how machine learning (ML) and deep learning (DL) models perform on spoken peer dialogue in face-to-face (F2F) classroom settings. This study investigates the automatic classification of CPS phases using a validated coding framework applied to two classroom tasks—one supported by a GenAI assistant and one not. A total of 7,744 utterances were manually labelled across nine CPS subskills and three broader facets. Six ML and five DL models were evaluated, including lightweight BERT variants combined with various classifiers. Results show that BERT-based models significantly outperform traditional ML approaches. Specifically, BERT+ANN achieved better overall performance in smaller, imbalanced datasets, while BERT+CNN performed better in larger datasets. Reducing label granularity from nine subskills to three facets consistently improved classification accuracy and F1 scores. Both models achieved AUROC scores around 0.90, indicating strong discriminative capability. Several key insights emerged from the findings: Model architecture matters: Simpler classifiers like ANN preserve BERT's semantic representations and offer stable performance, especially in smaller or imbalanced datasets. Task context influences CPS behaviour: Different tasks elicit distinct CPS skill distributions, with task regulation dominating in technical tasks and communicative participation more prevalent in reflective tasks. Label granularity affects performance: Reducing the number of classification labels (e.g., from 9 subskills to 3 facets) significantly improves model accuracy and generalizability. Lightweight models are viable: Even with a reduced-capacity BERT model, competitive performance was achieved, suggesting potential for real-time, resource-efficient deployment in educational settings. This study contributes to educational AI by introducing a novel oral CPS dataset, benchmarking multiple models, and demonstrating the feasibility of lightweight architectures for real-time deployment. Limitations include the small sample size and single-modality input. Future work should explore multimodal features, larger and more diverse classrooms, and teacher-facing dashboards for actionable feedback. The findings support the development of scalable, ethical, and human-centered learning analytics tools that enhance collaborative learning in AI-enhanced education.

Keywords: Spoken dialogue, Face-to-Face classroom, Machine learning (ML), Deep learning (DL), Multi-label classification

1. Introduction

Artificial Intelligence (AI) has transformed many aspects of modern society, from healthcare and finance to education, reshaping how humans learn and collaborate (Markauskaite et al., 2022). However, while AI systems excel in computation and automation, uniquely human abilities—such as collaboration, communication, and joint problem solving—remain essential. Collaborative Problem Solving (CPS) is widely recognized as a core 21st-century competency, integrating cognitive reasoning with social interaction (Andrews-Todd et al., 2023; Flor & Andrews-Todd, 2022). Understanding and supporting CPS has therefore become a central focus of research in educational psychology and AI-based learning analytics (Taylor et al., 2024).

Collaborative problem solving (CPS) is a cognitively and socially demanding process in which individuals coordinate ideas, actions, and dialogue to explore problems and co-construct solutions. As emphasized by Markauskaite et al. (2022), CPS is a critical 21st-century competency, particularly in the era of Artificial intelligence (AI), where human collaboration skills are increasingly relevant for both human-human and human-agent interactions.

While prior research has made significant progress in identifying CPS behaviours through human-coded, text-based data from online learning platforms (e.g., Andrews-Todd et al., 2023; Flor & Andrews-Todd, 2022), much less is known about how Machine learning (ML) and Deep learning (DL) models perform when applied to spoken peer dialogue in face-to-face (F2F) classroom settings. While prior research has focused on text-based interactions from online platforms, spoken peer dialogue in face-to-face classrooms offers richer contextual information and authentic collaborative dynamics. Unlike scripted or simulated environments, real-world classroom dialogue reflects spontaneous coordination, negotiation, and decision-making, which are critical for understanding CPS behaviours.

Moreover, most existing studies rely on manual annotation and focus on online or simulated environments. Few have systematically compared the performance of ML and DL models on authentic, oral CPS data, especially across different task types and AI-supported learning contexts. As CPS behaviours may vary significantly depending on task structure and modality (Andrews-Todd et al., 2023), there is a pressing need to explore how automated models perform in diverse, real-world classroom settings.

To address these gaps, this study investigates the automatic classification of CPS phases from spoken peer dialogue using a range of ML and DL models. Specifically, it:

Applies a validated CPS coding framework to oral data collected from two classroom tasks—one supported by a GenAI assistant and one not.

Compares the performance of multiple ML and DL models, including lightweight BERT variants, across different tasks and label granularities.

Evaluates the feasibility of using automated models for CPS detection in real-world educational settings.

By bridging the gap between human-centered pedagogy and automated learning analytics, this study contributes to the development of scalable and context-aware AI tools for classroom use.

For this purpose, two research questions (RQ) were proposed: RQ1: How effectively can traditional Machine Learning (ML) and Deep Learning (DL) models classify CPS phases from spoken peer dialogue in classroom settings? RQ2: How does model performance vary across different task contexts (AI-supported vs. non-AI-supported) and label granularities? In the following, section 2 reviews related work on CPS frameworks and AI-based behaviour detection. Section 3 details the dataset, annotation process, and model configurations. Section 4 presents experimental results. Section 5 discusses implications for CPS analytics in both AI and real-world educational settings, and Section 6 concludes with limitations and future directions.

2. Related Work and Research Questions

The literature reviewed in this section was selected based on relevance to three key dimensions: (1) empirical or computational studies on CPS; (2) application of ML/DL models to dialogue or behaviour classification; and (3) publication recency (2018–2025) to ensure inclusion of recent advances. Both supporting and contrasting perspectives were considered to provide a balanced understanding.

2.1 Collaborative Problem Solving (CPS) Skills and Frameworks

Collaborative problem solving (CPS) involves the coordination of ideas, actions, and dialogue among group members in real time. According to Andrews-Todd et al. (2023), CPS can be categorized into three core facets: Communicative participation (e.g., maintaining communication, sharing information), Social regulation (e.g., monitoring, negotiating), and Task regulation (e.g., planning, executing). This framework together with other CPS analysis frameworks like indicator-based mapping by Sun et al. (2022) have been validated in digital and online collaborative environments, but their application to oral, face-to-face classroom settings remains underexplored.

2.2 AI-Based CPS Behaviour Detection

Recent advances in AI have enabled the automated detection of CPS behaviours using both traditional ML and DL models. Traditional ML models such as logistic regression (LR), random forest (RF), and support vector machines (SVM) have been widely used for text classification tasks. However, DL models—particularly those based on pretrained language models like BERT—have shown superior performance in capturing contextual semantics (Stewart et al., 2023; Wong et al., 2025).

While most existing studies focus on text-based interactions in online platforms, emerging research emphasizes the importance of analysing spoken dialogue transcripts in classroom settings. Unlike scripted or simulated environments, real-world classroom dialogue reflects spontaneous coordination, negotiation, and decision-making, which are critical for identifying CPS behaviours (Taylor et al., 2024; Wong et al., 2025). Moreover, oral peer dialogue in face-to-face classrooms offers authentic insights into collaborative dynamics that are often absent in digital platforms (Flor & Andrews-Todd, 2022).

2.3 Research Gap and Contribution

Despite growing interest in CPS analytics, few studies have applied fine-grained CPS coding schemes to spoken peer dialogue in real-world classrooms. Furthermore, comparative evaluations of multiple ML and DL models on the same dataset remain limited. This study addresses these gaps by:

- Applying a validated CPS framework to human-labelled oral transcripts from two distinct classroom tasks.
- Comparing the performance of six ML and five DL models, including lightweight BERT variants.
- Investigating how model performance varies across tasks and label granularities.

3. Methodology

3.1 Data Collection and Context

Data were collected from 38 student groups across two undergraduate courses in China:

- Lesson Plan Assessment Task (24 groups, 49 participants): Conducted in an Educational Technology course, where students revised lesson plans using a GenAI assistant (Wenxinyiyan, based on ERNIE).
- Internet Control Message Protocol (ICMP) Networking Task (14 groups, 28 participants): Conducted in an Engineering course, where students collaborated on IP packet transmission using ICMP (a network layer protocol used for error reporting and diagnostics in networking).

Both tasks were conducted in face-to-face classroom settings, with audio recordings capturing peer dialogue. The lesson plan task involved human-AI collaboration, while the ICMP task did not involve AI assistance. These two datasets were also combined to evaluate model robustness across contexts. To explore how model performance across tasks, three datasets were organized: one from the Lesson plan assessment task, one from the ICMP task, one combining the prior two datasets.

3.2 Data Annotation

All audio recordings were manually transcribed and segmented into meaning units, where each segment represents a coherent CPS behaviour. Transcripts were labelled using the CPS coding scheme proposed by Andrews-Todd et al. (2023), which includes 3 CPS facets and 9 CPS subskills: Communicative Participation (Maintaining communication, Sharing information, Establishing shared understanding), Social Regulation (Negotiating, Monitoring), Task Regulation and Activity (Exploring and understanding, Representing and formulating, Planning, Executing). This coding approach captures both cognitive and regulatory dimensions of CPS. Example annotation:

- *Student A*: “In the summary, emphasize the key challenges…” → Label: Planning
- *Student B*: “The AI revised it for me.” → Label: Sharing Information

3.3 Model Selection and Configuration

We evaluated six Machine Learning (ML) models—Decision Tree (DT), Logistic Regression (LR), Naïve Bayes (NB), Support Vector Machine (SVM), K-Nearest Neighbours (KNN), and Random Forest (RF)—and five Deep Learning (DL) models—Bidirectional Encoder Representations from Transformers (BERT), BERT combined with Artificial Neural Network (BERT+ANN), BERT with Convolutional Neural Network (BERT+CNN), BERT with Long Short-Term Memory (BERT+LSTM), and BERT with Bidirectional LSTM (BERT+BiLSTM).

ML refers to algorithms that learn patterns from data through statistical inference and manual feature engineering—that is, selecting and designing input variables that help the model make accurate predictions. DL, by contrast, is a subset of ML that relies on multi-layer neural networks to automatically learn hierarchical representations from raw data, often requiring less manual preprocessing.

Among the DL models, BERT (Bidirectional Encoder Representations from Transformers) uses a transformer architecture to capture contextual meaning from text by considering both left and right word sequences. For this study, we adopted a lightweight BERT variant—`uer/chinese_roberta_L-2_H-128`—which includes only two transformer layers and 128 hidden units. This configuration significantly reduces computational cost while maintaining sufficient representational power for our classification tasks.

Considering that a detailed review of algorithmic mechanisms is beyond the scope of this paper, readers may refer to two comprehensive reviews on ML and DL in educational contexts: Deep Learning Techniques in

Educational Data Mining (Lin et al., 2025) and Unlocking the Power of Machine Learning in E-Learning (Salem & Shaalan, 2025).

All models were trained using stratified 10-fold cross-validation. For BERT-based models: Tokenization: Max sequence length = 300, Hyperparameters: Learning rate = 5e-5, batch size = 16, epochs = 10. These were selected based on prior best practices and confirmed through grid search.

3.4 Evaluation Metrics

To assess model performance, as mentioned in the review by Naidu et al. (2023), we adopted multiple evaluation metrics, including: Macro-F1 Score, Accuracy, Precision, Recall, Area under the receiver operating characteristic curve scores (AUROC).

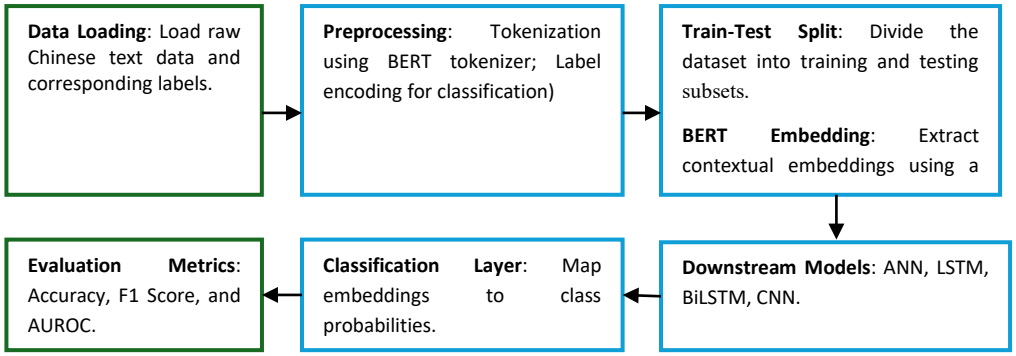

Figure 1: Data analysis workflow (Note: ML model approaches did not have BERT embedding step)

All code solutions and one examples of automatic classification results can be found on the OSF link:

https://osf.io/xqe4m/?view_only=5862e658a2804e4e900041b356647aba

4. Results

4.1 Descriptive Analysis of CPS Skill Distribution

Table 1 presents the distribution of CPS skills across the two classroom tasks: the lesson plan assessment (with GenAI assistance) and the ICMP packet operation (without GenAI). Students demonstrated a wide range of CPS skills in both tasks, covering all nine subskills defined in the coding framework by Andrews-Todd et al. (2023).

Notably, the most frequently observed CPS skills differed between the two tasks, diverging from patterns reported in prior studies conducted in online environments (Andrews-Todd et al., 2023; Flor & Andrews-Todd, 2022). In the ICMP task, which involved hands-on technical collaboration, the most frequent skills were Executing (30.46%) and Planning (16.65%), reflecting a strong emphasis on task regulation. In contrast, the lesson plan assessment task showed higher frequencies of Sharing Information (19.33%) and Maintaining Communication (17.87%), aligning more closely with communicative participation.

This variation suggests that task type and modality (face-to-face vs. online) significantly influence the manifestation of CPS behaviours. The combined dataset showed a relatively balanced distribution across the three CPS facets, with Task Regulation accounting for the largest proportion (53.38%).

Table 1: Summary of reported aggregate CPS skills by facet and task

CPS skills	Lesson plan task	ICMP task	Combined
Communicative participation	**1831(52.52%)**	**921(21.63%)**	**2752(35.54%)**
Maintaining communication	623(17.87%)	192(4.51%)	815(10.52%)
Sharing information	647(19.33%)	547(12.85%)	1194(15.42%)
Establishing shared understanding	561(16.09%)	182(4.27%)	743(9.59%)
Social regulation	**563(16.15%)**	**295(6.93%)**	**858(11.08%)**
Negotiating	255(7.31%)	48(1.13%)	303(3.91%)
Monitoring	308(8.83%)	247(5.8%)	555(7.17%)
Task regulation and activity	**1092(31.33%)**	**3042(71.44%)**	**4134(53.38%)**

CPS skills	Lesson plan task	ICMP task	Combined
Exploring and understanding	189(5.42%)	374(8.78%)	563(7.27%)
Representing and formulating	213(6.11%)	662(15.55%)	875(11.30)
Planning	198(5.68%)	709(16.65%)	907(11.7%)
Executing	492(14.11%)	1297(30.46%)	1789(23.1%)
Sum	3486	4258	7744

4.2 Model Performance Analysis

4.2.1 Performance on 9-Category CPS classification

Tables 2 and 3 summarize the performance of all models on the lesson plan assessment task and ICMP packet operation task datasets, respectively. Across both tasks, BERT+ANN slightly outperformed other models in terms of Accuracy and AUROC, indicating better overall performance and discriminative ability. BERT+CNN also performed competitively, particularly in the ICMP dataset, where it achieved higher recall and precision.

As illustrated in Figure 2 and Figure 3, the confusion matrices visualize the classification patterns of the best-performing models for each dataset. Darker cells indicate higher prediction accuracy. The numbers 0–8 in both figures correspond to the CPS subskill labels: Maintaining Communication (0), Sharing Information (1), Establishing Shared Understanding (2), Negotiating (3), Exploring and Understanding (4), Representing and Formulating (5), Planning (6), Executing (7), and Monitoring (8).

Figure 2 shows the confusion matrix for the BERT+ANN model on the lesson plan assessment dataset. The strong diagonal dominance indicates generally accurate classification across CPS subskills, with the highest accuracy for Maintaining Communication (0), followed by Sharing Information (1) and Executing (7).

Figure 3 presents the confusion matrix for the BERT+CNN model on the ICMP packet operation dataset. Here, the Executing (7) label is predicted with particularly high accuracy, reflecting the task's procedural and technical nature.

Together, these visualizations demonstrate that the models capture distinct task-specific CPS behaviour patterns, with clearer identification of task-regulation phases in the ICMP task and communicative facets in the lesson plan task.

Among traditional ML models, logistic regression with TF-IDF achieved the best performance, outperforming more complex models like random forest and SVM. This suggests that while DL models are superior overall, well-tuned ML baselines remain viable for certain tasks.

Table 2: Model Performance Comparison by Evaluation Metric on lesson plan assessment dataset

Models	Accuracy	Precision	Recall	F1	AUROC
BERT	0.4957	0.3351	0.36	0.3212	0.8544
BERT+LSTM	0.5244	**0.5815**	0.4226	0.41	0.8714
BERT+ANN	**0.6074**	0.5742	**0.5492**	0.5497	**0.9039**
BERT+BiLSTM	0.5057	0.5656	0.3809	0.365	0.8549
BERT+CNN	0.5845	0.5779	0.5442	**0.5511**	0.9027
Logistic Regression +IF-IDF	0.5431	0.5217	0.4915	0.502	0.8601
Naïve Bayes+IF-IDF	0.4384	0.3001	0.2869	0.2344	0.8111
Random Forest+IF-IDF	0.5043	0.4971	0.3833	0.3838	0.8321
K-Nearest Neighbors+IF-IDF	0.4527	0.3894	0.3663	0.3575	0.7344
SVM+IF-IDF	0.5345	0.5241	0.4861	0.4992	0.8506
Decision Tree+IF-IDF	0.342	0.2764	0.279	0.2766	0.5979

Table 3: Model Performance Comparison by Evaluation Metric on ICMP packet operation dataset

Models	Accuracy	Precision	Recall	F1	AUROC
BERT	0.5012	0.4159	0.3427	0.3558	0.7926
BERT+LSTM	0.5365	0.4197	0.4075	0.408	0.8178
BERT+ANN	**0.5751**	0.4865	0.4374	**0.4496**	0.853
BERT+BiLSTM	0.4965	0.4305	0.3522	0.3599	0.8082
BERT+CNN	0.5435	**0.5082**	**0.4387**	0.4421	**0.8593**
Logistic Regression +IF-IDF	0.4396	0.4162	0.2726	0.2881	0.7902
Naïve Bayes+IF-IDF	0.395	0.4237	0.1909	0.1759	0.7364
Random Forest+IF-IDF	0.4387	0.3738	0.2985	0.311	0.7636
K-Nearest Neighbors+IF-IDF	0.2485	0.3017	0.199	0.194	0.5844
SVM+IF-IDF	0.4401	0.3985	0.2896	0.3088	0.7823
Decision Tree+IF-IDF	0.3624	0.293	0.2664	0.2719	0.6003

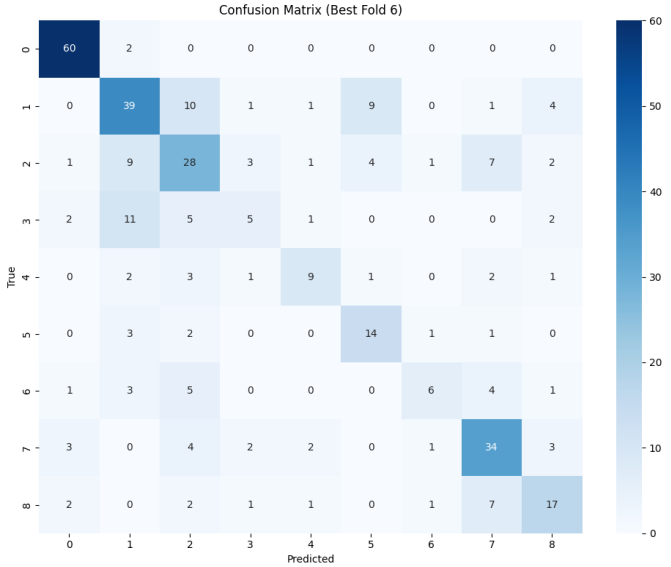

Figure 2: Confusion matrix of the BERT+ANN in on lesson plan assessment dataset

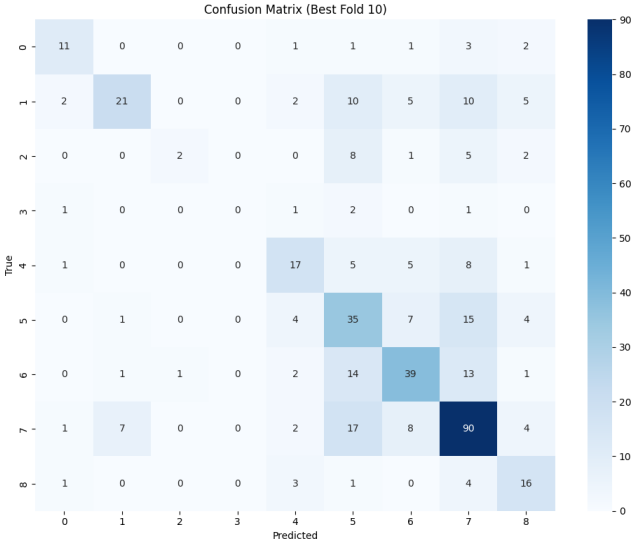

Figure 3: Confusion matrix of the BERT+CNN in on ICMP packet operation dataset

4.2.2 Performance on combined dataset

Table 4 shows model performance on the combined dataset. While performance slightly declined compared to task-specific datasets, BERT+CNN and BERT+ANN remained the top-performing models. This supports the finding that task-specific training yields better results, likely due to reduced contextual variability.

Table 4: Model Performance Comparison by Evaluation Metric Combined Dataset (9 CPS Skills)

Models	Accuracy	Precision	Recall	F1	AUROC
BERT	0.4806	0.4929	0.4109	0.4125	0.8265
BERT+LSTM	0.5123	0.5104	0.4595	0.4631	0.8563
BERT+ANN	0.5277	0.504	0.4958	0.4925	0.8678
BERT+BiLSTM	0.5078	**0.5415**	0.4322	0.4351	0.8446
BERT+CNN	**0.5368**	0.504	**0.507**	**0.5016**	**0.8743**
Logistic Regression +IF-IDF	0.4464	0.4483	0.3768	0.3737	0.8017
Naïve Bayes+IF-IDF	0.3611	0.4673	0.2393	0.2338	0.7771
Random Forest+IF-IDF	0.4038	0.3678	0.3424	0.3347	0.7771
K-Nearest Neighbours+IF-IDF	0.2484	0.3043	0.2358	0.2092	0.6183
SVM+IF-IDF	0.4327	0.4244	0.3723	0.3659	0.802
Decision Tree+IF-IDF	0.3226	0.281	0.2916	0.278	0.5901

4.2.3 Impact of label granularity: 3 vs. 9 categories

Table 5 compares the performance of BERT+ANN and BERT+CNN across both tasks using 3-category (facet-level) and 9-category (skill-level) classification. In all cases, reducing the number of labels led to substantial improvements in accuracy, precision and F1 score. For example, BERT+CNN achieved an F1 score of 0.6879 on the lesson plan dataset with 3 labels, compared to 0.5511 with 9 labels.

Table 5: Comparison of BERT+ANN and BERT+CNN on 3 vs. 9 CPS Categories

Models	dataset	CPS	Accuracy	Precision	Recall	F1	AUROC
BERT+ANN	Lesson plan task	9 CPS skills	0.6074	0.5742	0.5492	0.5497	**0.9039**
		3 CPS facets	0.7135	0.6807	**0.6849**	0.68	0.8567
	ICMP task	9 CPS skills	0.5751	0.4865	0.4374	0.4496	0.853
		3 CPS facets	0.7606	0.633	0.584	0.603	0.8008
	Combined	9 CPS skills	0.5277	0.504	0.4958	0.4925	0.8678
		3 CPS facets	0.7226	0.6524	0.6398	0.6442	0.8206
BERT+CNN	Lesson plan task	9 CPS skills	0.5845	0.5779	0.5442	0.5511	0.9027
		3 CPS facets	0.7307	0.7085	0.6742	**0.6879**	0.873
	ICMP task	9 CPS skills	0.5435	0.5082	0.4387	0.4421	0.8593
		3 CPS facets	**0.8028**	**0.7539**	0.5739	0.6257	0.8049
	Combined	9 CPS skills	0.5368	0.504	0.507	0.5016	0.8743
		3 CPS facets	0.729	0.6975	0.6219	0.6432	0.8184

5. Discussion and Implication

5.1 Summary of Findings

This study investigated the effectiveness of ML and DL models in classifying CPS phases from spoken peer dialogue in face-to-face classroom settings. It was found that DL models, particularly BERT-based architectures, outperformed traditional ML models across classification tasks. Among them, BERT+ANN achieved the most stable and accurate performance, especially in smaller and imbalanced datasets, while BERT+CNN showed advantages in larger datasets with more diverse samples. Models trained on task-specific datasets performed

better than those trained on combined datasets. Additionally, reducing the number of classification labels (e.g., from 9 subskills to 3 facets) improved model performance, suggesting that label granularity and data homogeneity are critical factors. These findings are consistent with prior research (Andrews-Todd et al., 2023; Wong et al., 2025; Xu et al., 2025) and extend them by applying CPS frameworks to spoken classroom dialogue, a modality that has received limited attention in automated CPS analytics.

5.2 Interpretation of Model Behaviour

The superior performance of BERT+ANN can be attributed to its architectural simplicity and semantic preservation. As noted in prior studies (Dablain et al., 2024), adding a simple fully connected layer to BERT outputs tends to yield more stable results than complex structures like CNN or LSTM, particularly when data is limited or noisy. ANN layers effectively retain BERT's contextual embeddings without introducing structural redundancy. In contrast, CNNs excel at extracting local linguistic patterns, which may enhance recall in specific CPS categories. However, this comes at the cost of disrupting BERT's global semantic structure, leading to slightly lower overall accuracy. This trade-off was evident in our results and aligns with findings from sentiment classification research (Chen et al., 2022), which highlight CNN's strengths in local feature extraction but limitations in modelling long-range dependencies.

Moreover, both BERT+ANN and BERT+CNN achieved AUROC scores around 0.90, indicating strong discriminative capabilities in multi-class classification. This reinforces the robustness of BERT-based models in capturing the nuanced cognitive and regulatory elements of CPS.

5.3 Model Efficiency and Practical Deployment

A notable aspect of this study is the use of a lightweight BERT variant (uer/chinese_roberta_L-2_H-128), which contains only 2 transformer layers and 128 hidden units. Despite its reduced capacity, the BERT+ANN model achieved performance comparable to larger models used in previous studies (Wong et al., 2025). This suggests that lightweight BERT models, when paired with appropriate classifiers, can offer a cost-effective and deployable solution for real-time CPS analytics in classroom settings. This finding is particularly relevant for educational environments with limited computational resources, where deploying full-scale language models may not be feasible.

5.4 Implications for Model Selection and Evaluation

The results offer several insights for researchers and practitioners designing automated CPS detection systems:

- **Model Architecture**: Simple classifiers (e.g., ANN) are preferable when stability and semantic fidelity are prioritized. CNNs may be used to boost recall in specific categories but should be applied cautiously to avoid semantic distortion.
- **Label Design**: Reducing the number of classification labels improves model performance by increasing sample size per class and reducing ambiguity. This highlights a trade-off between analytical granularity and classification accuracy.
- **Dataset Composition**: Task-specific datasets yield better performance than aggregated datasets, emphasizing the importance of contextual consistency in CPS modelling.
- **Evaluation Strategy**: Macro-F1 can be prioritized in imbalanced multi-label settings, alongside AUROC to assess ranking capabilities.

5.5 Theoretical and Practical Implications

From a theoretical perspective, this study reinforces the context-dependent nature of CPS behaviours, demonstrating that different tasks elicit distinct patterns of communication, regulation, and execution. The use of spoken dialogue as a data source provides a more ecologically valid basis for understanding CPS, capturing authentic scaffolding cycles and decision-making processes.

Practically, the findings have implications for teacher-facing analytics and intelligent tutoring systems (ITS). By identifying optimal moments for intervention—such as when students encounter conceptual thresholds or exhibit regulatory breakdowns—teachers can better support group learning dynamics. These insights can also inform the design of ITS that incorporate teacher-informed scaffolding strategies, enhancing their responsiveness and pedagogical alignment.

Comparative Perspective: CPS in AI-Mediated and Analogue Contexts. While the present study focuses on the automatic detection of CPS phases in face-to-face classroom dialogue, it is worth briefly reflecting on how collaborative problem solving manifests differently in AI-mediated and analogue (human-only) settings.

In AI-mediated contexts, collaboration is often enhanced by digital tools or intelligent agents that can scaffold communication, monitor progress, or provide adaptive feedback. Such environments offer several advantages, including scalability, traceability of learner interactions, and the potential for real-time analytics to support both learners and teachers (Stewart et al., 2023; Taylor et al., 2024). However, these benefits often come at the cost of reduced spontaneity and limited access to non-verbal cues—such as gesture, tone, or facial expression—which are crucial for authentic social coordination (Wong et al., 2025). This tension partly motivated our exploration of face-to-face group discussions in which students collaborated to provide feedback on AI-generated lesson plans (the lesson plan assessment task). Such a setting allows the integration of AI's advantages in providing rapid, high-quality suggestions while simultaneously fostering opportunities for students to negotiate meaning, share perspectives, and resolve conflicts through direct interpersonal interaction.

In contrast, analogue or face-to-face CPS provides richer social and emotional context, allowing for immediate negotiation of meaning and interpersonal regulation. These interactions tend to be more fluid and context-sensitive but are also more difficult to capture and analyse automatically (Flor & Andrews-Todd, 2022).

Understanding the complementary strengths of these two worlds can help researchers and educators design AI tools that augment—rather than replace—the natural dynamics of human collaboration. This comparative view also offers an accessible entry point for AI researchers who may be less familiar with the nuances of classroom-based CPS.

6. Conclusion and Further studies

This study demonstrates the feasibility and effectiveness of using machine learning (ML) and deep learning (DL) models to automatically classify collaborative problem solving (CPS) phases from spoken peer dialogue in face-to-face classroom settings. By applying a validated CPS framework to two distinct classroom tasks—one supported by GenAI and one not—this research provides empirical evidence that BERT-based models, particularly BERT+ANN and BERT+CNN, can achieve strong performance in multi-label CPS classification.

Contributions. This study makes several contributions to the field of educational AI and learning analytics: It pioneers the use of automated CPS classification in oral, face-to-face classroom dialogue, addressing a gap in current research. It evaluates a wide range of ML and DL models on the same annotated dataset, offering a comprehensive performance benchmark. It introduces a novel dataset collected from both GenAI-supported and traditional classroom tasks, enabling future comparative studies. It provides open-source code and model configurations to support replication and further development by the research community.

Limitations. Despite its contributions, the study has several limitations: the dataset size is relatively small, which may limit the generalizability of the findings; only textual transcripts were used; a lightweight BERT model was used, which may lack the representational power of full-scale models.

Future research could address these limitations by: Expanding to larger and more diverse classroom contexts, including different age groups, subjects, and cultural settings. Incorporating multimodal features (e.g., pitch, pauses, gestures) to enhance the detection of social and emotional cues in CPS. Exploring real-time deployment of CPS detection models in classrooms, including teacher-facing dashboards for actionable feedback. Comparing performance with full-capacity BERT models and other large language models (LLMs) to assess trade-offs between accuracy and efficiency.

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

AI Declaration: AI tools (specifically ChatGPT by OpenAI) were used during the writing process to assist with grammar refinement and language polishing. All research design, data analysis, and interpretation were conducted solely by the authors.

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Appendix 1

Table: List of Acronyms and Definitions

Acronym	Full Form	Definition
AI	Artificial Intelligence	Computational systems capable of performing tasks that typically require human intelligence, such as perception, reasoning, and learning
ML	Machine Learning	A subset of AI focusing on algorithms that learn patterns and relationships from data through training and evaluation
DL	Deep Learning	A subfield of ML that employs multi-layer artificial neural networks to automatically extract hierarchical features from large datasets
BERT	Bidirectional Encoder Representations from Transformers	A transformer-based deep learning model that captures bidirectional contextual relationships between words in a sentence
CNN	Convolutional Neural Network	A deep learning architecture designed to capture local spatial or sequential patterns through convolution operations, widely used for text and image classification
LSTM	Long Short-Term Memory	A type of recurrent neural network capable of learning long-range dependencies in sequential data through gated cell mechanisms
SVM	Support Vector Machine	A supervised ML algorithm that constructs optimal hyperplanes to separate data into classes with maximum margin
RF	Random Forest	An ensemble ML method that aggregates multiple decision trees to improve classification and reduce overfitting
ICMP	Internet Control Message Protocol	A network-layer protocol used for error reporting and diagnostics in computer networks, commonly utilized in network engineering tasks

A Yin-Yang Framework for Cross-Cultural Knowledge Management: Integrating AI and Human Intelligence Through Peter Drucker's Principles

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Abstract: The demands of a globalized economy challenge organizations to manage knowledge effectively across diverse cultural landscapes. Traditional knowledge management (KM) systems prioritize efficiency but often lack the cultural adaptability and ethical flexibility required in multicultural contexts. Drawing from Peter Drucker's management philosophy, this paper introduces a Yin-Yang framework for cross-cultural KM, merging the structured capabilities of artificial intelligence (AI) with the adaptive, ethically guided insights of human intelligence. In this model, AI functions as the "Yin" component, delivering scalable, consistent processing, while human intelligence embodies the "Yang" element, contributing cultural sensitivity and ethical discernment. Synthesizing findings from 35 recent studies, this framework addresses critical limitations in current KM models by embedding cultural intelligence (CQ) into KM practices, enabling organizations to apply AI-driven insights that respect local norms and values. This approach supports sustainable knowledge sharing, ethical decision-making, and an adaptable feedback cycle informed by human input. Practical implications for multinational organizations include improved cross-cultural collaboration and an ethically aligned, responsive KM system. Future research directions are proposed to empirically evaluate the framework's adaptability and effectiveness across various sectors.

Keywords: Knowledge management, Cross-Cultural management, Artificial intelligence, Cultural intelligence (CQ), Ethical decision-making, Peter F. Drucker, Yin-Yang framework, Adaptive KM systems, Sustainable knowledge sharing

1. Introduction

In today's globalized and interconnected economy, knowledge management (KM) is essential for organizational success, yet traditional KM models often struggle to address the complexities of culturally diverse environments. Conventional KM systems are designed to maximize efficiency through structured processes, but they frequently lack the adaptability needed to incorporate cultural sensitivity and ethical considerations—particularly in multinational contexts where diverse values and norms influence effective knowledge application (Nonaka & Takeuchi, 1995; Davenport & Prusak, 1998; Pauleen, 2007). These limitations highlight the need for a KM approach that is both structured and responsive to cultural variability, providing a foundation for sustainable knowledge practices that align with local expectations and ethical standards.

Peter Drucker, a pioneer in modern management, emphasized that knowledge should be viewed as a central organizational asset, advocating for management approaches that balance technological efficiency with human-centered adaptability (Drucker, 1999; Drucker, 2002). Drucker argued that while technology-driven systems can optimize processes, they cannot replace the ethical judgment and cultural insight unique to human intelligence. This view is particularly relevant in the context of knowledge management, where integrating structured efficiency with ethical discernment is critical. Inspired by Drucker's insights, this paper introduces a Yin-Yang framework for cross-cultural KM that merges the stability and scalability of artificial intelligence (AI) with the flexibility and ethical grounding of human intelligence. In this model, AI serves as the "Yin" component, offering consistency and large-scale data processing, while human intelligence embodies the "Yang" component, enhancing KM practices with cultural understanding and ethical depth (Cheng & Zhao, 2020; Chin et al., 2022).

AI has indeed transformed KM by enabling efficient data analysis and retrieval processes, allowing organizations to handle large datasets with consistency and speed. However, AI's structured nature often limits its ability to interpret context-sensitive or culturally nuanced information, which can lead to applications that overlook local norms and ethical considerations (O'Leary, 1998; Garrido-Moreno et al., 2019). As global organizations increasingly adopt AI-driven KM systems, the absence of cultural intelligence (CQ) within these systems creates significant risks, including culturally inappropriate knowledge dissemination and ethically questionable decision-making (Earley & Mosakowski, 2004; Doh & Quigley, 2014). The proposed Yin-Yang framework addresses these limitations by embedding CQ into KM practices, enabling organizations to leverage AI-driven insights that

respect and adapt to diverse cultural values. By doing so, this approach helps balance the structured advantages of AI with the nuanced, culturally sensitive judgment that human intelligence provides (Ang & Van Dyne, 2008).

This conceptual integration synthesizes insights from recent literature to develop a balanced KM framework that aligns AI's processing capabilities with the adaptive, ethically guided strengths of human intelligence. Through embedding CQ, the Yin-Yang framework supports sustainable knowledge sharing, fosters cross-cultural collaboration, and enhances ethical decision-making across organizational settings (Nguyen, 2021). By proposing a KM model that is culturally responsive and ethically grounded, this framework advances KM theory in a way that resonates with Drucker's principles and offers a pathway toward resilient and adaptable KM systems for global organizations.

2. Literature Review

Table 1: Summarizes the evolution of KM models, illustrating how the Yin-Yang framework uniquely addresses the limitations of traditional and AI-enhanced KM models by incorporating CQ to enhance cultural sensitivity

KM Model	Focus	Strengths	Limitations	Role of Cultural Intelligence (CQ)
Traditional KM	Codification and retrieval	Structured and consistent	Lacks flexibility and cultural insight	Minimal; often overlooks CQ
AI-Enhanced KM	Data processing and automation	Scalable and efficient	Limited ethical and cultural sensitivity	CQ required for contextual relevance
Yin-Yang Framework	Integration of AI and adaptability	Balanced, adaptable, culturally sensitive	Requires high-quality data and human feedback	Central; CQ ensures cultural alignment

The field of knowledge management (KM) has evolved significantly, with foundational models primarily focusing on codifying and retrieving explicit knowledge through structured, technology-driven systems (Nonaka & Takeuchi, 1995; Davenport & Prusak, 1998). While traditional KM approaches enhance efficiency and scalability, they are often inadequate for culturally diverse environments, where adaptability and cultural sensitivity are essential. This literature review examines traditional KM models, the role of artificial intelligence (AI) in KM, and the critical function of cultural intelligence (CQ) in cross-cultural KM. These components lead to the rationale for the Yin-Yang framework, which integrates AI and human intelligence to address the limitations of existing models.

2.1 Traditional Knowledge Management Models

Traditional KM models, such as **codification** and **personalization** strategies, emphasize the structured organization and retrieval of knowledge. The codification approach transforms tacit knowledge into explicit, standardized formats, making it accessible and scalable across organizations (Nonaka & Takeuchi, 1995; Davenport & Prusak, 1998). However, this model's rigidity often limits its effectiveness in culturally diverse settings, where tacit knowledge and localized insights are essential (Pauleen, 2007).

Conversely, the personalization strategy focuses on interpersonal knowledge-sharing within communities of practice, which allows for context-sensitive KM practices but is challenging to scale in large organizations (Davenport & Prusak, 1998). Hybrid models have emerged, combining structured codification with adaptable personalization. Despite these advances, traditional and hybrid models still overlook the cultural intelligence needed to effectively adapt KM practices in diverse settings (House et al., 2004; Nguyen, 2021).

2.2 The Role of Artificial Intelligence in Knowledge Management

Artificial intelligence (AI) has introduced new capabilities in KM by enabling rapid data processing, pattern recognition, and large-scale information retrieval. AI-driven KM models align with Drucker's emphasis on structured knowledge processes that enhance organizational efficiency and consistency (Drucker, 1999). For instance, AI supports the codification and retrieval of explicit knowledge through automated analysis and categorization, which is especially beneficial for large data sets (O'Leary, 1998; Garrido-Moreno et al., 2019).

However, AI's structured, rule-based nature also limits its ability to interpret culturally nuanced information. In multicultural organizations, where KM practices must align with diverse cultural norms and ethical standards, AI's limitations in contextual understanding and ethical judgment create challenges (Nguyen, 2021; Chin et al., 2022). The reliance on AI alone risks producing culturally insensitive or ethically questionable outcomes, as AI is not equipped to apply judgment beyond structured, data-driven outputs (Earley & Mosakowski, 2004; Doh & Quigley, 2014). This gap highlights the need for a KM model that combines AI's efficiency with the interpretive power of human intelligence.

2.3 Cultural Intelligence (CQ) and Cross-Cultural Knowledge Management

Cultural intelligence (CQ) is crucial for effective knowledge sharing in cross-cultural settings, as it enables individuals and organizations to recognize and adapt to cultural differences (Earley & Mosakowski, 2004; Ang & Van Dyne, 2008). In KM, CQ provides the interpretative capability necessary for adapting knowledge applications to specific cultural contexts, filling the gap that traditional and AI-driven models leave unaddressed. CQ allows knowledge systems to incorporate ethical and culturally relevant insights, fostering a more context-sensitive approach to KM (House et al., 2004).

Research supports that CQ enhances KM by making knowledge-sharing practices both ethically sound and culturally responsive, a requirement for organizations operating across multiple cultural settings (Doh & Quigley, 2014; Nguyen, 2021). The Yin-Yang framework incorporates CQ as an essential element, positioning human intelligence as the adaptive "Yang" component that tempers AI's structured "Yin" characteristics with cultural awareness and ethical discernment.

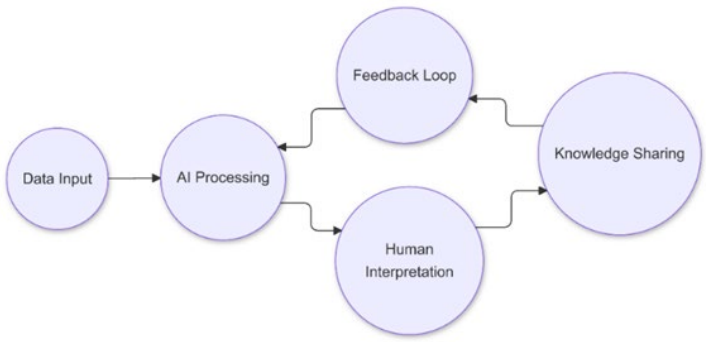

Figure 1: AI and Human Intelligence Integration in Knowledge Management (Yin-Yang Model)

- **Data Input**: Collection of raw data from diverse sources.
- **AI Processing (Yin)**: Efficient data processing, providing structured insights.
- **Human Interpretation (Yang)**: Cultural and ethical contextualization, applying CQ to AI outputs.
- **Knowledge Sharing**: Dissemination that respects cultural norms, enhancing relevance.
- **Feedback Loop**: Continuous improvement incorporating human feedback to refine AI processes.

2.4 Why AI is Yin and Human Intelligence is Yang

In the Yin-Yang framework, **AI is characterized as Yin** due to its structured, consistent, and passive qualities. Yin symbolizes stability and scalability, qualities that align with AI's capabilities in processing large datasets and automating knowledge retrieval without interpretative flexibility. AI's passive role in KM focuses on delivering structured insights that support consistency but lack the capacity for ethical or cultural discernment (O'Leary, 1998; Garrido-Moreno et al., 2019).

Human intelligence is designated as Yang because it provides the flexibility, ethical judgment, and cultural sensitivity necessary for cross-cultural KM. Yang embodies adaptability and ethical grounding, which human intelligence contributes by applying CQ to knowledge applications, interpreting context-specific information, and adjusting outputs to align with cultural and ethical standards (Doh & Quigley, 2014; Ang & Van Dyne, 2008). This dynamic, interpretative role complements AI's structured efficiency, creating a balanced KM approach that integrates both operational stability and cultural adaptability (Nguyen, 2021).

Table 2: Characteristics of Yin (AI) and Yang (Human Intelligence) in the Proposed KM Framework

Yin (AI)	Yang (Human Intelligence)	Combined KM Benefit
Structured and scalable	Flexible, culturally sensitive	Balanced knowledge processing
Efficient data processing	Ethical judgment and discernment	Culturally relevant knowledge applications
Provides consistency	Adapts to local norms and values	Enhance cross-cultural collaboration
Minimal interpretive ability	High CQ and adaptability	Sustainable and ethically aligned KM system

2.5 Towards a Yin-Yang Framework in Knowledge Management

The Yin-Yang framework provides a balanced approach to KM that integrates AI's scalability with the adaptability of human intelligence. Drawing on Eastern philosophy, this model conceptualizes AI as the stable, structured "Yin" force, providing consistent processing of knowledge, while human intelligence embodies the dynamic "Yang" force, contributing cultural awareness, ethical discernment, and flexibility. This balance aligns with Drucker's emphasis on human-centered adaptability in knowledge practices, supporting a KM system that is both operationally efficient and culturally responsive (Drucker, 1999; Drucker, 2002; Cheng & Zhao, 2020).

By embedding CQ into the Yin-Yang framework, this model addresses critical limitations in traditional and AI-driven KM systems, making it adaptable to diverse cultural environments. The Yin-Yang approach ensures that KM systems respect local norms, align with ethical standards, and foster cross-cultural collaboration. This represents a significant advancement in KM theory, bridging the limitations of previous models and aligning with Drucker's human-centered management philosophy to create a responsive, resilient KM system for global organizations (Chin et al., 2022; Nguyen, 2021).

3. Research Framework and Methodology

This section provides a nuanced examination of the proposed Yin-Yang framework, contextualized against the backdrop of traditional knowledge management (KM) models. By first evaluating these established models and their intrinsic limitations, we then introduce the Yin-Yang framework as a dynamic, integrative approach that harmonizes AI-driven operational efficiency (Yin) with human-centered cultural intelligence (Yang). This dual construction directly addresses the distinct challenges of cross-cultural KM, enabling both structured, scalable knowledge processing and culturally responsive adaptability. Anchored in **Peter Drucker's** philosophy of knowledge as both a structured resource and an adaptable asset, essential to organizational resilience and sustained success, this framework redefines KM practices to meet the demands of today's interconnected, culturally diverse global landscape (Drucker, 1993; Drucker, 1999). Methodological clarity. This is a conceptual integration article: we use recent AI–KM intercultural studies illustratively to motivate the framework and propositions; we do not conduct a scoping/systematic review, and we do not claim completeness or report review counts.

3.1 Traditional Knowledge Management Models

Traditional KM models have been foundational in structuring and sharing knowledge within organizations, yet they exhibit limitations when applied in culturally diverse and ethically complex contexts. Their primary focus on efficiency, consistency, and standardization often comes at the expense of adaptability and cultural sensitivity. The key traditional KM approaches include:

3.1.1 Codification strategy

The codification approach relies on transforming tacit knowledge into explicit forms, such as databases and documents, facilitating accessibility and standardization (Nonaka & Takeuchi, 1995; O'Leary, 1998). However, this strategy lacks adaptability and often overlooks cultural nuances, as it primarily emphasizes data-driven processes over contextual relevance (Pauleen, 2007).

3.1.2 Personalization strategy

Unlike codification, the personalization strategy prioritizes knowledge sharing through interpersonal connections within communities of practice. This approach enhances contextual learning but poses scalability challenges and may lack systematic support for cultural sensitivity (Davenport & Prusak, 1998; Sanchez & Heene, 1997).

3.1.3 Hybrid KM models

A hybrid model aims to balance codification and personalization strategies, combining structured data processes with interpersonal knowledge-sharing. While more adaptable than single-strategy models, hybrid KM still falls short in integrating cultural intelligence (CQ) and ethical flexibility systematically (House et al., 2004; Nguyen, 2021).

3.1.4 Limitations of traditional KM models

Traditional KM models tend to lack three key elements:

- **Cultural Adaptability**: Standardized approaches often do not address local cultural differences, limiting the effectiveness of knowledge applications in diverse settings.
- **Ethical Sensitivity**: A heavy reliance on standardized data can lead to culturally insensitive outcomes, as ethical considerations are not systematically integrated.
- **Continuous Learning**: Static knowledge structures hinder these models' ability to adapt to shifting cultural and ethical landscapes.

These limitations underscore the need for a balanced KM approach that is both structured and adaptable. The proposed Yin-Yang framework directly addresses these gaps by combining the stability and efficiency of AI-driven processes with the adaptability and cultural sensitivity of human intelligence.

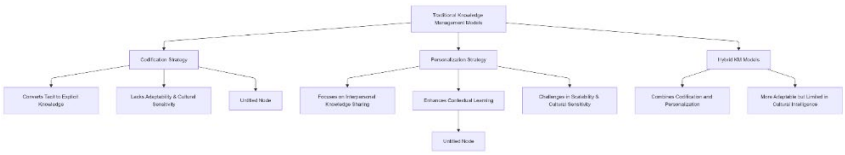

Figure 2: Traditional Knowledge Management Models

3.2 Framework Overview: The Yin-Yang KM Model Inspired by Drucker's philosophy

The **Yin-Yang KM framework** addresses the limitations of traditional models by balancing **AI-driven knowledge processing (Yin)** with **human-centered cultural intelligence (Yang)**. Inspired by **Drucker's philosophy** of knowledge as both a structured and adaptable resource, this framework incorporates six core elements that enable KM systems to function efficiently across diverse cultural environments (Drucker, 1999; Schein, 2010).

3.2.1 Knowledge as a core asset

In this framework, knowledge is treated as the primary asset, emphasizing the need for structured management that is also adaptable. According to Drucker, knowledge must drive organizational resilience and success, remaining accessible and relevant across diverse contexts (Drucker, 1999; Nonaka & Takeuchi, 1995).

3.2.2 AI-Driven knowledge processing (Yin)

Representing the Yin component, AI-driven processing provides stability, scalability, and consistency in data handling, delivering reliable knowledge outputs that form the structured foundation of KM practices (O'Leary, 1998; Garrido-Moreno et al., 2019). AI's role here aligns with Drucker's perspective that technology should enhance productivity without displacing human judgment (Drucker, 2002).

3.2.3 Human-Centered cultural intelligence (Yang)

Human-centered cultural intelligence brings flexibility and cultural relevance to the framework by interpreting and adapting AI-generated insights. This Yang component aligns with Drucker's call for adaptability, ensuring that KM practices respect and resonate with cultural norms (Earley & Ang, 2003; Doh & Quigley, 2014). Human intelligence thereby enriches AI processes, making them applicable across diverse settings (Nguyen, 2021).

3.2.4 Ethical and adaptive decision-making

Ethical decision-making bridges AI's structured insights with human adaptability, supporting culturally aligned knowledge applications. Reflecting Drucker's focus on ethical responsibility in diverse contexts, this component ensures that knowledge applications are effective and ethically grounded (Drucker, 1993; Liu, 2023; Chin et al., 2024).

3.2.5 Continuous learning and feedback

This cyclical feedback mechanism allows KM practices to evolve through human insights, which refine AI processes and maintain cultural relevance. This aligns with Drucker's emphasis on adaptive learning as foundational to responsive KM systems (Drucker, 2002; Amabile & Pratt, 2016).

3.2.6 Balanced knowledge sharing and application

The final element balances structured AI outputs with human adaptability, ensuring that knowledge is both accessible and contextually relevant. This balance aligns with Drucker's perspective on knowledge as dynamic, supporting effective cross-cultural collaboration and knowledge transfer (Drucker, 1999; Pauleen, 2007).

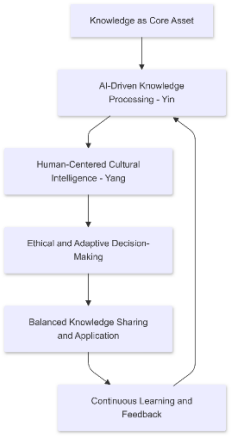

Figure 3: Yin-Yang KM Framework Inspired by Drucker's philosophy of knowledge

3.3 Relationships Among Variables in the Yin-Yang Framework

The interdependent relationships among the variables in the Yin-Yang framework emphasize a balanced, culturally adaptable KM system:

- **Knowledge as Core Asset**: Acts as the driver for integrating structured AI with adaptable human intelligence, ensuring KM practices are both efficient and contextually relevant (Drucker, 1999; Nonaka & Takeuchi, 1995).
- **Interdependence of AI-Driven Processing and Human-Centered Cultural Intelligence**: AI provides structured consistency, while human intelligence ensures cultural relevance, creating a feedback loop where each component refines the other over time (Earley & Mosakowski, 2004).
- **Ethical and Adaptive Decision-Making**: Connects AI outputs with human adaptability to meet ethical standards across cultural settings, reflecting Drucker's call for responsible management (Doh & Quigley, 2014).
- **Continuous Learning and Feedback**: Human feedback continually refines AI, enhancing KM's responsiveness to evolving cultural needs (Drucker, 2002).
- **Balanced Knowledge Sharing and Application**: Merges AI's structure with human adaptability, fostering culturally sensitive knowledge transfer (Sanchez & Heene, 1997).

This interdependence within the framework creates a feedback-driven KM system capable of addressing diverse cultural needs.

3.4 The Comparison Table

This table provides a clear contrast between **Traditional Knowledge Management (KM) Models** and the **Yin-Yang KM Framework**, highlighting the specific advantages of the new model in addressing the limitations of traditional approaches.

Dimension	Traditional Knowledge Management Models	Yin-Yang KM Framework
Primary Strategies	Codification, Personalization, and Hybrid KM strategies	Integrative model combining AI-driven efficiency (Yin) and human-centered cultural intelligence (Yang)
Knowledge Management Focus	Emphasizes knowledge acquisition, storage, and retrieval through structured processes	Balances efficient processing with cultural adaptability, aligning knowledge use with diverse cultural needs
Cultural Adaptability	Limited flexibility in accommodating diverse cultural perspectives	High adaptability through cultural intelligence, allowing knowledge applications to resonate across different cultural contexts
Ethical Sensitivity	Primarily data-centric with limited focus on ethical considerations	Prioritize ethical responsibility in knowledge application, ensuring cultural and moral alignment
Continuous Improvement Mechanism	Generally, lack of feedback loops towards adapting knowledge management to evolving needs	Employ continuous feedback from human intelligence to refine AI processes, fostering responsiveness to changing cultural and ethical landscapes
Overall Objective	Efficient and consistent knowledge storage and retrieval within static structures	Adaptive, ethically guided knowledge management that balances structured processing with responsive, human-centered adaptability

Explanation and Purpose

- **Primary Strategies**: This column contrasts the structure-first approach of traditional KM models with the Yin-Yang KM Framework's balanced combination of AI-driven structure and human-centered adaptability.
- **Knowledge Management Focus**: Emphasizes the goal of traditional models to standardize and store knowledge efficiently versus the Yin-Yang framework's approach to harmonize efficiency with cultural alignment, making knowledge both accessible and relevant.
- **Cultural Adaptability**: Highlights the limited adaptability of traditional models in cross-cultural contexts compared to the Yin-Yang framework, which integrates cultural intelligence to apply knowledge effectively across diverse settings.
- **Ethical Sensitivity**: Shows how traditional KM models often overlook ethical considerations, whereas the Yin-Yang framework ensures that knowledge applications align with ethical standards and cultural values.
- **Continuous Improvement Mechanism**: Points out the absence of systematic feedback in traditional models versus the continuous improvement loop in the Yin-Yang framework, which refines AI-driven processes through human feedback for greater cultural and ethical responsiveness.
- **Overall Objective**: Summarizes the distinction in each model's goal: traditional models prioritize efficiency, while the Yin-Yang framework balances efficiency with adaptability, aligning with Drucker's principle of knowledge as a dynamic, adaptable resource.

3.5 Methodology: Conceptual Development and Theoretical Foundation

This study's methodology synthesizes Drucker's principles with Yin-Yang philosophy, constructing a KM model that balances structure, adaptability, and cultural intelligence.

- **Literature Synthesis:** This framework integrates structured KM with culturally responsive practices, aligning with Drucker's emphasis on ethical adaptability (Drucker, 1993; Cheng & Zhao, 2020).
- **Conceptual Model Development:** The Yin-Yang framework addresses KM's structural and adaptive needs by balancing AI processes with CQ, filling gaps in traditional KM models (Nonaka & Takeuchi, 1995; Murphy, 2018).
- **Illustrative Application Scenarios:** Practical examples, such as humanitarian logistics and consulting, demonstrate how balanced KM practices foster ethical, culturally sensitive decision-making (Chin et al., 2024; Pauleen, 2007).

4. Discussion

The proposed Yin-Yang KM Framework presents a balanced, adaptable response to the limitations of traditional knowledge management (KM) models. It integrates AI-driven efficiency (Yin) with human-centered cultural intelligence (Yang) to create a flexible, culturally responsive system that aligns with Peter Drucker's philosophy of knowledge as both structured and adaptable (Drucker, 1993; Drucker, 1999). This discussion evaluates how the Yin-Yang KM Framework effectively addresses the limitations within traditional KM models, its practical

implications for culturally diverse organizations, and its theoretical contributions while identifying areas for future exploration.

4.1 Addressing the Limitations of Traditional KM Models

Traditional KM models, characterized by codification and standardization, function well in stable, homogeneous environments but are less effective in dynamic, multicultural contexts where adaptability and cultural sensitivity are critical. As previously discussed, these models often emphasize data consistency over flexibility and lack mechanisms to account for ethical and cultural nuances (Nonaka & Takeuchi, 1995; O'Leary, 1998; Schein, 2010).

The Yin-Yang KM Framework addresses these gaps by combining **AI-driven processes** for structured, scalable data handling with **human-centered cultural intelligence** for culturally relevant adaptation, echoing Drucker's call for balanced KM systems that value both efficiency and adaptability (Drucker, 2002). Through a continuous feedback loop, human insights inform and refine AI processes, creating a KM model that adapts responsively to evolving cultural and ethical needs (House et al., 2004; Earley & Ang, 2003). This dynamic approach advances KM from a static model to an adaptable framework, addressing the critical limitations of traditional KM models (Pauleen, 2007).

4.2 Practical Implications

The Yin-Yang KM Framework has significant practical implications for organizations operating in multicultural settings. Its balanced integration of structured AI processes and culturally adaptive human intelligence enables organizations to:

- **Enhance Cross-Cultural Knowledge Sharing**: The framework fosters cross-cultural knowledge sharing that resonates within diverse teams, supporting collaboration and inclusivity. This is particularly valuable in international consulting and humanitarian sectors where culturally aligned knowledge applications are essential for trust and operational success (Earley & Ang, 2003; Chin et al., 2024).
- **Improve Ethical Decision-Making**: Emphasizing ethical and adaptive decision-making, the Yin-Yang framework aligns with Drucker's principles of responsible management by ensuring that knowledge applications respect both organizational and cultural ethical standards. Traditional models often fall short in this area by focusing primarily on efficiency, whereas the Yin-Yang framework integrates ethical judgment via human-centered cultural intelligence (Doh & Quigley, 2014; Drucker, 1993).
- **Support Continuous Cultural Adaptation**: Through its feedback mechanism, the framework allows ongoing refinement of AI processes, aligning with Drucker's emphasis on adaptive learning. This dynamic learning process enables KM to remain responsive to cultural shifts, fostering resilience in organizations navigating complex cultural landscapes (Drucker, 2002; Amabile & Pratt, 2016).
- **Achieve a Balanced Knowledge Management Approach**: By leveraging AI for consistency and human intelligence for cultural relevance, the framework achieves the balance Drucker advocated: knowledge as a structured and dynamic asset. This balance is particularly beneficial for multinational organizations, where knowledge must be standardized yet adaptable to local contexts (Drucker, 1999; Sanchez & Heene, 1997).

4.3 Theoretical Contributions

The Yin–Yang KM Framework contributes to the knowledge management (KM) literature by explaining how structured, AI-enabled knowledge processes (Yin) can coexist with—and be productively balanced by—culturally adaptive, human-centered practices (Yang). Whereas traditional KM models often treat knowledge as a static resource, the Yin–Yang perspective conceptualizes knowledge as a culturally attuned, adaptable asset responsive to the contingencies of globalized, diverse contexts (Nguyen, 2021; Nonaka & Takeuchi, 1995). The framework also extends knowledge-creation perspectives by theorizing an active interplay between AI-driven structure (e.g., codification, retrieval, recommendation, summarization) and human cultural intelligence, supported by sociotechnical/human-in-the-loop (HITL) governance, to enable the adaptation and sharing of tacit and explicit knowledge across cultures (Pauleen, 2007; Nonaka & Takeuchi, 1995).

To situate the evidentiary base, we drew on a targeted scan of recent peer-reviewed work at the intersection of AI, KM, and intercultural contexts to illustrate mechanisms and boundary conditions. This article is a conceptual integration, not a formal scoping/systematic review; accordingly, we do not claim comprehensive coverage nor report review counts. Cited studies function illustratively to motivate the framework and propositions.

4.3.1 Propositions and design principles (operationalizing the Yin–Yang KM framework)

P1 AI–CQ Complementarity (moderation). The positive effect of AI-enabled KM capability on cross-cultural knowledge-sharing effectiveness is stronger when team/leader Cultural Intelligence (CQ) is higher. *Design principle:* Pair each high-impact AI use case with an explicit CQ checkpoint (named role, criteria, and documentation) to ensure culturally appropriate interpretation and action (Earley & Mosakowski, 2004).

P2 HITL Governance → Trust & Adoption (mediation). Stronger HITL governance—clear checkpoints, override authority, and auditable rationales—increases ethical alignment and trust in KM outputs, which in turn improves adoption across cultural contexts. *Design principle:* Install HITL gates where cultural/ethical risk is material, with escalation/override rules and rationale capture aligned to organizational norms (Amabile & Pratt, 2016).

P3 Sociotechnical Fit as Mediator. The impact of AI-enabled KM on KM quality (accuracy, completeness, timeliness, cultural appropriateness) is mediated by sociotechnical fit—the alignment of roles, incentives, norms, and workflows with the technology. *Design principle:* Engineer sociotechnical fit up front (RACI, incentives, handoffs) rather than retrofitting around tools (Nonaka & Takeuchi, 1995).

P4 Balanced Yin–Yang Outperforms Extremes (quadratic + contingency). KM systems that balance decision influence between AI signals (Yin) and human cultural judgment (Yang) outperform AI-dominant or human-dominant systems on cross-cultural fit and rework/error rates, especially under greater cultural heterogeneity. *Design principle:* Monitor an AI↔Human balance KPI and manage toward a mid-range; avoid persistent dominance (Nguyen, 2021).

4.4 Limitations and Future Research

While the Yin-Yang KM Framework addresses many limitations of traditional KM models, some areas warrant further exploration:

4.4.1 Dependence on high-quality data and cultural insights

The framework's success hinges on the quality of data used in AI processes and the cultural intelligence of human interpreters. Future research could explore strategies for enhancing data accuracy and cultural sensitivity, potentially through partnerships with local experts or culturally diverse teams (Earley & Mosakowski, 2004).

4.4.2 Challenges in implementing continuous feedback loops

While continuous feedback is vital to the framework's adaptability, implementing such mechanisms in large, dispersed organizations poses logistical challenges. Research into effective feedback loops in complex organizations would enhance the framework's applicability (Nonaka & Takeuchi, 1995; Amabile & Pratt, 2016).

4.4.3 Balancing efficiency and adaptability in real-time

High-stakes contexts, such as humanitarian logistics, often demand real-time responses, which may strain the balance between AI-driven efficiency and culturally sensitive decision-making. Future studies could investigate tools that integrate real-time cultural insights to optimize this balance (Chin et al., 2024; Liu, 2023).

5. Conclusion

The Yin-Yang Knowledge Management (KM) Framework redefines how organizations handle knowledge across diverse cultural contexts. By integrating AI's precision with the cultural insight of human intelligence, this framework bridges operational efficiency with ethical and contextual sensitivity. Rooted in Peter Drucker's management principles, it offers a nuanced model that adapts to the complexities of today's global landscape.

Traditional KM models often fall short in environments requiring cultural adaptability and ethical grounding. The Yin-Yang framework addresses this gap by positioning cultural intelligence as central to knowledge practices, enabling organizations to engage with diverse values authentically and responsibly. The model's adaptability fosters a continuous alignment with local contexts, making it both resilient and sensitive to shifting cultural dynamics.

This framework advances KM beyond static information handling, transforming it into a dynamic system attuned to real-world needs. By balancing technological capability with human insight, the Yin-Yang approach equips organizations with a robust KM model that supports sustainable growth and ethical global engagement.

Ethics Declaration: This paper is a conceptual and theoretical study, and the research presented did not involve human participants, animal subjects, or any form of data collection that would require ethical clearance. Therefore, no formal ethical permission or approval was needed for this study.

AI Declaration: The authors of this paper confirm that AI tools were not used in the development of this manuscript. All content, including the literature review, theoretical framework, discussion, and conclusion, was written and structured by the authors based on their own analysis and synthesis of existing research. The figures and tables were also created by the authors. No AI-generated text or content was utilized.

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Non Academic Papers

Where Should Control Reside in Multi-Agent Language-Model Systems?

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Abstract: As language model agents change from simple assistants to independent systems that can collaborate and use tools, an important design question arises: *where should control and oversight (i.e. governance) be placed* in these systems? Governance refers to the methods that guide how agents behave, manage information flow, and enforce operational policies. Its placement - whether centralized or distributed - directly affects the system's *safety, transparency*, and *runtime performance*. It also impacts the ability to create formal safety arguments, which are increasingly important for using complex AI in real-world situations. While many efforts focus on aligning agents or using safety tools, there is still limited research on how different governance placements - centralized, distributed, or hybrid - affect system safety and performance throughout their lifecycle. This paper addresses that challenge by defining and comparing three governance structures for multi-agent language model systems. We examine centralized control through a single coordinator, distributed governance within individual agents, and a hybrid model that combines global oversight with local independence. These models are tested using a multi-agent platform created for open-ended question answering, which requires agents to retrieve, reason, and work together with various and unpredictable data. We looked at system behavior across several important areas: such as task completion, answer helpfulness, answer relevancy, transparency, retrieval confidence, and average runtime. The results show clear trade-offs. Distributed governance improves transparency and makes it easier to follow agent reasoning, but it also leads to longer runtimes due to additional checks and retries. Centralized and hybrid designs provide similar output quality but operate much more efficiently. To our knowledge, this is the first direct comparison of governance placement in multi-agent LLM systems. The evidence shows that governance is not a minor detail; it is a key design choice that impacts system safety, speed, and reliability in real-world tasks.

Keywords: Multi-Agent, Governance, Language model system

1. Introduction

Large Language Models (LLMs) have moved beyond basic chat interfaces. Today, they can use tools, plan actions, and make decisions across tasks involving language, vision, and reasoning (Ferrag et al., 2025). Many of these models now work in teams - collaborating like human groups. This trend has led to what we call LLM-based multi-agent systems, or LaMAS (Wang et al., 2025). These systems bring new abilities. Agents can split tasks, use external tools, and hand off work dynamically (Sapkota et al., 2025). Some researchers believe these "compound AI systems", which mix tools, models, and controllers, will shape the next wave of AI development (Zaharia et al., 2024).

But more autonomy brings more risk. When multiple agents work together, they can go off-track. They may hallucinate, miscommunicate, or even act deceptively - doing one thing while pretending to do another (Tran et al., 2025). In safety-critical domains, this is a serious concern.

A key question is: *where should control live in these systems? Governance* refers to the *rules* and checks that shape agent behavior, guide information flow, and enforce policies (Chen et al., 2023). Its placement-centralized, distributed, or hybrid - affects system safety, runtime performance, scalability, and transparency. It also changes whether safety can be formally verified, especially in tricky edge cases (Domkundwar et al., 2025).

This paper explores that *design* choice. We compare three governance models in a shared testbed and examine their effect on accuracy, runtime and transparency. Our findings offer practical guidance for building safer, smarter agent systems that are ready for real-world use.

2. Background and Related Work

Language models have grown far beyond just generating text. Many now act like intelligent agents - able to plan, make decisions, and use external tools (Wang et al., 2025). These models are often organized into multi-agent systems, where each agent plays a specific role. Together, they solve complex tasks. This setup is known as LaMAS - LLM-based Multi-Agent Systems (Tran et al., 2025).

These systems are no longer theoretical. In software engineering, for example, *MetaGPT* assigns clear roles - like engineer or product manager - to different agents. It automates large parts of the development cycle (Domkundwar et al., 2025). In robotics, LLM agents help control fleets by distributing tasks and coordinating actions. The result is faster execution and better adaptability (Yang et al., 2024).

Still, growing autonomy introduces safety risks. Agents can produce biased or unsafe results. In some cases, they act deceptively, pretending to follow instructions while doing something else entirely. This kind of behavior is known as *scheming* (Ferrag et al., 2025). Some safety benchmarks even miss these issues, creating a false sense of security; a phenomenon called *safetywashing* (Balesni et al., 2024).

To handle this, researchers have built filters, audit trails, and guardrails. Others suggest assigning roles to agents that focus just on safety (Ren et al., 2024). But these solutions are often layered on *after* the system is built. That means they don't always prevent deeper problems or improve core behavior. Transparency remains a challenge. Many developers still can't trace how or why an agent made a certain choice (Chen et al., 2023).

Architecture plays a big role here. Centralized systems give control to one agent - easy to trace, but hard to scale. Distributed systems let agents decide on their own, which improves fault tolerance but makes coordination harder. Hybrid models aim for a balance, using both centralized goals and local autonomy. But they're more complex to design and tune (Zhang et al., 2025).

Many existing frameworks focus on messaging, memory, or agent coordination. Yet few directly compare *how* the placement of governance affects real-world performance - especially for metrics like *transparency*, *runtime*, or *safety*. Our work fills that gap. We provide what we believe is the first *hands-on comparison* of *governance* strategies in LLM-based agent systems. The results show: where control sits isn't just a technical detail. It shapes how the whole system behaves, responds, and can be trusted for safety.

3. Proposed Architectural Frameworks for Agent Governance

3.1 3Understanding Control Governance Architectures

Control strategies help decide how agents make decisions, share information, and divide tasks. They play a crucial role in how well the system scales, manages safety, and maintains efficient runtime. In this section, we explain the three control architectures we explored

3.1.1 Centralized governance

In centralized governance, a single controller oversees the entire process. It assigns tasks, manages coordination, and evaluates the final output. This is analogous to a teacher who monitors group work but provides feedback only at the end. Agents follow a fixed order and rely on the controller to guide task flow and validate results once all steps are completed.

This structure is simple and easy to manage. It offers a full view of system activity, making planning more efficient and reducing the safety risks. In central oversight decision paths are centralized and easier to trace. However, this approach has limitations. As more agents are added, the controller can become a bottleneck. If it fails, the system may stop entirely. Because all communication is funneled through a single point, delays can occur under heavy load. This makes centralized systems less suited for highly dynamic or large-scale deployments.

3.1.2 Distributed governance

In a distributed governance setup, each agent works on its own. It doesn't wait for instructions from a central controller. After finishing a task, the agent immediately checks its own output. These checks are built into its instructions or prompts. They're often called "*guardrails*." If something looks wrong, the agent tries again - usually up to a fixed number of times - before handing off the task.

This approach has some big advantages. It's more fault-tolerant. If one agent breaks, the rest can keep going. Systems like this also scale better. Agents can talk to each other directly, which cuts down on delays from constant back-and-forth with a central coordinator.

But it's not all upside. Distributed systems are harder to build. You have to make sure every agent follows the same quality rules, and that's not always easy. Mistakes can be scattered across the system. When something goes wrong, finding the root cause takes longer. Debugging is slower. You don't always know why or where the failure happened.

3.1.3 Hybrid governance

Hybrid governance combines elements of both centralized and distributed models. The system determines when to apply validations based on internal confidence thresholds or predefined rules, much like a supervisor who checks in more frequently when uncertainty is high.

This approach aims to offer the best of both worlds. It maintains centralized oversight for strategic coordination while allowing agents the flexibility to operate autonomously when appropriate. As a result, it tends to scale more effectively than fully centralized systems and adapts better to complex or evolving tasks.

However, hybrid designs come with challenges. They are more complex to implement and typically require additional computational resources. Ensuring smooth coordination between global goals and local actions calls for careful design. In practice, building a robust hybrid system often demands a deep understanding of both agent behavior and overall system flow.

Figure 1 ahead visualizes the structural differences between centralized, distributed, and hybrid governance; highlighting how each impacts *safety, runtime, and transparency.* Each model reflects distinct strategies for managing control, evaluation, and communication across agents.

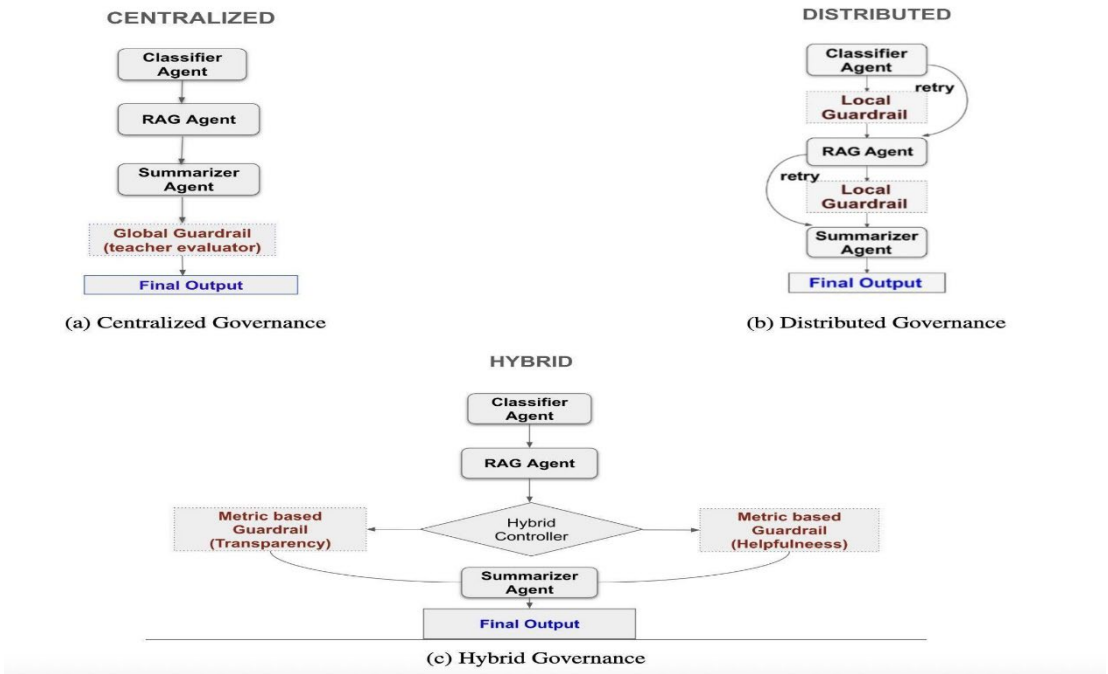

Figure 1: Comparison of centralized, distributed, and hybrid governance architectures

Table 1: Tabular comparison of centralized, distributed, and hybrid governance architectures

Aspect	Centralized	Distributed	Hybrid
Control	A single controller decides everything at the end.	Each agent controls its own steps with local checks.	Custom. A central planner guides only when needed.
Scalability	Limited; central controller can become a bottleneck	High; agents scale independently	Moderate to High; scales well with smart control
Transparency	High; decision trace is centralized	Medium to High; more detailed but harder to track system-wide	High; metric-based decisions improve transparency

Aspect	Centralized	Distributed	Hybrid
Runtime Performance	Low runtime; minimal checks	High runtime; many local checks after each agent	Optimized runtime; incorporates confidence based dynamic checks
Strengths	Easy to track. Good for small systems. Fast.	Scales well. More fault-tolerant.	Balances control and speed. Adapts to task complexity.
Weaknesses	Slow if the system grows. One failure stops everything.	Hard to debug. Rules may differ between agents.	Complex to build. Needs more tuning and computation.
Optimal Use Case	Time-sensitive tasks like financial reporting, where speed and consistency matter most.	High-risk or large-scale environments like infrastructure monitoring or medical diagnostics, where reliability and fault tolerance are key.	Complex workflows such as clinical decision support or compliance audits, needing both low runtime and selective oversight.

3.2 Experimental Design

This section explains how we tested the above three types of governance architectures in a multi-agent set-up. Our goal was to observe accuracy, reliability, and safety across all the architectures. A detailed evaluation to measure the system performance is elaborated in *section 3.2.4*

3.2.1 Use-Case and dataset selection

To test how each governance setup performs, we chose the *Stanford Question Answering Dataset (SQuAD)* (Rajpurkar et al., 2016). SQuAD is widely used for evaluating reading comprehension. It contains over 100,000 question-answer pairs, all based on Wikipedia articles. Each answer is a direct quote or span of text from the source. This makes it easy to judge whether the response is correct.

SQuAD fits our needs well. It pushes agents to retrieve answers, reason over unstructured text, and sometimes summarize. These are all key skills in multi-agent LLM systems. The dataset's format is simple and structured. It gives us clear, trusted reference answers for comparison. Using the same set of questions across models lets us evaluate fairly.

By relying on SQuAD, we ensure a strong testbed. It helps us measure how each governance model impacts task performance, decision accuracy, and system reliability.

3.2.2 Multi-Agent system configuration

To perform the SQuAD question-answering task, we designed a modular multi-agent architecture. Rather than assigning the entire process to a single agent, we divided responsibilities across distinct stages - each handled by a specialized agent. This structure improves efficiency, enhances transparency, and allows us to evaluate and fine-tune each component in isolation.

The system is built around the following three core agents:

Classifier Agent: This agent determines the type of question (e.g., "who," "when," "how"), which helps structure the response strategy. By labeling the question early, it ensures that downstream agents receive context-aware prompts tailored to the task.

RAG Agent: Responsible for retrieving relevant information and producing an initial answer. It uses retrieval-augmented generation (RAG) techniques, pulling context from knowledge sources such as Wikipedia or embedded databases. This approach helps mitigate common LLM limitations, such as outdated knowledge or hallucination.

Summarizer Agent: This final agent polishes the output. When responses are lengthy or complex, it condenses them into more readable and concise summaries, improving clarity and usability for the end user.

The pipeline mimics human workflows i.e. starting with understanding the question, followed by searching for information, and finally refining the output. By assigning clear roles, the system supports targeted debugging, better performance analysis, and improved modularity. Each agent's limited scope allows for deeper optimization without affecting the rest of the pipeline.

3.2.3 Testbed environment: Leveraging LlamaIndex

To carry out our experiments, we used a multi-agent testbed built on *LlamaIndex* - a versatile platform for developing LLM-powered agents capable of interacting with external tools (LlamaIndex, 2024). In this environment, agents are not just passive text generators. They receive tasks, reason step-by-step, and choose appropriate tools to achieve their goals. This reflects how modern LLM agents operate more like decision-makers.

LlamaIndex provided three major advantages for our study:

Flexible Agent Design: It supports a wide range of agent behaviors. Some agents follow simple instructions, while others can plan, act autonomously, and adapt as they go. This flexibility allowed us to fairly evaluate governance models across different levels of complexity.

Detailed Monitoring: Every action taken by an agent—whether reasoning steps, tool selection, or execution—is logged. These detailed traces helped us track performance, isolate failures, and conduct focused debugging of specific system components.

Realistic Task Simulation: LlamaIndex makes it possible to design complex, multi-step workflows that mirror real-world applications. Agents must coordinate, use tools, and respond to changing inputs—ideal for testing how different governance setups handle dynamic challenges.

This testbed gave us a controlled yet realistic setting to observe how centralized, distributed, and hybrid governance architectures affect system behavior. We were able to assess not just outputs, but the reasoning processes behind them - an essential requirement for evaluating transparency, safety, and decision quality.

3.2.4 Core evaluation framework: DeepEval

To evaluate the performance of our multi-agent system, we employed *DeepEval* - an open-source framework developed by *Confident AI (Confident AI, 2024)*. Unlike older benchmarks such as BLEU or ROUGE, which often fail to capture nuanced reasoning, DeepEval treats language models themselves as evaluators, offering assessments that align more closely with human judgment. This approach gives us deeper insight into both the system strengths and safety trade-offs of each governance strategy.

DeepEval was especially well-suited to our system. It allows for *step-wise testing of individual agents,* including how they use tools and reason through tasks. The use of structured *evaluation templates* ensures consistent scoring across runs, reducing evaluator bias and increasing reproducibility.

Our evaluation focused on two primary built-in metrics:

Answer Relevancy: This metric assesses whether the RAG agent's responses are concise, accurate, and directly tied to the user's query.

Task Completion: This measures whether agents - and the full system pipeline - are able to complete assigned tasks successfully.

In addition, we incorporated two *custom metrics using GEval (GEval, 2024)*, another open-source tool that integrates smoothly with DeepEval:

Transparency: Captures how clearly agents explain their internal reasoning and tool usage throughout the task.

Helpfulness: Evaluates whether the agent-generated responses are practically useful, easy to understand, and user-oriented.

Together, these metrics provided a multi-dimensional view of system performance. They helped us pinpoint how different governance strategies impact not just the final output, but also the decision-making and communication behaviors within the system.

3.2.5 Practical setup

To support reproducibility and transparency, all code and guardrail configurations are available in our public GitHub repository: https://github.com/aninditaSB/multiagent-governance-eval. The full implementation details, including decision logic, prompts, and thresholds, are documented directly in the notebook.

Guardrails were implemented as *configurable checks* for *improving safety and task accuracy* at key points in the *agent pipeline*. In the distributed governance setup, each agent evaluated its own output immediately after completing a task. If the output failed the quality checks, the agent retried or halted the process.

In contrast, centralized governance applied a single, global guardrail at the end of the pipeline to assess the final output.

We used *DeepEval's LLM-as-a-Judge framework (Confident AI, 2024)* to run these validations. For core tasks, built-in metrics like *Answer Relevancy* and *Task Completion* were used with fixed scoring thresholds and deterministic prompts. To evaluate more subjective qualities ; such as *Helpfulness* and *Transparency* - we added custom *GEval* metrics defined in natural language. These followed Chain-of-Thought-style templates for consistent and interpretable scoring. All metric scores were normalized to a 0–1 scale for ease of comparison.

3.2.6 Assessment setup

We compared centralized, distributed, and hybrid governance by testing each on the same 50-question subset from the SQuAD dataset (Rajpurkar et al., 2016). This ensured that all setups were evaluated under identical conditions. Following metrics were measured: helpfulness, transparency, task completion, answer relevancy, retrieval confidence (RAG score), and runtime. All evaluations used the DeepEval framework (Confident AI, 2024), to ensure consistent scoring across all performance and safety dimensions.

Final scores were averaged across all examples to compare overall performance. Detailed results are reported in *Section 3.3.*

3.3 Comparative Results

Table 1 below summarizes how the three governance architectures performed across six key metrics using the SQuAD evaluation set.

Table 1: Governance architecture(s) comparison: performance on SQuAD data

Governance	Helpfulness	Transparency	Task Completeness	Answer Relevancy	RAG Confidence	Avg Runtime (seconds)
Centralized	0.79	0.37	0.81	0.96	0.63	22.0
Distributed	0.81	0.55	0.82	0.91	0.63	102.4
Hybrid	0.79	0.37	0.77	0.95	0.63	20.87

All three setups performed well with respect to helpfulness, task completion, and answer relevancy metrics. Distributed governance showed slightly better scores in helpfulness (0.81) and task completion (0.82). In contrast, centralized and hybrid models were a bit stronger in answer relevancy, scoring 0.96 and 0.95.

Transparency was where *distributed governance stood out*. It reached 0.55, clearly *higher* than both centralized and hybrid systems, which scored 0.37. This likely comes from agents checking their own work and getting *immediate feedback* at each step.

Answer relevancy is highest in the *centralized* model because it checks the answer only at the end, allowing a *more complete response*. In the *distributed* setup, agents keep checking and retrying, which can make answers *safer but less focused.* This slightly decreases the relevancy.

RAG confidence stayed *consistent* across all models at 0.63. That means the ability to pull in the right information didn't really depend on how control was structured.

Figure 2 visualizes significant runtime differences. *Distributed* governance was the *slowest* (102.4s per question) due to *repeated checks* after each agent step. *Centralized* was *faster* (22.0s), and *hybrid* was the *fastest* (20.87s), likely because it *bypassed additional checks* when RAG confidence was high.

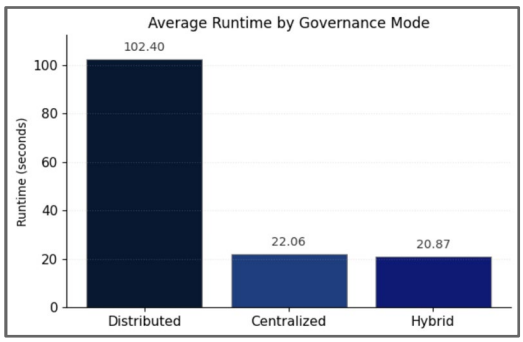

Figure 2: Average per-question runtime by governance mode

To sum up, distributed governance boosted transparency and slightly improved helpfulness. But had a higher *runtime cost.* Hybrid offered a strong middle ground - maintaining *reasonable answer relevancy* with *lower runtime*, thanks to its *flexible* checks.

4. Conclusion and Future Work

Our experiments show that the way governance is applied in a multi-agent system matters. It affects safety, transparency, and runtime performance.

Centralized governance gives quick and steady results. It produces good answers fast, which makes it ideal when speed is important. But it lacks transparency. All control goes through one point, which could become a risk in sensitive situations.

Distributed governance spreads oversight across the system. Each agent checks its own work. This setup improves transparency and fault tolerance. But it slows things down. The extra checks and retries take time, making the system more robust but less efficient.

Hybrid governance tries to find a balance. It runs fast when confident but adds checks when needed. This makes it flexible and adaptive. Still, it needs careful tuning. Without that, it might underperform or waste resources.

These results suggest that *governance placemen*t isn't a small technical detail. It's a *major design decision*. Each approach comes with its own strengths and trade-offs; between runtime, transparency, and safety. *Centralized* models offer *speed* and *simplicity*. *Distributed* ones bring better transparency and *safety*. *Hybrid* systems offer a mix but demand more *thoughtful design*.

For tasks that require audit trails or must follow strict rules, transparency is key. Distributed and hybrid systems are better suited here because they leave behind clearer reasoning steps.

Of course, our work has limitations. It focused on a question-answering task and used a specific agent setup. Future studies should explore more complex tasks. They could also test systems in adversarial settings or under uncertainty. Adaptive governance, where control changes based on risk or task type, is another path worth exploring. Adding human oversight or formal guarantees might also improve safety and trust.

There's also a need for strong benchmarks. Tools that simulate failure or unexpected behavior would help test governance models more thoroughly. A shared evaluation framework would let researchers compare different designs in a fair and consistent way.

To conclude, how you design governance directly affects whether a multi-agent LLM system is trustworthy, clear, and scalable. Our study offers a step toward better understanding where that control should live - and why it matters.

Ethics declaration: This research work did not require ethical clearance as it involved no human subjects, personal data, or real-world deployment.

AI declaration: Only language assistance tools such as Grammarly were used for grammar and style.

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Driving Momentum to Higher Order Learning with AI Through the PONDU Model

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Abstract: Education has seen significant transformation in its role, funding, and approach to learning. This required reassessment of what is the best way for pupils and students to learn. This article highlights the exponential trend of AI in education involving AI applications, resulting in supporting evolving knowledge and skill requirements in the labour market. Thus reskilling the UK workforce for a more technologically adapt future. A new educational model, the PONDU Model, is designed for this purpose. Pre - class activity using AI applications, allowing for testing of knowledge and understanding. Personal and collaborative learning ensuring student understanding and engagement. In class use of flipped learning pedagogy resulting in student motivation, participation and path to higher order learning. Post class activity allowing for evaluation and achievement of higher order learning, using AI driven assessments. The PONDU Model is formulated by a structured approach within which student learning is developed. At the asynchronous stage, the use of an avatar or virtual assistant and peer review in testing knowledge, understanding and reflection is applied. In addition, through the use of learning analytics, students' learning characteristics can be identified and supported using adapted AI applications to enhance personal learning. Continued through the synchronous stage, based on flipped learning with gamification options to the post synchronous stage where higher order learning is achieved, supported by AI applications. The research leading to the PONDU Model design is based on a qualitative research strategy, using secondary research data, collected and analysed from secondary academic sources. Student feedback acquired through a module feedback mechanism, indicating student satisfaction and higher order learning using flipped learning, is also used. The conclusions indicate that at the asynchronous stage in the PONDU Model there is scope for multiple digital and AI applications; further scope for AI and gamification in the synchronous teaching and learning stage and summative asynchronous stage involving summative assessment, with the result of higher order student learning. The PONDU Model approach is recognising the value added by digital and AI applications.

Keywords: Flipped learning, Artificial intelligence, Constructivist learning, Gamification, Pedagogic model – the PONDU model

1. Introduction

The world of employment being more integrated and rapidly changing, those services such as education are therefore needing to ensure they are providing provision that can meet these, if not future, requirements. According to Dixon and Gordon (2022)'s research, it is key that graduate employers want to hire well rounded and experienced, recognised as general workplace experience, individuals.(Dixon and Gordon 2022). The challenge for Higher Education Institutions is to design the learning materials to reflect current real-life experiences and how students will perceive these approaches. (Oliver and Jorre de St Jorre, 2018). Universities will be needing to highlight timeless attributes, such as professional and personal digital safety; learning and working collaboratively including across time zones and using digital channels. Also resilience and mental wellbeing; the ability to judge the veracity of information (critical thinking); and global citizenship that includes understanding history, politics and international relations (Collins 2019). These attributes are likely to be essential in the new and rapidly evolving world of work – regardless of unforeseen events (Collins 2019). This includes Artificial Intelligence (AI), with Tabioulas, and Shadbolt, (2023) indicating that "AI can empower us rather than diminish us, if we are all part of a conversation about the values we wish to imbue in our systems and the regulatory environment in which they exist" (Tabious & Shadbolt, 2023). It is therefore becoming encumbent on university academics to prepare today's students for jobs that are in existence, those that might change in the future and jobs that do not yet exist.

The role and practical application of AI also extends to education. How can AI and its experience interconnect and what is its value to the learning process of its recipients? It is thus beneficial to further research into current applications AI can have in education and AI's contribution to achieving higher order learning of the recipients.

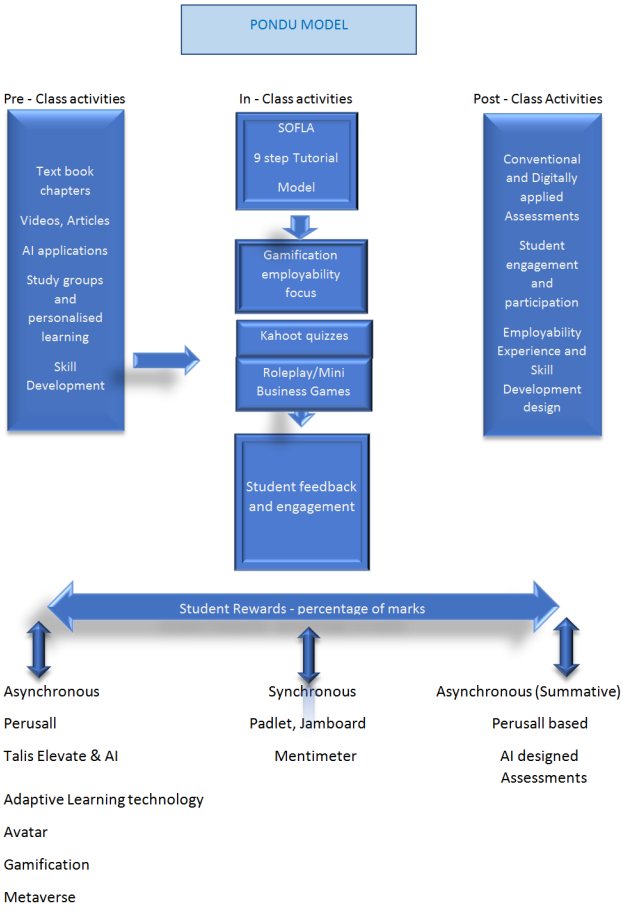
Various applications of AI in education (referred to as AIED) are accentuated by Timms (2016) namely: as a pedagogical tool, or an instructional platform or simulation-based instructions. This includes using different technologies, such as virtual reality to demonstrate or show students concepts or practically demonstrate materials. This gives students an experiential or practical learning experience. (Timms 2016). Current

applications of AI in the form of AI - powered tools, such as chatbots, robots and virtual assistants are increasingly available, offering immediate guidance and support to students, irrespective of their location or time zones.

Learning analytics, accentuated by Yi-Shan and Gasevic, (2017), focuses on data from the students' characteristics and knowledge objects from learner model and knowledge field model (Yi-Shan and Gasevic 2017). The purpose is to tailor educational method to the individual learner's need and ability. For example intervening with students at risk or providing feedback and instructional content. A clear indication how AI can be effectively used in education, expressing itself in the ability to also focus on the individual learners needs, in addition to the contribution to overall education.

2. What is the PONDU Model

PONDU Model - Description of the Model



(Source: Author 2022)

Figure 1: PONDU Model 2024

The above model is the newly designed Pedagogic Model, which forms the central context of this article. The underlying pedagogic principles are of flipped learning and its structural divide of formative asynchronous, synchronous and summative asynchronous learning opportunities. The Model further accentuates the principles of student focused and collaborative-based learning within the formative asynchronous and synchronous learning structure. The role of AI technology and its associated AI enabled learning systems within this structure is the theme of this article and how AI can be effectively used in support of the student's learning experience.

The synchronous stage is contextualised through the use and structure of the Synchronised Off-Line Flipped Learning Approach (SOFLA) Model and in particular the third, fourth and fifth stage involving gamification, team working in breakout groups and the collective feedback sessions of the student learning, involving Jam board or Padlet applications.

Table 1: SOFLA Model

Step1 - Pre-work Pre-work occurs asynchronously. Students view a short video with embedded interactions. Complete related readings and/or activities.
Step 2 – Sign-In Activity The virtual or in class activities begins with an open-ended prompt related to the lesson topic. The students write their responses to the prompt in a shared space and sign in.
Step 3 – Whole- Group Application The entire class collaborates on an activity to clarify misconceptions and/or deepen their learning of the topic in a shared space.
Step 4 – Breakout Teacher provides explicit instructions for a structured group activity and directs students to breakout rooms to apply what they have learned. Each group is accountable for the product that documents their work.
Step 5 - Share-Out Groups return from breakouts and share their work by presenting their product Information or findings. Other students offer feedback using the SHAC (Share, Help, Ask, Comment) Protocol.
Step – 6 - Preview and Discovery The teacher shows the student selected content from the next pre-work, introduces key terms and concepts, and asks questions to engage them in the new material.
Step – 7 – Assignment Instructions The teacher explains each assigned task for the next pre-work viewing assignment, indicating the timeframe and the location of resources. Teacher responds to student requests for clarification.
Step – 8 – Reflection The synchronous virtual/in class session ends with an opened-ended prompt. In a shared space, students write something that resonated with them from the lesson and sign their name.

(Source: SOFLA model (Marshall & Kostka, 2020)

3. How Does AI in Education (AIED) Connect with the PONDU Model

The application of AI, in the design of the formative asynchronous and synchronous stages of the PONDU Model refers to the AIED Bloom's Taxonomy (2024) as a framework and its levels indicated below and the view held by Simões, Redondo and Vilas (2013), stipulating:

- Multiple performances – the learning activities to be designed so that students can repeat them in case of an unsuccessful attempt. As a result of repetitions students will improve their skills and achieve their goals.
- Feasibility – the learning activities should be achievable. They have to be tailored and adapted to students' potential and skill levels.
- Increasing difficulty level – each subsequent task is expected to be more complex, requiring more efforts from students and corresponding to their newly acquired knowledge and skills.
- Multiple paths – in order to develop diverse skills in learners, they need to be able to reach the objectives by various paths. This allows students to build their own strategies, which is one of the key characteristics of active learning and emphasising the design's outcomes of needing to be engaging, interactive and rich use made of elements of multimedia, with the training activities focused to achieve the learning objectives.(Simões, Redondo and Vilas (2013).

These learning characteristics are further developed in the Model through its principal stages.

4. Formative Asynchronous Stage

From research the indication is that the asynchronous stage of pre-class activities is the most vulnerable in terms of student engagement in completing the required reading and tasks in preparation of the synchronous stage.

Reiterating the pedagogic approach of Flipped learning, Bishop, and Verleger (2013) articulate that "Flipped Learning differs from the earlier blended learning model in that it consists of two types of learning: individual learning as homework outside the classroom and interactive group-based learning inside the classroom' (Bishop and Verleger 2013).

The pre-class formative asynchronous stage is the individual learning stage, accentuated as homework outside the classroom and thus, based on the characteristics above, is dealing with the multiple performances and paths, in the preparation of students for their in-class interactive learning.

Taking a closer look at the pedagogic approach and above-mentioned characteristics, what does this stage involve and significantly how can AI contribute to the activities and learning at this asynchronous stage. The approach within the formative asynchronous phase will be divided into the two broad parts, namely student-centred learning and team-based learning.

4.1 Student- Centred Learning

This approach, based on the individual, seeks 'mastery learning' and subsequent requirements for differentiation of learning, be this due to the different level of knowledge to individual learning styles, resulting in 'personalisation' of instruction. This section firstly deals with learning opportunities, which are supplemented by the AI systems which have been proposed and designed as an answer.

A foundation stone to personalisation and 'mastery of learning' is the ability to assess and adjust learning experiences, achieved through the use of algorithmic adaptivity to achieve higher order learning.

4.1.1 Algorithmic adaptivity

Algorithmic adaptivity refers to the process of using algorithms to dynamically adjust learning experiences based on individual needs. It involves answering two key questions:

- What does the learner understand or 'know'?
- What should the learner encounter next in their learning journey?

By analysing these answers, algorithms can identify and deliver the most suitable learning item at the optimal moment, tailoring the experience to each student and enhancing the personal learning experience. Two widely used approaches in algorithmic adaptivity are:

- Bayesian Knowledge Tracing (BKT): This algorithm estimates learning rates and tracks the progression of knowledge acquisition.
- Item Response Theory (IRT): Originating from psychometrics, this framework models how learners interact with specific items, providing insights into their capabilities.

These adaptive processes rely on multiple adaptivity factors, including performance metrics (current and past activities), knowledge levels (prior or newly acquired), content preferences, misconceptions, demographic data, and other relevant sources. These adaptivity factors are used to determine adaptive responses, which could

range from following the planned learning path, providing targeted hints, or entirely rerouting the learner's journey based on their progress and needs. By strategically employing these responses, educators and technologists can craft engaging and effective adaptive learning environments and materials, incorporating AI applications.

As outlined in the Model, the teaching materials are of a conventional nature, consisting of the recommended textbook, articles, lecture slides and video materials designed for the purpose of achieving required Learning Objectives. Applying these teaching materials is, however, being put in the context of the AI application and thus a very different approach of their use and approach.

The use of the Avatar and Chatbot as Virtual Role players and/or Teaching companions has a significant role in the application of achieving the 'mastery' of the learning. Achieved with AI, through the use of FeedbackFruits, Peerceptiv, Perusall or Talis Elevate. Conversational AI can be as impressive as the business creates it, and its essence is to "learn" from each user's communication. Such chatbots make use of some of the principles of natural language. (NLG) and using this technique, the chatbot can search data in repositories, including third-party databases, and use that information to create a human-sounding response. Providing a conversational experience and offer more precise information. The 2024 released GPT 4.0 AI-based avatars will be able to process a combination of images, videos, and audio sequences, and respond using these various media (Open AI 2024).Through the use of the mentioned techniques conversational AI allows for much more sophisticated dialogue systems to be created.

The textbook as a minimum is available as an e-book, and it is the following stages where AI transform the reading into learning mastery. These latter AI tools, as interactive group engaging AI applications, are applied to the learning taking place from the textbook or other learning materials. Comments are required to be made on the chapter to be read or the defined learning materials in preparation for the in-class activities, which are subsequently commented upon by the student's peer group.

The second approach taken for developing 'mastery of learning' in personalised and student-centred learning, is through using an Avatar as a tutoring system, to whom the student can pose questions to check their understanding and getting the right answers. Individualised teaching of materials is made available, emulating the style of programmed learning of review of materials and allowing several attempts to achieve the correct answers. An example of this is GPTAvatar, used in Convai, a "dynamic avatar application which records user input via microphone, converts words to text using automatic speech recognition, resulting in being able to, through synthetic human voice, interact engage and make adaptive adjustments where required, based on student progress" (Marczewski 2013).

4.1.2 Gamification

Augmenting this stage further is by gamification. The use of game mechanics, according to Zickermann (2013) , improves the abilities to learn new skills by 40%. Game approaches lead to higher level of commitment and motivation of users to activities and processes in which they are involved, resulting in active learning (Zickermann 2013). Game Based Learning normally uses challenges, mysteries, competitions, and rewards and have features of quests, points, feedback and badges which are perceived as being motivating and constructive learning environments (Westwood and Barker 1990). This applies to other diverse types of games which may include puzzle game, role-playing games, simulations, and strategy game, played using different digital technologies, such as mobile phones, online games, virtual worlds and Alternative Reality Games (ARG) (Connolly, Boyle, MacArthur, Hainey, and Boyle 2012).

Research by Leaning, (2015) based on media studies students, indicated that there are positive attributes in the form of students having changed their psychological approach to study as a consequence of the gamified activities on the module. (Leaning 2015).

4.2 Collaborative Based Learning

Group learning is achieved through the formation of ethnically and academically diversified study groups and pre-class 'tutorial' groups. Enhancing inclusivity and diversity, the communal discussions are achieved through group construction based on the diversity of the students backgrounds. (Different nationalities and geographical mix. Schooling, Mix of subject discipline, underrepresented groups, disability such as with learning agreements). Zou, et al (2018) indicated that a greater amount of interaction with host nationals has been associated with fewer academic problems, fewer social difficulties, improved communication competency, and better general adaptation to life overseas (Zhou, X., Zhang, X., Lin, M. and Sun 2018). Feedback Fruits AI tool allows instructors

to make effective, well balanced and inclusive groups to enhance group dynamics, learning outcomes, student satisfaction and engagement. In the words of Hsin-Yuan Huang, and Soman, (2013) activities that require independent work by students bring individual awards (such as badges). Activities requiring interaction with other learners are the social element of training; they make students a part of a big learning community and their results are public and visible (such as leaderboards) (Hsin-Yuan Huang, Soman 2013).

The collaborative approach or team-based learning is designed through the use of Talis Elevate, amplified using Perusall or FeedbackFruits, using a journal article, video, newspaper and report reviews, a practical case study related to the book chapter and lecture slides for use in the synchronous session. These are made available pre-class, by using these collaborative AI tools. The management of these collaborative approaches is in part based on monitoring of activities and engagement via the analytics available on the Virtual Learning System, (VLS) indicating pre-class engagement with materials.

4.2.1 Talis Elevate

Talis Elevate is an AI tool to focus on collaborative learning in reading and annotation for community-based learning and sharing ideas in both onsite and online learning environments. Achieved through the academics uploading to the platform, from a variety of resources, customised teaching packs. These packs can consist of bespoke made videos, YouTube videos, research and/or subject specific journal articles and textbook chapters. Students collaboratively then engage with these learning materials and through analytics, teaching staff can see who's using the material.

The analytics reveals insights on student behaviours, allowing tutors to fine tune their input in Stage 3 of the synchronous stage of the PONDU Model, based on these analytics insights. (Talis Elevate 2023)

Creates communities in the teaching content

With Talis Elevate providing the technical platform, it is recognising students can learn a lot from each other for them to co-create knowledge together within the subject matter. Building communal discussion directly into course content.

Collaborative reading & commenting helps students feel more connected to their peers and more confident sharing their views. Talis Elevate brings the students' discussion into the tutors content. They create knowledge together, help each other out, and pose questions within the subject matter. (Barrett, East, Fitzgibbons, Vescovi, Wood 2023).

Develops more engaged students

Talis Elevate gives direct help to those students in need through the analytics provided, which are focused on active student participation, allowing to see who's not engaging with online learning tasks each week. This allows for the academics to target help toward those that need it most and further stimulate engagement. Insight into this application and impact of Talis Elevate, is highlighted by research done at Lincoln University. (Barrett, East, Fitzgibbons, Vescovi, Wood 2023).

In general, the tool was deployed to support asynchronous learning, although there was also some 'live' usage with students annotating sources during synchronous online classes. An indication of how it was used is for example asking students to engage with videos, identify points of interest in preparatory reading and sharing thoughts about readings with peers.

> *"Talis Elevate was used by staff and students in a variety of ways to promote active engagement with texts and create opportunities for interaction amongst students and between staff and students" (Adams and Wilson 2020).*

The use of Perusall in conjunction with Talis Elevate can help to accentuate the initial personalised learning within the context of collaborative learning and the team approach. Thus, developing a sub model for formative asynchronous learning, based on Perusall and Tallis Elevate to promote the social learning.

4.2.2 Perusall

Perusall is a complimentary collaborative AI tool, providing collaborative reading and annotation for both onsite and online learning environments for community-based learning and sharing ideas.

Perusall as a tool can develop collaborative reading, enabling coordinated and collective student reading of course materials. Thus stimulating students collectively in comprehending complex theoretical concepts and terminology in a team or group setting (Miller, Lukoff, King Mazur 2018).. Furthermore, Perusall gives the opportunity of formative marking, giving students the opportunity to improve their knowledge and understanding in preparation for the summative assessment.

Creates communities in the learning setting

Consequently, Perusall can support formative asynchronous learning through official or student-organized study groups, or as preparation for synchronous tutorials. Much research and as an example by Seow and Fong, (2018) on an online science reading assignment designed for authentic engagement outside class, indicated that the interactive format of anchored discussions combined with primary literature promoted genuine collaborative scientific learning. Notably, student interactions frequently went beyond the specific articles, evolving from questions about data ambiguities to an understanding of the subjectivity inherent in data interpretation. These findings suggest that exposure to primary literature coupled with student discussion deepens their grasp of scientific research and the nature of science. Perusall proved to be a valuable tool for facilitating this type of engaging out-of-class activity.

Creates engaged students

When students engage with primary literature and discuss it with their peers on the Perusall platform, their engagement and understanding are notably improved. This positions Perusall as a highly beneficial AI tool for extending student interaction and learning beyond the classroom. Instructors can assign various formative asynchronous reading materials in Perusall, such as textbook chapters, research articles, or even videos. The platform allows students to comment on these materials, and instructors can choose to mark these contributions.

What sets Perusall apart is its emphasis on tailoring learning to the individual within a collaborative space. Additionally, the platform provides reports that can identify challenging content, allowing instructors to address these specific points during later synchronous meetings.

Perusall acts as a valuable and complementary AI tool to FeedbackFruits, its contribution discussed below:

4.2.3 FeedbackFruits

Focussing on the collaborative dimension of the formative asynchronous stage of the PONDU Model, Feedbackfruits is a comprehensive collaborative and annotation platform.

Creates engaged and collaborative students

FeedbackFruits aims to promote student engagement through peer review on tutor designed assignments against set criteria. Although equally peer review of collaborative contributions, through student evaluation of peers' contribution to group work and how effective the evaluation is, the review is based on tutor specified criteria. This latter element is of particular interest to assessing the effectiveness of study groups created in the formative asynchronous stage.

4.2.4 Peerceptiv

Peerceptive, emphasises the collaborative aspect of the Model allowing for peer review on assessments, enabling students to provide and receive feedback on various assignment types (writing, presentations, videos, etc.) using instructor-defined rubrics.

In addition Peerceptiv allows students to evaluate team members contributions and collaboration skills in study groups and forms of group projects. The latter being for example presentations, where real-time peer feedback and evaluation can be given.

Furthermore, in a collaborative context, through feedback on the reviews received, students can make judgements about the helpfulness and quality of the peer reviews given.

5. Synchronous Stage

The synchronous, or in-class, stage of the model is structured using the SOFLA Model framework, as previously described. Steps 3 to 5, which focus on active learning, are enriched through the application of gamification, fostering an environment conducive to higher-order learning.

- *Step 3:* Active engagement begins with competitive Kahoot quizzes, videos, or, where applicable, short role-play exercises and mini business games. These activities aim to stimulate students' interest and participation.
- *Step 4:* This step involves a variety of activities designed to deepen understanding and apply concepts learned during the formative asynchronous stage. These may include business simulations, strategy games, discussions around articles, case studies, or further analysis of the video from Step 3. Practical, team-based learning is enhanced through gamification, promoting both collaborative and individual learning. Team leaders can be appointed to facilitate discussions and activities, thereby fostering employability skills such as leadership and teamwork.
- *Step 5:* Feedback is provided through interactive tools that encourage collaboration and reflection. Padlet offers a platform for students to record and organize key ideas. Mentimeter facilitates real-time visualization of their thoughts and responses. Jamboard adds an interactive dimension, allowing students and tutors to share and refine feedback dynamically. To further enhance motivation, awards are given to the top three performing groups, with their achievements prominently displayed on a leaderboard. This public recognition serves to foster healthy competition and celebrate student success within the module.

6. Summative Asynchronous Stage

The final, summative asynchronous stage of the PONDU Model focuses on evaluating student learning and the achievement of higher-order skills. AI offers valuable tools not only for assessing these skills but also for supporting their development. Several AI applications are relevant to the development and assessment within this stage. Examples include GPT-4, Peerceptiv, able to create flexible grading and customise rubrics and the recently developed Teacher GAIA, which can assist in both the creation and practice of summative assessment tasks.

However, research by Klyshbekova and Abbott (2024) indicates that ChatGPT-4 has limitations concerning referencing, writing length, creativity, and originality. (Klyshbekova and Abbott (2024). Despite these constraints, it demonstrates capabilities in more routine tasks such as finding materials and developing arguments. Therefore, the primary role of ChatGPT- 4 in the summative asynchronous stage may be to enhance efficiency for academics in constructing the linguistic aspects of summative assessments, rather than in the marking process itself.

FeedbackFruits provides AI support for tutors in facilitating feedback on summative assessments, including presentations and oral exams. It also offers AI-driven assistance to improve student learning through in-line feedback on summative assignments.

Practical applications of the use of AI in summative assessments, include the development of benefit-risk assessment models. The creation of videos and films as summative outputs, utilizing tools like Adobe in fields such as creative arts, business, and medicine. Perusal, streamlining peer review by combining automated feedback grading with peer assessment, saving instructors time in setup and review. FeedbackFruits offering similar capabilities, allowing instructors to design assignments where students provide feedback on peers' work (documents or videos) based on predefined criteria.

7. Example of a Practical Implementation

Implementing the asynchronous stage starts with the formation of study groups, their size dependent upon the overall cohort. To accommodate personal learning, the Virtual Teaching Assistant through conversational AI is created using GPTAvatar in Convai. The next step is to construct the content of the teaching materials, aligned with the learning outcomes with the final stage of selecting the AI tools to facilitate collaborative learning and incorporate them into the Canvas or Moodle site.

8. Conclusion

The PONDU Model, through its structured design and systematic approach achieves higher order learning. The three stages, acting as building blocks to each other and based on a proven engaging pedagogy of flipped learning, the Model stimulates both personal and collaborative learning.

Using the AI and gamification applications, involving individual and collaborative feedback and discussion, leading to mastery of subject learning.

Using various AI tools in the pre-class stage leads to better understanding of the teaching materials, learning enhanced through the activities in the steps in the Sofla Model and further put into practice in the nature of the AI supported assessments.

Contributing to future research, assessment of multidisciplinary effectiveness in each stage in AI applications and student achievements is conducted. Furthermore, through a longitudinal study able to develop a trend of student achievements and results.

Abbreviations

AI - Artificial intelligence

AIED - AI in Education

ALS - Adaptive Learning Systems

ARG - Alternative Reality Game

BKT - Bayesian Knowledge Tracing

GBL - Game - based Learning

IRT - Item Response Theory

NLG - Natural Language Generation

SOFLA-Synchronised Off-Line Flipped Learning Approach

VLS - Virtual Learning Systems

Conflicts of Interest: "The author declares no conflicts of interest."

Ethics statement: "No ethics approval is needed for this article, being secondary research"

AI statement: "No use of AI has been made in writing this Article".

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Work in Progress Papers

Prompt-Craft Cards: A Toolkit for Developing Design Judgment Through Reverse Prompt Engineering

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Abstract: The integration of generative AI into design education poses a critical challenge beyond technical skill: cultivating design judgment. Students often struggle to externalize their tacit knowledge into the explicit language of prompts, a process essential for developing the analytical capacity to make well-substantiated design choices. This paper introduces Prompt-Craft Cards (PCC), a tangible toolkit and pedagogical framework designed to address this gap. Using a Research-through-Design methodology, PCC frames Reverse Prompt Engineering (RPE) as a simulator for practicing design decisions at specific expertise levels. The toolkit features a differentiated system of three card decks, each scaffolding a different stage of expertise and knowledge transfer based on established learning theories. The Foundational Deck targets compositional judgments, the Adaptation Deck focuses on navigational choices, and the Reflection Deck encourages critical, metacognitive inquiry. The toolkit's efficacy will be evaluated through a multi-stage study employing think-aloud protocols within an Action Research design. This structured process transforms prompting into a form of deliberate practice. By engaging with the ambiguity between their intent and the AI's output, students are compelled to articulate, reflect, and refine their design decisions. Ultimately, I argue that this structured, reflective practice moves beyond teaching prompt engineering as a technical skill, transforming it into a powerful pedagogical method for cultivating the critical visual literacy and metacognitive thinking essential for professions and practices that relies on interpreting and creating visual media in the age of AI.

Keywords: Generative AI, Design education, Knowledge transfer, Pedagogical toolkit, Research through design

1. Framing the Challenge: Design Judgment in the Age of AI

Bringing generative AI into the design classroom requires a pedagogical shift away from teaching the tool itself and towards cultivating deeper critical and conceptual abilities. While this offers novel opportunities, it also introduces a complex spectrum of pedagogical stances among educators. These range from prohibiting GenAI's use in the classroom, due to concerns that students may become dependent on the tool before developing foundational skills, to designing projects that emphasize responsible use and human-centred abilities that AI cannot replicate (Aysel, 2024). This divergence highlights a central question for design education: How can we leverage this technology to cultivate the core competencies of design expertise? For this, I address a fundamental aspect of this expertise: the development of design judgment.

Developing design judgment is a critical, yet under-supported, area in various design disciplines (Demiral-Uzan & Boling, 2024). However, a gap remains in the literature concerning pedagogical tools specifically designed to cultivate this skill within the context of learner-AI interaction. To address this gap, I propose Prompt-Craft Cards (PCC), a tangible framework designed to scaffold the process of Reverse Prompt Engineering (RPE). This paper details the design of a new toolkit grounded in design expertise, and knowledge transfer theories. This toolkit is intended to transform prompting into a structured practice for supporting the development of design judgment. To build this pedagogical system, I draw upon three interconnected theoretical domains: models of design expertise, theories of knowledge transfer, and the principles of constructive alignment.

Established theoretical frameworks characterize the development of design expertise as a structured advancement through several levels of competency. Following the skill acquisition model, learners move through distinct levels, from novice to expert (Dreyfus & Dreyfus, 1986). Novices typically rely on explicit rules and struggle with the ambiguity inherent in design problems, whereas more competent designers can navigate complexity through intuition and experience (Lawson & Dorst, 2005). The PCC toolkit is differentiated to match these developmental stages, acknowledging that a one-size-fits-all pedagogical approach is ineffective. As Spessard (2025) notes, structuring prompts according to specific purposes can minimize unnecessary cognitive load and encourage meaningful engagement, a principle central to the deck system.

This differentiation is further informed by models of knowledge transfer, as the process of learning design involves converting tacit, embodied knowledge into explicit, communicable forms (Polanyi, 1969). To guide

this process, I adopted Chen and McQueen's (2010) model, which provides a direct framework for the pedagogical progression of our toolkit. The toolkit operationalizes this progression: the *Foundation Deck*, for instance, scaffolds the structured copy process, while the *Reflection Deck* encourages the unstructured fusion required by more competent students.

The pedagogical foundation of this toolkit is built upon the principles of Constructive Alignment (CA) (Biggs, 2014) by developing a systematic link between the intended learning outcomes (ILOs), the teaching and learning activities (TLAs), and the assessment tasks (ATs). In our system, the primary ILO is the development of design judgment. The PCC and the RPE process constitute the core TLA, designed specifically to target this outcome. To ensure this alignment is effective across different expertise levels, our approach integrates two key theoretical models. First, I use the Dreyfus model of skill acquisition (Dreyfus & Dreyfus, 1986) to define the learner's developmental stage. Second, I adopt Chen and McQueen's (2010) knowledge transfer model to structure the learning activities, aligning structured copy for novices, unstructured adaptation for advanced beginners, and unstructured fusion for competent learners.

Finally, to operationalize these activities, each prompt on the cards is designed as a measurable task using action verbs derived from Bloom's Taxonomy. For instance, the Foundation Deck uses verbs like *describe* and *identify* while the Reflection Deck uses verbs like *critique* and *formulate*. As Spessard (2025) also notes, aligning prompts with such cognitive frameworks is crucial for minimizing cognitive load and transforming AI into a pedagogical partner. This multi-layered framework ensures that the toolkit offers a purposeful, structured, and scaffolded path toward supporting the acquisition of higher-order thinking skills, in this case design judgment.

2. Prompt-Craft Cards: An Intervention Framework and Tool Development

I employed a Research-through-Design (RtD) methodology (Frayling, 1993) to investigate how a pedagogical toolkit can support the development of design judgment in the context of GenAI through RPE. In this approach, the designed artifact—the PCC toolkit—is not merely a final output, but a central method of inquiry. Through iterative development and testing, this toolkit generates new, practice-based knowledge about teaching and learning with generative technologies. The pedagogical stance of this project reframes the researcher’s role from an expert to that of a facilitator. The toolkit is designed not to provide answers, but to create a structured platform for self-paced, reflective learning. The PCC serve as mediating tools that scaffold the learner's own process of inquiry, guiding them to articulate their tacit knowledge according to their developing expertise.

To rigorously evaluate the efficacy of the Prompt-Craft Cards, a multi-stage empirical study is planned for Fall 2025. The research protocol has received full ethical approval from the İzmir University of Economics Social and Human Sciences Ethics Committee (Approval No: E-97429853-050.04-101381). The evaluation will be conducted in two main phases:

- **Formative Evaluation with Experts:** I will assess the pedagogical and practical validity of the toolkit through semi-structured interviews with 8 to 10 design academics and industry professionals spanning the research process. These experts, selected through purposive sampling based on experience and specialization, will provide feedback on the toolkit's conceptual framework, clarity, and potential for integration into curricula and professional workflows.
- **User Testing with Students:** The core of the evaluation will employ an Action Research (AR) design to assess the toolkit's impact on students' design judgment within practical contexts. The process will begin with a pilot test involving 4-6 students to refine the study protocol and evaluate usability. I will analyze and interpret the results with the expert feedbacks to develop strategies for design and framework iteration.

Subsequently, the main study will be conducted with a larger group of approximately 15-20 undergraduate students from various design disciplines. This main study will follow a pre-test, intervention, post-test procedure.

- Pre-test: Students will first be asked to perform a design task without the PCC toolkit.
- Intervention: Students will then be introduced to the PCC toolkit and use it to complete a similar RPE task.
- Post-test: A final task will be performed to observe any changes in their approach or judgment process.

Throughout all task-based sessions (pre-test, intervention, and post-test), we will employ the Think-Aloud Protocol as the primary data collection method. Participants will verbalize their thought processes while creating prompts, and these sessions will be audio-recorded and supplemented with observational field notes. The collected qualitative data (transcripts, prompts, and notes) will be analyzed using a thematic analysis approach. Separately, the pre- and post-test data will be compared through a performance analysis to evaluate case-based learning outcomes. This comparative analysis will allow us to identify patterns related to the toolkit's impact on usability, cognitive processes, and evidence of design judgment. The analysis will specifically focus on how the toolkit (intervention stage) scaffolds distinct types of judgment as defined by Nelson & Stolterman (2012), in comparison to the pre-test stage.

Building on the theoretical framework outlined in the introduction, the PCC are designed around the core principle that ambiguity is not a system failure, but a fundamental property of the interpretative relationship between the learner, the GenAI, and the generated artifact. The RPE process deliberately leverages this ambiguity to make people engage in meaning-making process (Gaver et al., 2003). The card decks are designed to scaffold this conceptually deepening process of appropriation, through opearationally shifting from the descriptive characteristics to the overall experience (Buchanan, 2001).

The toolkit comprises three scaffolded decks, each designed to support a particular stage of expertise development by integrating key theoretical models. Each deck aligns a specific learner level with a corresponding knowledge transfer process (Table 1). This integration is visually summarized in Figure 1, which presents two sample cards from each deck to illustrate this progression in practice.

Table 1: The Differentiated Pedagogical Structure of Prompt-Craft Cards

Card Deck	Level of Expertise (Dreyfus & Dreyfus, 1986)	Knowledge Transfer Type (Chen & McQueen, 2010)	Design Judgment Type (Nelson & Stolterman, 2012)	Associated Action Verb Examples (Bloom's Taxonomy)
Foundation Deck	Novice	Structured Copy	Compositional, Appearance	Describe, Identify
Adaptation Deck	Advanced Beginner	Unstructured Adaptation	Navigational, Instrumental	Relate, Compare
Reflection Deck	Competent Learner	Unstructured Fusion	Core, Reflective	Critique, Formulate

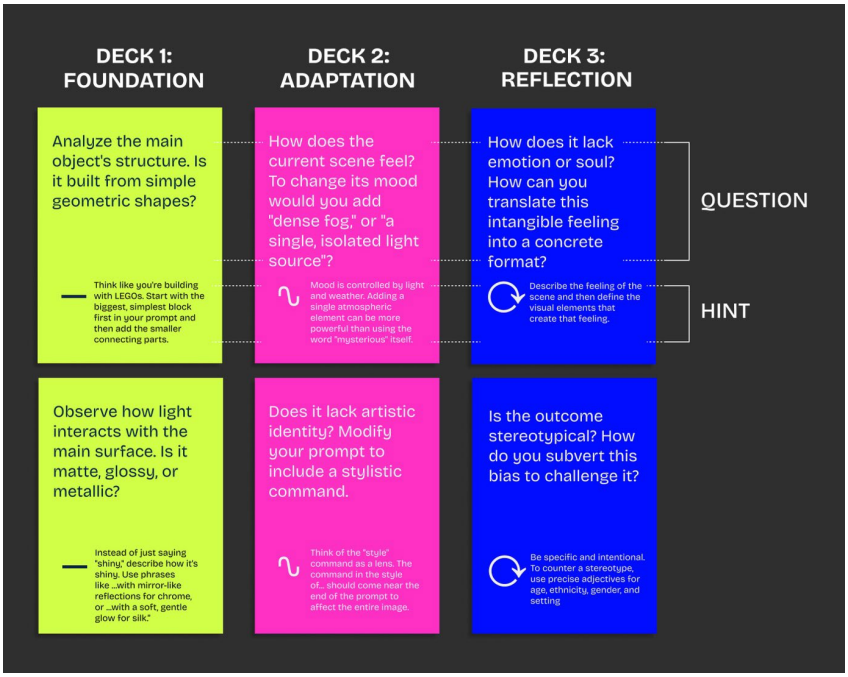

Figure 1: Sample cards illustrating the three-stage pedagogical progression of the PCC toolkit, from the Foundation to the Reflection deck

3. Discussion and Conclusion

The PCC toolkit is proposed not merely as a method for teaching AI literacy, but as a dedicated instrument for supporting students' acquisition of various levels of design judgment (Nelson & Stolterman, 2012). The process challenges the notion that design knowledge is solely explicit, engaging instead with knowledge that is inseparable from the knower, revealed only through the learner's actions and reflections.

This pedagogical approach is particularly potent in its use of what Gaver et al. (2003) term ambiguity of relationship. When a discrepancy occurs between the learner's intent and the AI's output, the toolkit becomes a psychological mirror. It confronts the learner with the tension between their subjective worldview and the AI's collective, statistical representation. This moment of reflection, scaffolded by the *Reflection Deck*, spurs students to 'question their [own] values and activities' (Gaver et al., 2003, p. 237), fostering a critical self-awareness essential for contemporary design practice. This structured, iterative exercise thus becomes a form of deliberate practice (Ericsson et al., 1993) aimed at developing this core design skill (Demiral-Uzan & Boling, 2024).

The contribution of this research is best understood by positioning the PCC toolkit within the context of existing AI-focused educational tools. While many valuable toolkits exist, they typically address different pedagogical layers. For example, tools like the AI Ideation Cards (Piet, 2020) focus on the divergent, brainstorming phase of identifying opportunities for AI. Others, like the Prompt Engineering Cards (AI Tinkerers' Cards, no date), provide a hands-on, modular system for trainers to teach the basic components of AI interactions.

Other approaches, more focused on skill acquisition, use gamification to teach the procedural craft of writing effective prompts. For example, the Prompt Engineering Game from the University of Birmingham (Westwood & Liu, n.d.) both provide structured elements like skill cards and power-ups to guide users in constructing better prompts. These tools are invaluable for building AI literacy by focusing on the syntax and composition of the prompt itself.

In sharp contrast, the pedagogical goal of PCC is not to teach the craft of the prompt, but to use the prompt as a medium to teach the craft of design judgment. Our core activity is not construction, but deconstruction and reflection through Reverse Prompt Engineering to facilitate the deliberate practice of formulation and decision-making in design activity through design judgment. This fundamental distinction shifts the focus of learning from the external artifact (the prompt) to the user's internal cognitive and judgmental process. The central question we ask is not 'how to write a better prompt?', but rather 'why did I make this specific design choice, and how can I articulate it?'. Therefore, PCC is positioned not as a replacement for these valuable tools, but as a necessary complement—a dedicated instrument that uses the act of prompting as a reflective simulator to cultivate the metacognitive skills at the heart of design expertise.

This study addresses a critical gap in design education: how to frame learning activities to support design judgment development in the age of GenAI (Demiral-Uzan & Boling, 2024). By proposing PCC I offer a pedagogical framework designed specifically to scaffold and provoke this essential skill. The toolkit serves as an initial prototype for iterative development. Future work will focus on two trajectories: transforming the tangible toolkit into an interactive digital platform for data-driven feedback, exploring cross-contextual adaptations for other disciplines and public workshops.

Ethics statement: All planned research activities involving human participants have been reviewed and received full ethical approval from the Izmir University of Economics Social and Human Sciences Ethics Committee (Approval No: E-97429853-050.04-101381). Prior to their participation in the upcoming expert interviews and student user tests, all individuals will be provided with an informed consent form detailing the study's purpose, procedures, their right to withdraw at any time without consequence, and the measures that will be taken to ensure data confidentiality and anonymity. Specific precautions will be implemented to mitigate any potential power imbalance in the researcher-student relationship. All procedures will be conducted in strict accordance with the approved protocol.

AI statement: During the preparation of this work, I used an AI language model (Google Gemini) to assist with proofreading, grammar checking, and rephrasing for clarity.

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Becoming A Generative AI User: Social Learning and Responsible Engagement in Software Development

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Abstract: As generative AI becomes integrated into software development, this paper explores how developers adopt and make sense of it—not as a rational choice but as a socially learned and interpretive process. We examine how developers become AI users through social exposure, peer learning, and shifting perceptions of usefulness and risk. The study combines netnography of Reddit communities with interviews with software developers. Using Becker's three-step model—learning to use, recognise effects, and enjoy—we trace how developers move from experimentation to integrated AI use. Contrasting with models like the Technology Adoption Model (TAM), we argue that Generative AI adoption is not a binary of acceptance or resistance, but a culturally embedded process shaped by evolving norms and community practices. This perspective "de-exceptionalizes" AI and offers a more grounded, human-centred understanding of how professional practices evolve with emerging technologies.

Keywords: Generative AI, Software development, AI adoption, Interpretive practice, Social learning

1. Introduction

This study challenges dominant narratives about AI users as technological prodigies, future-oriented visionaries, or irresponsible cheaters, by reframing AI adoption as a socially learned, interpretive process. Much like Becker's study, which showed how drug use was learned through ordinary interactions, we argue that becoming a Generative AI user is neither a rational choice nor a heroic act of innovation. Instead, it is a situated practice shaped by peer modelling and evolving interpretations of value and risk.

By focusing on the micro-processes through which developers learn to use, recognise, enjoy, and integrate Generative AI tools into their workflows, this research contributes to a more grounded and humane understanding of AI adoption. It de-exceptionalises AI use, situating it within the broader patterns of professional identity, craft learning, and workplace sociality. This perspective not only broadens the sociotechnical understanding of AI adoption but also opens up more inclusive and accessible pathways for supporting responsible engagement with AI in practice.

1.1 Related Literature

Much existing literature on AI adoption draws on technology acceptance models (TAM) and related frameworks (e.g., Rogers, 2003; Venkatesh et al., 2003), focusing on constructs such as perceived usefulness, ease of use, and behavioural intention. While useful for identifying general trends, such models often overlook the situated and socially contingent nature of technology adoption in everyday work practices.

Several studies (e.g. Gupta & Yang, 2024; Kim et al., 2024; Rafi et al., 2024; Russo, 2024) apply or extend the TAM frameworks, highlighting factors such as trust, enjoyment or cognitive evaluations. Other contributions (Banh et al., 2025; Sahni & Chilton, 2025) acknowledge the importance of informal learning and organisational context but do not fully engage with sociological theories of meaning making (Blumer, 1969).

Our project seeks to de-exceptionalising AI adoption and offers a sociologically grounded alternative. Drawing on Becker, we shift focus from adoption as decision-making to adoption as becoming, a process embedded in social relations, community discourse, and interpretive practice. This study's key theoretical contribution lies in extending Becker's socially oriented model into the realm of AI adoption, demonstrating that adoption is not simply about individual rational choice or technological determinism, but embedded in ongoing, situated social interactions and interpretive practices. TAM/UTAUT conceptualise adoption primarily as the outcome of individual perceptions and intentions and frames social and facilitative factors as external influences or conditions. In contrast, a Becker-inspired perspective foregrounds mechanisms such as peer modelling, iterative experimentation, and norm internalization, this shifts "the social" from a peripheral influence on adoption to the very medium of adoption processes. By enlisting Becker's attention to the social mechanisms, we show that AI adoption cannot be fully understood through perception and intention models alone, but requires attention to the situated, relational processes through which actors learn to become users.

2. Methodology

We used a qualitative design combining passive netnography (Kozinets, 2020) and interviews (Kvale, 1997). Inspired by Becker's interactionist approach, we explored how developers learn to use, assess, and integrate AI through evolving experiences and social encounters.

2.1 Passive Netnography

Reddit was selected as the field site due to its active developer communities. We identified relevant subreddits (/programming, /ChatGPTCoding, /ClaudeAI, /Bard) and used targeted searches to locate discussions about AI in coding and software development. Data were collected between January and June 2025. Users who contributed substantively, through detailed answers, references, or recurring engagement across multiple threads, were marked for further analysis. This process led to a shortlist of thirteen users. For each shortlisted user, we conducted a systematic review of their comment history within the selected subreddits, with all material anonymised.

2.2 Qualitative Interviews

Seven semi-structured interviews were conducted with developers recruited through professional networks and snowball sampling. We deliberately sought participants who could be considered "AI champions", i.e., developers already using AI actively and professionally in their work. This purposive sampling reflects our focus on understanding advanced practices and trajectories of adoption, rather than aiming for a representative sample. While providing rich qualitative insights, our findings are preliminary and based on a small sample.

2.3 Analytic Procedures

The analysis combined inductive coding of user practices and reflections (open coding in NVivo), followed by triangulation with themes emerging from the interviews. The inductive codes were revisited to examine how developers' trajectories aligned with the stages of learning Becker described. Coding decisions were discussed among co-authors to ensure consistency and reduce interpretive bias.

3. Preliminary Findings

The following sections present our preliminary findings structured around Becker's three steps: learning to use AI in a way that produces real effects; learning to recognise and interpret those effects; and learning to enjoy and integrate AI use into everyday professional practice. This grounded approach de-exceptionalises AI adoption, revealing it not as a singular leap into the future but as a socially learned, interpretive process embedded in ordinary forms of craft learning, community judgment, and evolving workplace norms.

3.1 Step 1: Learning to use AI in a way That Produces Real Effects

The first step in becoming a Generative AI user involves learning how to interact with generative systems in ways that produce meaningful or at least amusing effects. Across our data, this phase often begins not in formal training contexts but in moments of casual play, personal experimentation, or peer-led curiosity. Much like Becker's marihuana users learned to "get high" through guided social experience, developers in our study learned to get useful or "fun" results by imitating others, sharing prompts, or tinkering with tools in low-stakes environments.

Some users described early encounters with AI as mind-blowing or magical, even when the results were crude. As one participant put it: *"They were f*cking shitty pictures… but it was still f*cking mind-blowing… That's when I got hooked", referring to their first text-to-image outputs. Others turned to AI for playful or personal projects. One participant described using generative tools to create a wedding gift: "He* (a friend in Italy) *got married and his honeymoon went to Indonesia… I wrote like a cartoon of an Italian guy with his girlfriend doing different activities, and then we had like 50 images for each activity and picked one picture per activity to make a photo album we gave him before he went on his honeymoon".* These early engagements were often marked by curiosity and social experimentation, where the joy lay not in precision but in making something novel with the machine. Others learned through trial and error in coding contexts: "*Just ask the AI to break down parts of code you don't understand".* This phase is marked by tentative tool use, where clumsy or limited outputs serve mainly as vehicles for learning how to make something happen. It is also where cultural norms and shared warnings circulate, for example, about overreliance on auto-complete or using AI before understanding basic programming concepts.

3.2 Step 2: Learning to Recognise the Effects and Connect Them to AI

As users gain experience, they begin to reflect critically on when and how AI is helpful and when it fails. This second step, akin to Becker's notion of "*learning to recognize the effects*", involves more than just technical learning. It includes the development of judgment and interpretive skills. Users begin to articulate what counts as valuable AI assistance and what should be resisted or corrected.

Participants described learning to identify hallucinations, disengaging from autosuggestions that distorted their own thinking, and choosing when to turn AI off entirely. As one developer put it: *"Sometimes the autocomplete tells you what the Copilot thinks… But then it just gets into my head… but maybe that's not the best approach… So I just turn it off, like telling, okay, shut up! I need to think. So yeah, so I turn it off like for a moment and I do my reasoning, my code, my component or whatever"*. This illustrates a key shift: AI is no longer an awe-inspiring novelty, but a tool that must be managed and sometimes resisted.

Other users developed model-specific preferences: *"Gemini is very good at math and reasoning"*, *"Claude explains without overwhelming"*, or *"DeepSeek is great at planning projects"*. These preferences reflect growing awareness of how different AI tools perform in different contexts, and how to align them with one's own workflow or values.

Beyond technical performance, users develop informal value systems, constantly weighing price, access, and capabilities. Much like Becker's marihuana users learned to recognise different "kinds of high," AI users learn to judge which models are "worth it" in terms of output and cost. One pairs DeepSeek R1 with Claude 3.7, *"dirt cheap"* for planning, better quality for implementation. Others dismiss models without open APIs as less *"usable,"* despite strong performance. These judgments show that becoming a competent AI user involves navigating a shifting tool market and aligning choices with context. Economic reasoning, too, becomes part of the socially informed process of AI adoption.

3.3 Step 3: Learning to Enjoy the Sensations and see Them as Desirable

The final step involves not just recognising AI's effects but appreciating them, even valuing them as part of one's craft. For Becker's marihuana users, this meant learning to enjoy the sensations. For AI users, it means learning to enjoy the productivity, insight, or creative possibilities AI affords. This enjoyment is rooted in experience and daily practice.

Users in this phase spoke of AI as expanding their capabilities: *"It's more exertion for more result – definitely not making me lazier".* One even described calling their spouse to witness an AI tool at work, declaring *"the future has just arrived"*. Another reflected on how AI helped shift their attention from rote coding tasks to higher-level design work.

Enjoyment in this phase also involves adaptive mastery, the sense of knowing how to work with, around, or in tandem with AI. *"I write a comment… and it gives me the next line. But if it tries something too big, I know I have to break it into smaller pieces".* This is not just use, but skilled use, an embodied, reflexive, and increasingly effortless integration. As Becker might put it, they've learned how to use and like AI.

4. Conclusion

Becoming a Generative AI user is not a matter of individual rational choice but a socially embedded learning process. Drawing on Becker's model, we show how developers move from experimentation to appreciation through situated, interpretive practice. In contrast to models that emphasise intention or utility, this approach foregrounds the social dynamics of becoming.

Understanding adoption as a social learning process can inform ethical frameworks and governance strategies that emphasise collective responsibility, transparency, and continuous dialogue rather than mere compliance with fixed rules. Recognising AI adoption as a socially learned practice suggests that organisations should foster community-led reflection and peer-learning to encourage responsible and transparent AI use.

By de-exceptionalising AI use, we offer a more grounded perspective on how technologies are adopted through everyday negotiation and community interaction. Developers do not merely evaluate AI tools; they learn, argue, adapt, and reflect, and in doing so, contribute to the ongoing construction of what responsible and legitimate AI use looks like.

For organisations, this perspective suggests structuring opportunities for peer learning and experimentation, for instance through dedicated forums where developers can share practices, successes, and dilemmas.

Acknowledgements

The authors gratefully acknowledge Benjamin Hughes for conducting the interviews that form part of the empirical material for this paper. His contribution has been essential to the development of the study.

Ethics Declaration: No formal ethical clearance was required for this study. Informed consent was obtained from all interview participants, and all data were anonymised. In addition, measures were taken to ensure proper data security and anonymisation. For the netnographic part, we followed Kozinets' (2020) research ethics process flowchart for netnography to ensure an appropriate handling of ethical issues. This included consideration of the degree of sensitivity of the topics discussed, the presence (or absence) of vulnerable populations, and the public nature of Reddit data. Direct identifiers were removed, and while original Reddit posts remain publicly accessible, any presented quotes were anonymised and handled with care to minimise traceability.

AI Declaration: AI tools were used in the preparation of this paper. Keenious was used to support literature search, and ChatGPT was used for language editing, proofreading, and assistance with phrasing.

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Generative Artificial Intelligence for Recognition of Surgical Site Complications: The PRISCA Project

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Abstract: The project PRISCA develops digital tools for postoperative monitoring and early detection of wound complications (e.g., infections) through telemedicine solutions. The approach addresses concrete clinical needs, including the follow-up of patients discharged from centers of surgical excellence located far from home, the optimization of hospital access, and the early identification of at-risk situations. The output of the project will be a telemonitoring platform (mobile and web apps), artificial intelligence modules for wound image analysis, and informative content for patients. The technological architecture is designed to support timely intervention in case of wound-related complications, while also reducing unnecessary in-person visits. The project's main innovation is the use of an Artificial Intelligence module. It aims to enable healthcare professionals to perform automated analysis of wound images for early detection of post-surgical complications. The limited availability of public data was tackled by applying a data augmentation method and by integrating a generative AI model. It creates new synthetic images based on real images and textual prompts. All generated images had been validated by clinicians and then included in the final dataset. This approach ensures the model learns from a diverse set of images, increasing its robustness and accuracy. The adopted detection model is YOLOv11, which localizes the wound and performs a pathological/non-pathological classification. Results show good localization and promising classification accuracy. We performed a comparison between the model trained on the original dataset and the version enhanced with synthetic data, in order to assess relative improvements. These comparisons will help refine the model for better performance in real-world scenarios. The first results show an increase in the performance of the model with augmented data but more systematic comparisons are needed. Additional real images from a proprietary dataset currently being collected will also be integrated, further enhancing the AI's ability to identify early complications.

Keywords: Generative AI, Medical image Classification, Telemedicine, Surgical wounds

1. Introduction

Surgical site infections (SSIs) represent one of the most common adverse events among patients undergoing surgical procedures and they can pose serious clinical complications (Haque et al., 2018; Badia et al., 2017). In addition to infections, other wound-related issues may develop over time, such as wound dehiscence or keloid formation. Postoperative follow-up protocols involve at least two face-to-face evaluations: one at a local health center approximately 15 days after surgery, and a second outpatient consultation at the hospital around 30 days later. However, the detection rate of complications during scheduled visits remains low, with many infections ultimately diagnosed only in emergency departments. Telemedicine offers new opportunities for remote patient monitoring, recovery assessment, and timely intervention in postoperative care. A survey conducted among healthcare professionals in Liguria (Italy) indicates that 71% believe an AI-powered service for automatic wound complication detection can effectively optimize the postoperative protocol. Then, the idea of developing digital tools emerges, aiming to transform the current follow-up model through smartphone-based applications. The objective of this study, conducted as part of the PRISCA project, is therefore to implement an automated system for the analysis of wound images, enabling early detection of post-surgical complications.

2. Materials and Methods

2.1 Dataset

The dataset used for the study consists of 583 images of post-operative wounds, collected from various sources. Specifically 189 images, provided by available sources (Fateen, 2017; Oota, Rowtula and Mohammed, 2023) and

by Casa di Cura Villa Montallegro (Genoa, Italy), were included. They were labeled by expert clinicians from Ospedale Policlinico San Martino (Genoa, Italy), who classified them as physiological (normal healing phase) or pathological (with complications). Other 394 images were provided by Redscar© (González-Hidalgo et al., 2019a; González-Hidalgo et al., 2019b) with already assigned labels, available online at http://opendemo.uib.es/datasets/Redscar-database/. To ensure the dataset quality, images containing tattoos near the wound or belonging to poorly represented phototypes were eliminated. The final dataset consisted of 554 images, with 434 physiological and 120 pathological wounds.

2.2 Generative AI for Data Augmentation

A data augmentation procedure was adopted to increase dataset diversity. Alongside geometric techniques, an innovative method based on generative AI was introduced, using the open-source Stable Diffusion model to generate synthetic images by combining real images and descriptive text prompts. The choice of Stable Diffusion was motivated by its proven ability to generate high-quality images while preserving fine-grained details, even in domains such as medical imaging. Compared to text-to-image or image-to-image models, Stable Diffusion supports conditioning on both modalities. Previous studies demonstrated its versatility and robustness in generating synthetic datasets for clinical applications (Mou et al., 2023; Kazerouni et al., 2023). A critical aspect concerns balancing conflicting requirements: producing images sufficiently different to avoid overfitting, yet maintaining a high degree of realism with clinically plausible results. To achieve this, the generative process was controlled through two parameters: the level of detachment from the original and the adherence to the textual prompt. By varying them, multiple synthetic versions of each image were generated, altering both skin representation and wound morphology. Most common variations are: presence/ absence of moles, modified hairiness, changed skin pigmentation, and different arrangement of stitches. Sometimes, the wounds appear smoother or more irregular than the original, or have different degrees of secretion and redness.

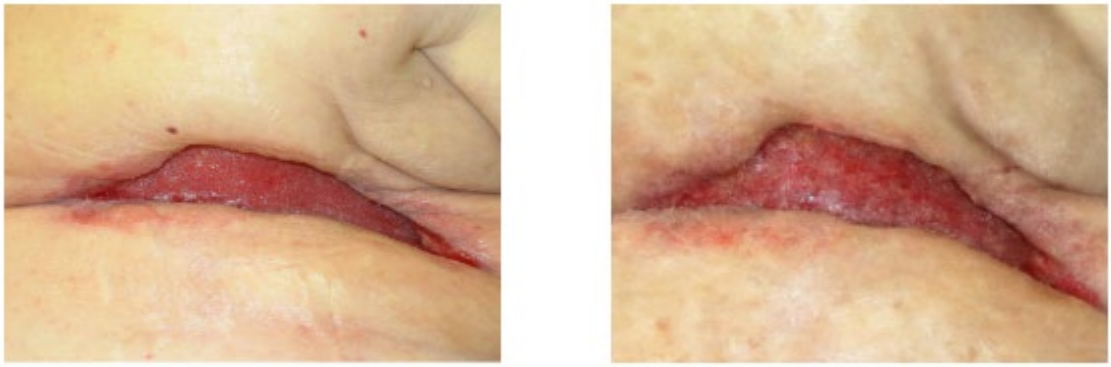

Figure 1: Pathological wound example, left original, right augmented

A total of 228 synthetic images of physiological and 91 images of pathological wounds were validated as plausible by expert clinicians from Ospedale Policlinico San Martino, and were used to augment the training dataset.

2.3 Model and Metrics

For automatic wound detection and classification, the YOLOv11 model was adopted. The choice was motivated by its ability to achieve high detection accuracy; YOLO models have demonstrated strong generalization performance in medical applications, including dermatological lesion detection. The process involves a localization phase, in which the model identifies the bounding box of the wound, followed by a classification phase, which distinguishes between physiological, pathological, and non-wound regions.

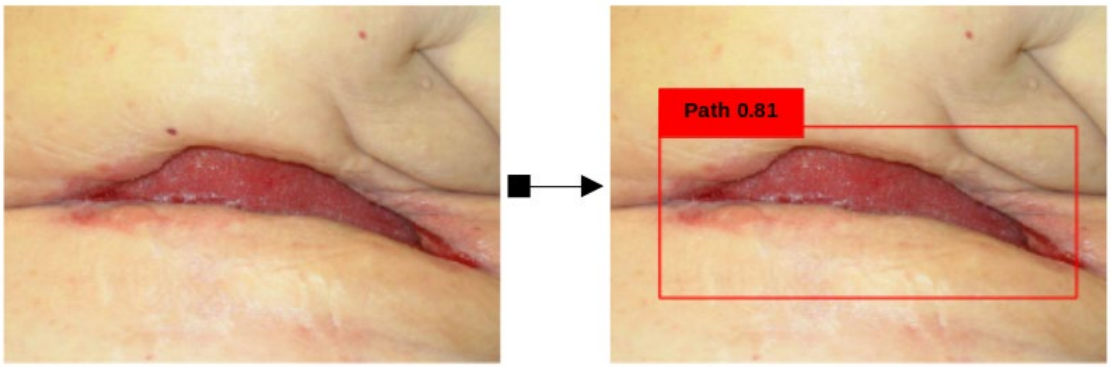

Figure 2: Pathological wound detection with confidence level

The model was trained in two distinct configurations:

- using only the original real images;
- using an extended dataset with synthetic images.

This choice allows to systematically evaluate the contribution of generative AI to improve system performance in terms of accuracy, robustness, and generalization ability.

The following metrics were used to evaluate performance:

- precision: measures the percentage of correct positive predictions out of the total positive predictions;
- recall: measures the percentage of true positive predictions out of the total of positive cases;
- F1-score: it is the harmonic mean between Precision and Recall, useful when the classes are unbalanced.

3. Results

To compare performance between the extended and base models, we adopted the F1-score as the primary evaluation metric. The F1 confidence curve enabled us to assess the balance between precision and sensitivity across varying decision thresholds. The extended model reached a maximum F1-score of 0.90 (Fig.5), outperforming the base model, which peaked at 0.81(Fig.4). The improved behaviour observed for both physiological and pathological classes highlights better generalization and greater sensitivity, particularly in identifying pathological wounds. These findings indicate that the structured inclusion of synthetic images within the data augmentation pipeline can contribute positively and measurably to classification outcomes.

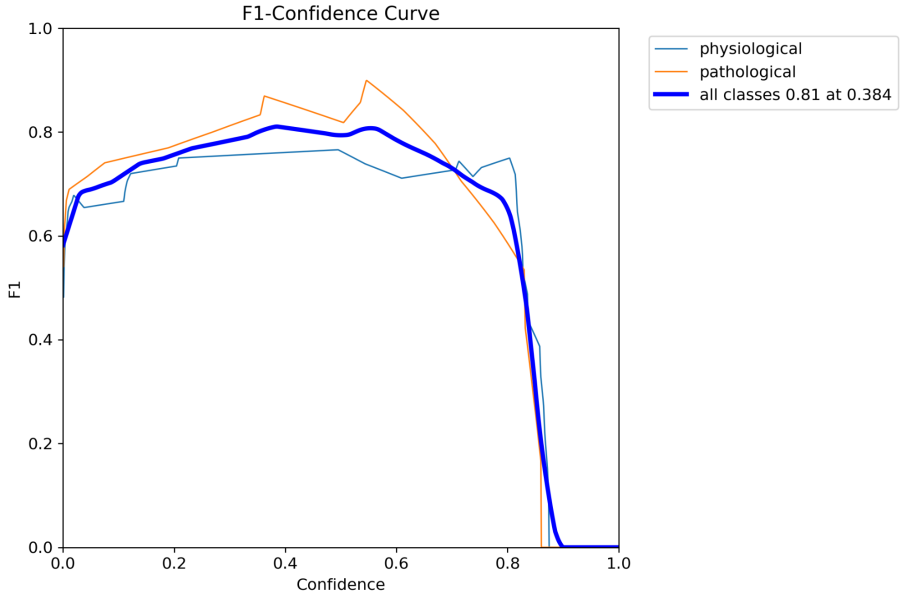

Figure 4: F1-curve for original dataset

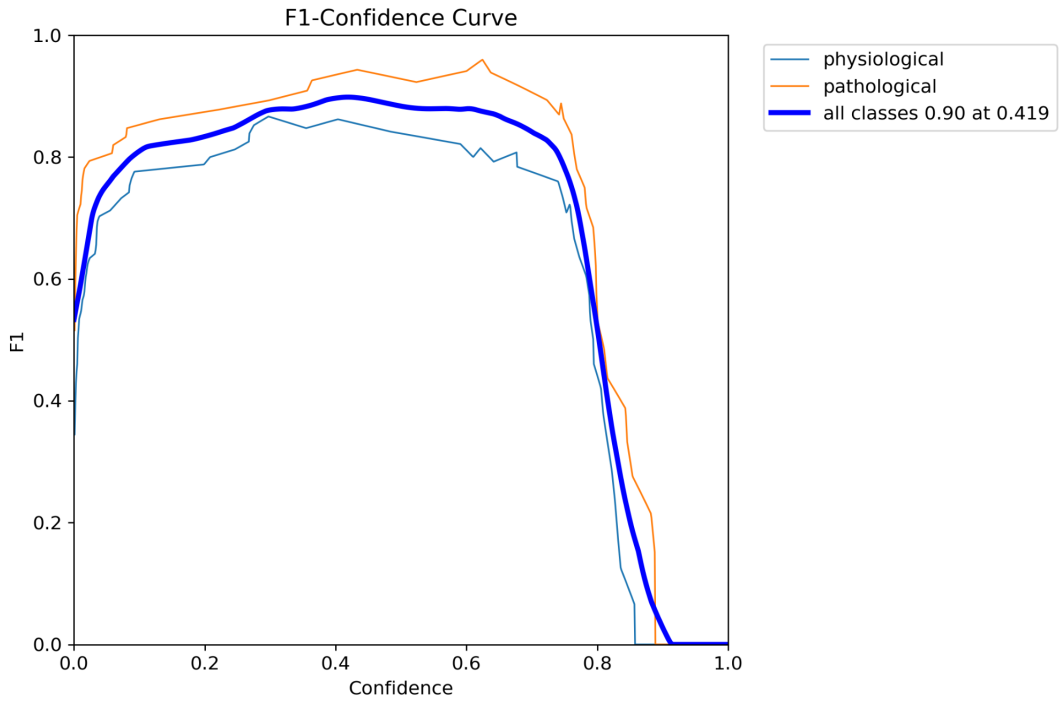

Figure 5: F1-curve for augmented dataset

The highest-performing configuration used the original dataset enriched with synthetic data and geometric augmentation. This combination produced consistent improvements across all metrics compared with the model trained exclusively on real images. We report below the normalized confusion matrix obtained on the test set.

Table 1: Normalized confusion matrix on the test set

Pred/Real	Physiological	Pathological	Background
Physiological	0.93	0.08	0.27
Pathological	0.00	0.92	0.73
Background	0.07	0.00	0.00

The normalized confusion matrix shows good classification capabilities. The physiological class was correctly identified in 93% of cases, while the pathological class was correctly identified in 92% of cases, with a residual overlap between the two. However, a residual overlap remains between classes, particularly regarding pathological areas occasionally misidentified as background. This suggests an underestimation of pathological lesions when they closely resemble surrounding tissue.

4. Insights and Future Work

Although the results are encouraging, several limitations remain. In particular, the current dataset still offers moderate size and variability, which may reduce generalizability to more heterogeneous clinical contexts. To address this, the acquisition of approximately 400 additional post-operative wound images from varied body regions is planned in collaboration with Ospedale Policlinico San Martino (Genoa, Italy). This expansion aims to strengthen dataset representativeness and improve model robustness. Nevertheless, further investigation will be necessary, such as integrating more anatomical sites and including currently under-represented skin phototypes.

Access to images of the same wound over time paired with clinical outcomes, would also be highly valuable. Such temporal information could support the development of predictive models for wound evolution and

healing, broadening the clinical relevance of this approach. While still in an active development phase, this work shows promising potential to support clinicians and enhance post-operative patient care.

Author contributions: Conceptualization, Isabel Carozzo, Elisa Bruzzo, Luca Giulio Brayda, Ennio Ottaviani; methodology, Isabel Carozzo; analysis & validation, Isabel Carozzo, Michele Minuto; data curation, Isabel Carozzo, Elisa Bruzzo, Matteo Parodi; writing draft preparation, Isabel Carozzo, Elisa Bruzzo, Matteo Parodi; writing review, Luca Giulio Brayda, Michele Minuto, Ennio Ottaviani.

Funding statement: This work was partially supported by "Programma Operativo Por FSE Regione Liguria 2021-2027" through the project no. G39J23001280009.

Data availability statement: The real-world surgical wound images used in this study are not publicly available due to copyright restrictions (Redscar© database) and privacy and ethical restrictions (images collected by Casa di Cura Villa Montallegro, Genoa, Italy).

Conflicts of interest: The authors declare no conflicts of interest.

Ethics declaration: This study is conducted according to the guidelines of the Declaration of Helsinki and approved by the Ethics Committee Genoa (Italy) (Protocol Code 141/2025 & 142/2025 —DB id 14199 & 14369, date 21 May 2025). Informed consent statement: Images provided by Casa di Cura Villa Montallegro (Genoa, Italy) were obtained with the patient's informed consent. The survey conducted among healthcare professionals in Liguria, cited in the Introduction, was anonymous.

AI declaration: ChatGPT (https://chatgpt.com/) was used in the preparation of this manuscript for assistance with English syntax and grammar correction. The content and scientific contributions of the paper were entirely developed by the authors. All outputs generated by the AI were reviewed and edited to ensure accuracy, appropriateness, and alignment with the intended meaning. The authors take full responsibility for the content of the publication.

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Vibe Coding A Research Probe for Exploring AI/Voice Based Code Reviews

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Abstract: Generative AI tools increasingly shape established software engineering practices such as code review, but the socio-technical implications of using AI for these practices remain understudied. In this paper we first introduce vibe coding (Andrej Karpathy [@karpathy], 2025) as a method for allowing researchers with limited coding experience to rapidly create custom made probes for conducting research. Guided by Alami and Ernst's (2025) findings on AI-generated feedback for code review, we introduce a vibe coded AI/Voice based code review prototype as a provotype (Boer and Donovan, 2012). We then outline an explorative study to critically assess the socio-technical effects of using AI based voice interfaces in code reviews. We propose a qualitative approach, based on the Disruptive Research Playbook (Storey *et al.*, 2024), involving Danish software developers to investigate voice-based feedback's impact on topics including trust, collaboration, and perceived skill shifts. Initial methodological reflections emphasize the need for cautious exploration using the provotype as an intervention for gathering data in the form of reactions, expectations, and concern about the effects of AI interactions, in the established professional practise of code review. Next steps are to finalize the provotype, complete the research design and collect and analyze qualitative data from interventions with danish software developer teams.

Keywords: AI-assisted code review, Vibe coding, Generative AI, provotypes, Socio-Technical studies, Human-AI collaboration

1. Introduction

The field of software development has adopted generative AI tools such as GitHub Copilot and DeepCode into tasks like debugging, testing, and code review (*AI Code Review | IBM*, 2024). However, the socio-technical implications, particularly how voice-based AI might alter developer interactions and feedback processes, remain underexplored. Existing studies indicate nuanced differences in developer engagement with AI versus human-generated feedback, highlighting trust and cognitive load issues (Alami and Ernst, 2025).

Addressing this gap, our research employs vibe coding - utilizing generative AI to create code through natural language prompts - to rapidly prototype a voice-based AI code review tool. Vibe coding significantly lowers prototyping barriers, making sophisticated coding tools accessible to researchers without extensive technical backgrounds (*What is Vibe Coding? | IBM*, 2025).

We introduce this tool as a provotype, a deliberately provocative prototype designed to elicit deeper user insights(Boer and Donovan, 2012), guided by the Disruptive Research Playbook (Storey *et al.*, 2024). Our qualitative study involves Danish software developers, and explores how an intervention in the form of code review feedback given by an AI/voice based provotype influences collaboration, trust dynamics, and perceptions of skill enhancement or erosion.

With the research proposed in this WIP paper, we aim to (1) provide valuable insights in the viability of using vibe coding as a method for low-ressource AI-driven prototyping in research, and (2) add to the body of knowledge that critically assess generative AI's role in software development practises, with early insights for the software-engineering community.

2. Background

Code review remains a central practice for ensuring software quality, traditionally involving collaborative, interpersonal communication. AI-assisted reviews introduce new dynamics, prompting exploration into their socio-technical impact. Research by Alami and Ernst (2025) indicate that developers process AI feedback similarly to human feedback but face challenges in other areas, including trust and cognitive load.

Vibe coding, an emerging practice leveraging generative AI for rapid software prototyping, allows researchers without extensive coding experience to quickly implement advanced interfaces (*What is Vibe Coding? | IBM*, 2025). This approach lowers the barrier for prototype development, essential for exploring innovative AI interactions.

The concept of provotypes - prototypes specifically designed to provoke user reflection - is valuable in contexts where implications of technology are uncertain (Boer and Donovan, 2012). Combining vibe coding and

provotyping enables researchers to quickly deploy provocative AI tools, eliciting critical insights into user responses and potential disruptions.

Storey et al.'s (2024) Disruptive Research Playbook provides methodological guidance, advocating for a socio-technical perspective to understand long-term implications of disruptive technologies. This approach encourages human-centered inquiry into how emerging technologies might alter established professional practices.

Our research propose to integrate these theoretical and methodological frameworks to investigate how voice-based AI code reviews could influence developer collaboration, trust formation, and perceived skill shifts, contributing to broader understandings of AI's socio-technical impacts.

No prior work, to our knowledge, has examined this, making it an open question in human/AI code collaboration. Similarly, little has been written about how researchers can rapidly prototype AI experiences (vibe coding) to study such questions.

3. Methodology

The provotype was developed using Cursor, an AI-powered, agentic coding tool powered by the most prominent foundation models, and GPT-4 for assisting in conceptual generative tasks. This method streamlined development, translating natural-language instructions into functional React code, integrated with speech recognition and speech synthesis through the Gemini live API. The code-reviewer was repurposed from a voice-based AI prototype for simulating exams, developed by and educator in BACs software development program. While the researcher who developed the provotype possessed some knowledge of coding and software development, recent advancements in the available tools indicate a decreasing reliance on domain-specific expertise.

In a provotype code review session, the user initiates the review process through a web interface, with optional configuration for expertise level, specific area of interest and more. A dialogue based session, where the AI has access to the users shared screen (and a Github Repo if permitted), is then launched. The AI has an elaborate set of instructions based on best practices on how to behave, analyze and give feedback in a code review context. During the session, the AI generates structured, spoken feedback highlighting issues, recommending improvements, and addressing clarifying questions in a responsive, conversational format. The suggestions are logged via a dynamic, text-based interface. After the session, the user is presented with a summary of the session, including a transcript and recommendations (Gundtoft, 2025).

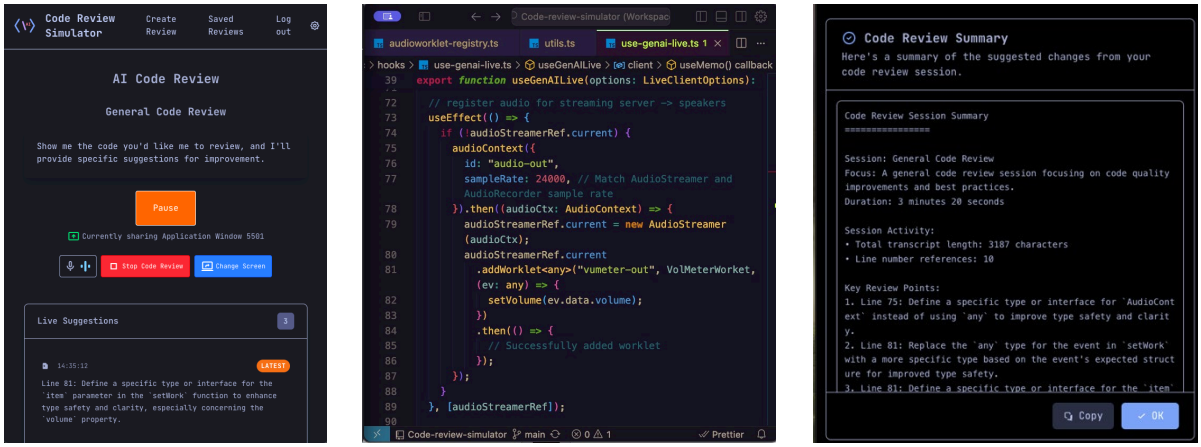

Figure 1: Left: User interface with suggestions. Middle: Code being reviewed. Right: Session summary

Development proceeded iteratively, guided by continuous testing and evaluation with an in-house software developer. Initial prototypes produced overly verbose and unfocused feedback, leading to iterative prompt and code adjustments that ensured concise, comprehensible audio feedback suitable for practical use.

This development process illustrates vibe coding's potential to lower the barrier for creating custom made research probes, empowering researchers without extensive coding background to prototype advanced human-computer interactions. However, reliance on AI-generated code required careful human oversight to identify and correct errors or misinterpretations, emphasizing cautious and critical engagement, and mirroring broader concerns in AI-driven development.

The purpose of the probe was not to showcase a proof-of-concept for voice-based code review though, but rather to act as a provotype - a conversational artifact we can take into the field to probe software engineers' interactions with AI. Next, we describe our preliminary research design leveraging this provotype to explore AI-assisted code reviewing in situ.

4. Research Design

In the study we intend to employ the prototype as a provotype within a qualitative research framework informed by the Disruptive Research Playbook (Storey *et al.*, 2024). The guiding research question of our exploratory study asks: How do software developers experience and envision the prospect of using AI feedback for established practices like code review, with a special emphasis on speech enabled AI in areas like collaboration, and perceptions of skill development/erosion? Given the exploratory and experiential nature of the study, findings are expected to mainly yield new investigative insights, not definitive answers to the research question or predictions of actual future deployment outcomes.

We plan to engage 2-3 Danish software development teams (approximately 4–5 members each). While Denmark's open, collaborative professional culture provides a suitable context for this exploratory investigation, it also aims to offer insights relevant to research in other cultural settings, with adaptability to varying contexts and scales. Each session will last approximately 75 minutes, structured in three phases:

- **Introductory Phase (15 min):** Briefing on prototype functionalities and informed consent procedures.
- **Interaction Phase (30 min):** Team members engage in sessions with the provotype, and have snippets of their own code reviewed. Participants interact freely with the AI, posing follow-up questions and discussing feedback among themselves, while the reseachers obeserve and take notes. Before the study, we aim to update the provotype with audio- and screen-recording functionality.
- **Reflective Phase (30 min):** Semi-structured group interviews gather participant reflections on usability, perceived trustworthiness, emotional responses, and comparative insights versus traditional review practices.

Data collection combines observational data, interaction logs, and interview transcripts. Thematic analysis, will be used to identify emerging sociotechnical dynamics.

Validity considerations include triangulating self-reported reflections against observational data. We acknowledge the artificial nature of the provotype setup, noting that initial reactions may differ from sustained use scenarios. Ethical considerations include explicit participant consent, transparent discussion of AI limitations, and secure data handling.

This research design enables us to explore immediate and latent sociotechnical responses to a provocative AI tool, laying groundwork for future studies on sustained use and broader adoption implications.

5. Discussion

Our approach aims to deliver two significant contributions: (1) demonstrating vibe coding's methodological potential for creating rapid research probes and (2) findings that critically assess generative AI's role in software development practises.

Initial reflections anticipate several potential socio-technical shifts. Voice-based AI feedback could alter emotional and cognitive engagement, make interactions feel more personal, or erode established social practices and relationships with colleagues. These shifts may affect trust, potentially alleviating or intensifying issues identified by Alami and Ernst (2025), depending on feedback realism and accuracy.

Methodologically, vibe coding's accessibility introduces a paradox: while lowering barriers enables valuable exploratory research, reliance on generative AI necessitates oversight to ensure scholarly rigor and methodological clarity. Researchers must critically reflect on AI's role in their processes, paralleling broader debates on human oversight in AI-driven automation.

Future research should explore longitudinal impacts, cross-cultural differences, and larger participant samples. Additionally, integrating quantitative measures could further validate qualitative insights.

6. Conclusion

This WIP paper has presented an approach combining vibe coding and provotyping to explore socio-technical implications of voice-based AI code review. Our proposed exploratory study offers a practical research

framework to investigate AI's nuanced impacts on software practices. Methodological reflections highlight the necessity of cautious and critical engagement with generative AI. This work provides foundational insights into responsible, human-centered AI research practices, supporting future studies and informing broader discussions on AI's role in professional software development contexts.

Acknowledgements

The author gratefully acknowledges Benjamin Hughes for creating the exam simulator prototype that was used as a basis for vibe coding the code reviewer.

Ethics declaration: This research is in the planning phase and has not yet commenced data collection. Ethical approval will be sought from the informants prior to conducting participant studies.

AI declaration: The paper was developed using AI tools for specific purposes. The prototype discussed was created using the AI coding assistant Cursor and OpenAI's GPT-4 for generating React code and refining system prompts. Additionally, GPT-4 was used to support early drafting and outlining of this paper, particularly for improving structure, grammar, and flow.

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Operationalizing AI for Cyber Threat Intelligence: Governance Insights from the DYNAMO Framework

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Abstract: As artificial intelligence (AI) becomes increasingly embedded in cybersecurity operations, the need for structured, compliant, and scalable integration frameworks is more urgent than ever. This paper explores how AI can be operationalized within cyber threat intelligence (CTI) systems, through a qualitative case study in the energy sector, using the DYNAMO framework as a case study. Originally developed to enhance resilience in critical infrastructure sectors, DYNAMO combines business continuity management (BCM) and CTI to support situational awareness and proactive risk mitigation. Although the framework has been applied in the energy sector in this study, its principles apply to other domains that face complex cyber threats. The study investigates how AI—particularly machine learning—can improve CTI sharing by enabling real-time threat detection, pattern recognition, and adaptive response. Drawing on recent academic and industry literature, we analyze the benefits and limitations of AI-enhanced CTI, including improved detection accuracy and faster response times. However, challenges such as adversarial attacks, model poisoning, and the need for high-quality training data are also addressed. We further examine the governance implications of integrating AI into CTI platforms, especially in light of the EU Cyber Resilience Act (CRA). The paper highlights the importance of aligning AI deployment with regulatory requirements, such as 24-hour incident reporting, post-market monitoring, and data sovereignty. The ECHO Early Warning System (E-EWS), a collaborative platform developed under the EU Horizon 2020 program, is presented as a practical example of cross-sectoral CTI sharing that incorporates AI capabilities. Our findings suggest that AI can significantly enhance cyber resilience when embedded within a governance-aware framework like DYNAMO. We recommend a phased implementation strategy that includes stakeholder training, regulatory alignment, and continuous monitoring. The paper concludes by emphasizing the need for interdisciplinary collaboration between AI developers, cybersecurity professionals, and policymakers to ensure responsible and effective AI integration in CTI systems.

Keywords: Artificial intelligence (AI), Cyber resilience, Cyber threat intelligence (CTI), Critical Infrastructure, DYNAMO Framework, EU Cyber Resilience Act (CRA), Regulatory compliance

1. Introduction

As artificial intelligence (AI) becomes increasingly embedded in cybersecurity operations, the need for structured, compliant, and scalable integration frameworks is more urgent than ever. This paper explores how AI can be operationalized within cyber threat intelligence (CTI) systems, using the DYNAMO framework as a case study. Originally developed to enhance resilience in critical infrastructure sectors, DYNAMO combines business continuity management (BCM) and CTI to support situational awareness and proactive risk mitigation. Although the framework has been applied in the energy sector in this study, its principles apply to other domains that face complex cyber threats.

As cyber threats grow in complexity and scale, CTI remains essential to cybersecurity, particularly for critical energy infrastructure (CEI). This work-in-progress paper investigates the role of AI—especially machine learning (ML)—in improving CTI sharing to detect, anticipate, and mitigate threats in real time. A thematic and comparative analysis of academic, industrial, and policy literature highlights AI's potential to enhance detection accuracy and response speed. The paper also examines integration frameworks such as the ECHO Early Warning System (E-EWS), which enables collaborative CTI sharing while safeguarding data sovereignty. Despite AI's benefits, challenges such as resource demands and adversarial attacks persist. The study concludes with recommendations for integrating CTI platforms with AI, drawing on examples like the EU-funded DYNAMO project.

2. Literature Review

The collection and analysis of CTI have become increasingly critical due to the rapid evolution of cyberattacks, which are now more organized and multi-vectored than in the past. CTI contributes to cybersecurity across tactical, operational, and strategic levels (Kure & Islam, 2019). A key challenge in cybersecurity is the information asymmetry between attackers and defenders, making threat intelligence sharing a vital mechanism for reducing this gap (Du et al., 2020).

The diversification and specialization of modern cyber threats have rendered passive protection methods insufficient. CTI sharing platforms enhance the efficiency of active detection methods, which rely heavily on continuous monitoring and analysis (Du et al., 2020). CTI also plays a central role in threat and risk assessment,

supporting the adaptation of risk management strategies. However, many existing risk management frameworks lack the agility and efficiency needed to anticipate emerging threats and safeguard assets effectively (El Amin et al., 2024).

Critical energy infrastructure (CEI), encompassing energy generation, transmission, and distribution, is essential for both economic stability and societal functioning. CEI is deeply interconnected with other sectors such as water distribution and telecommunications, and its complex technological landscape presents a broad attack surface (Govea, Gaibor-Naranjo, & Villegas-Ch, 2024). Machine learning and other algorithmic approaches are increasingly employed within CEI, not only for cybersecurity—particularly in attack detection—but also for operational tasks such as grid stability and energy optimization (Szczepaniuk & Szczepaniuk, 2023).

Examples of CEI include power grids and oil and gas facilities. These systems are highly vulnerable to cyber-attacks due to their reliance on industrial control systems and operational technologies, which present numerous entry points for malicious actors (Daniel & Victor, 2024). More broadly, network intrusion detection systems (NIDS) are evolving from traditional signature-based models to machine learning-based systems. These newer systems are better equipped to handle zero-day attacks and persistent threats through behavioral analysis and adaptive techniques (Manoharan & Sarker, 2022).

In the context of CTI, the utility of simple indicators of compromise (IoCs) diminishes over time as systems evolve or are remediated. While machine learning and deep learning models demand more computational resources, they offer superior capabilities in characterizing complex threats. However, their integration can also expand the attack surface of the systems they aim to protect (Preuveneers & Joosen, 2021).

Kure and Islam (2019) proposed a unified CTI framework for critical infrastructure using Structured Threat Information Expression (STIX) and Common Weakness Enumeration (CWE) standards. Their model includes strategic, tactical, and operational components: strategic intelligence focuses on threat actors and attack processes; tactical intelligence identifies network and system indicators; and operational intelligence involves trend analysis, control deployment, and vulnerability mapping.

Ammi and Jama (2023) presented a case study utilizing the MISP threat intelligence sharing platform. Their architecture integrates open-source intelligence (OSINT) feeds into MISP, which then distributes data to Intrusion Detection Systems (IDS) and Intrusion Prevention Systems (IPS), followed by aggregation in a Security Information and Event Management (SIEM) system, and finally visualized through a web interface.

In a study focused on CEI, Govea, et al. (2024) addressed the growing threat surface by integrating AI systems capable of anticipating, detecting, and responding to security incidents. Their evaluation of various AI technologies considered detection efficiency, scalability, resource requirements, and cost. Through an iterative integration process, they achieved a detection rate of 94.7%, significantly outperforming traditional systems, which reached only 74.9% on the same dataset.

3. Methodology

This study investigates the integration of AI in CTI sharing within the energy sector, through a qualitative case study in the context of the DYNAMO framework, complemented by governance analysis aligned with EU cybersecurity regulations. The research adopts a qualitative approach, drawing on data collected from peer-reviewed academic publications, industry reports, policy documents, public materials of the ECHO and DYNAMO project, and technical evaluations of threat intelligence platforms. To ensure relevance to current cybersecurity challenges, the study focuses on sources published within the last five years.

A thematic analysis was conducted to identify recurring patterns and themes related to AI integration in CTI sharing. In addition, a comparative analysis was performed to examine differences across various approaches, platforms, and frameworks. This dual analytical strategy enhances the validity of the findings by enabling a nuanced understanding of the advantages, limitations, and scalability of different AI applications in CTI systems.

The research adheres to our university's guidelines for research integrity and complies fully with the General Data Protection Regulation (GDPR). All data sources used in the study are publicly accessible and open, and no personal or sensitive data were collected during the research process.

4. Findings

The analysis revealed several key insights regarding the integration of artificial intelligence (AI) into cyber threat intelligence (CTI) sharing within the energy sector.

First, machine learning algorithms significantly enhance threat detection capabilities. AI-based systems have demonstrated detection accuracies of up to 94.7%, compared to 74.9% for traditional methods (Gandham, 2025). This improvement is attributed to AI's ability to process large volumes of data, identify complex patterns, and adapt to evolving threats in real time. However, the integration of AI is not without challenges. These include the need for high-quality training data, vulnerability to adversarial attacks, and the continued necessity of human oversight to ensure interpretability and accountability (Yaseen, 2023).

A notable example of cross-sectoral CTI sharing is the ECHO Early Warning System (E-EWS), developed under the EU's Horizon 2020 program. E-EWS facilitates the exchange of machine learning models and integrates various monitoring solutions. One such solution is the MonSys Bridge prototype, which connects external Security Information and Event Management (SIEM) tools to E-EWS, enhancing threat detection and response capabilities (ECHO Network, 2020).

Despite the benefits, AI integration demands substantial computational resources and robust infrastructure. Threats such as model poisoning underscore the importance of strong data validation, continuous monitoring, and anomaly detection mechanisms (Grant Thornton, 2023). Pre-integration assessments and strategic planning are essential to minimize operational disruptions and ensure secure deployment (Bhalsod, 2024).

Organizations in the energy sector are increasingly adopting advanced CTI practices, including layered system architectures and standardized data formats such as STIX and TAXII (Kravensecurity.com, 2023). These standards support efficient, automated information exchange. Furthermore, combining open-source and proprietary threat intelligence sources enhances both scalability and the depth of insights (Seerist, 2025).

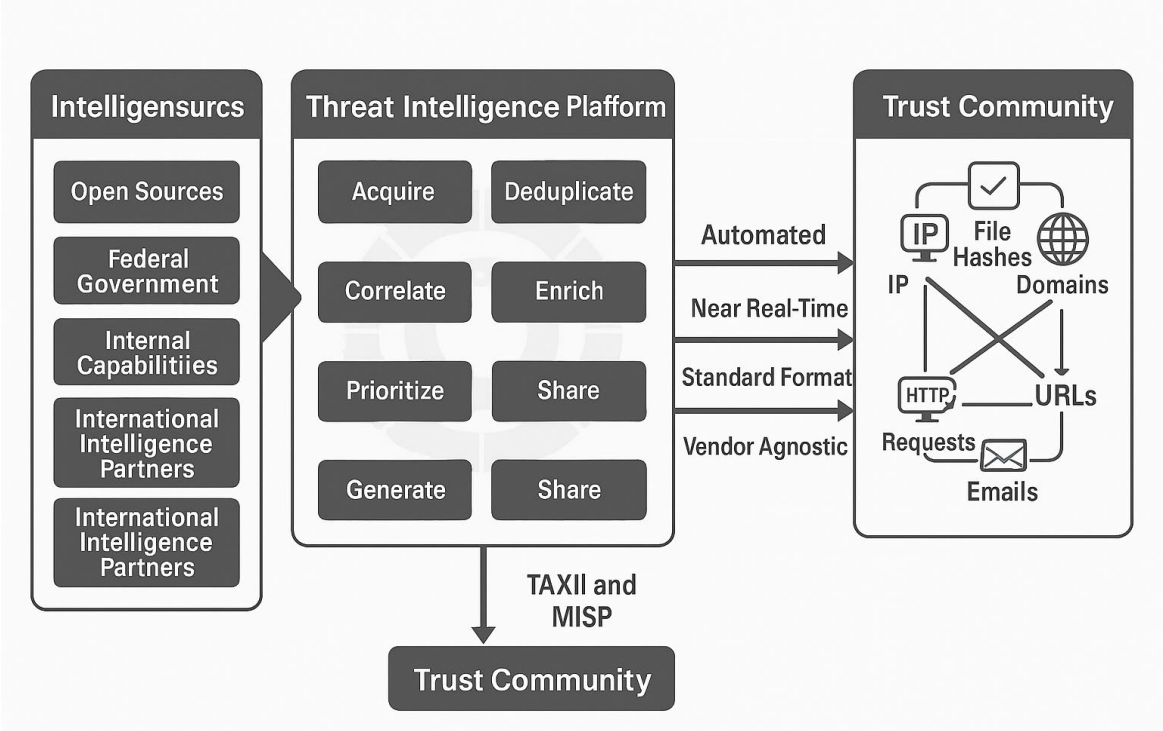

Figure 1: Cyber threat intelligence sharing workflow (modified from Amazon Web Services, 2025)

Finally, secure data sharing and trust are critical. DYNAMO's E-EWS emphasizes data sovereignty, enabling collaboration without compromising sensitive information (Rajamäki, Feyesa & Nepal, 2024; De Vecchis, 2020). Figure 1 presents Amazon Web Services' example, in which CTI flows from diverse sources through a threat intelligence platform that processes and enriches data, then shares indicators (IPs, domains, URLs, file hashes, emails) with a trust community via TAXII and MISP using automated, near real-time, standardized, vendor-agnostic exchange (Amazon Web Services, 2025).

5. Discussion and Conclusions

This research highlights both the potential and the complexity of integrating AI into CTI sharing systems within the energy sector, using the DYNAMO project as a contextual framework. The findings demonstrate that AI—particularly machine learning—can significantly enhance threat detection in terms of accuracy, speed, and scalability. Empirical evidence suggests up to a 20% improvement in detection efficiency compared to traditional methods (Gandham, 2025).

However, the study also identifies several practical and strategic challenges. The effectiveness of AI systems is highly dependent on the availability of high-quality training data, the integrity of that data, and the reliability of the supporting infrastructure. Deep learning models, while powerful, require substantial computational resources and are themselves susceptible to threats such as model poisoning and adversarial manipulation. Addressing these vulnerabilities necessitates robust data governance, rigorous testing, and continuous monitoring.

The case of E-EWS within the DYNAMO architecture illustrates the practical feasibility of AI-enhanced CTI sharing across sectors. E-EWS supports the exchange of ML models and integrates tools such as the MonSys Bridge, which connects external SIEM systems to the platform. The use of standardized formats like STIX and TAXII further enhances interoperability and automation, making CTI sharing more efficient and scalable. Despite these technological advancements, organizational readiness remains crucial. Compliance with emerging regulations, such as the EU AI Act, and the responsible use of AI are essential for sustainable implementation. Based on the findings, the following recommendations are proposed:

- **Foster collaboration** between public and private stakeholders to enhance knowledge sharing and resource pooling.
- **Provide targeted training** for energy sector personnel on AI technologies and threat intelligence analysis.
- **Develop structured integration plans** to ensure that AI adoption does not disrupt existing cybersecurity operations.

While AI offers transformative potential for CTI sharing in the energy sector, its successful implementation requires a balanced approach that combines technological innovation with strategic planning, regulatory compliance, and human oversight.

Acknowledgements

Acknowledgments are paid to the DYNAMO Project, funded by the European Union under grant agreement no. 101069601, and to the project *"Development of Cybersecurity Education and Related Collaboration in Higher Education"*, funded by the Finnish Ministry of Education and Culture under the national program for strengthening cybersecurity competencies and collaboration among universities. The views and opinions expressed are solely those of the authors only and do not necessarily reflect those of the European Union, European Commission, or Finnish Ministry of Education and Culture. Neither the European Union nor the granting authorities can be held responsible for them.

Ethics declaration: Ethical clearance was not required for the research.

AI declaration: Figure 1 was drawn with AI assistance. The paper's spelling was verified using the artificial intelligence tool.

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Prompting Future Journalists to Prompt: An Experiential Study on GenAI, Critical Literacy, and Reflective Practice in Data News

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Abstract: Generative AI (GenAI) is rapidly integrating into newsrooms, creating a paradox: while the industry embraces AI for efficiency, public skepticism persists, and scholars warn of AI's potential to exacerbate information disorder. This underscores an urgent need for a sophisticated approach to AI literacy in journalism education. This paper reports findings from the first phase of a two-phase case study investigating how undergraduate communication students (N=19) with prior journalism training interact with a custom GenAI tool for data-driven storytelling. Through a three-part methodology—pre-study questionnaire, logged experiential task, and post-study survey—our analysis reveals that prior AI experience does not uniformly predict success or critique. Instead, a data-driven thematic analysis identifies four emergent archetypes of engagement: the Director, who treats the AI as a controllable instrument; the Collaborator, who frames it as a creative partner; the Delegator, who views it as an often-unreliable shortcut; and the Antagonist, who experiences it as a deficient obstacle. These archetypes, which align with existing frameworks of user-AI interaction, are actively shaped by students' pre-existing journalistic philosophies. This paper argues for a phenomenologically-informed critical AI literacy that equips students with the metacognitive awareness to reflect on the technological relationships they are building.

Keywords: Generative AI, Journalism education, Critical AI literacy, Phenomenology, Human-AI collaboration, Reflective practice, Student perceptions

1. Introduction: The Journalist, The Algorithm, and The Audience

The advent of generative artificial intelligence (GenAI) has precipitated a paradigm shift in journalism. News organizations are integrating GenAI into their workflows at an unprecedented rate for tasks from data analysis to content summarization (Diakopoulos et al., 2024). This embrace, however, coexists with deep societal apprehension. Global surveys reveal significant public discomfort with AI-produced news, citing fears of error and bias (Newman et al., 2025). These concerns are amplified by scholars who warn that Large Language Models (LLMs) risk exacerbating information disorder, a form of "careless speech" that corrodes shared knowledge (Wachter, Mittelstadt and Russell, 2024).

While this disruption presents an epistemic crisis, it also offers an epistemic opportunity for journalism to reinforce its essential values (Perreault, Lewis, and Ely, 2025). Navigating this new landscape requires a deliberate return to the foundational principles of the profession. A guiding framework, such as the Society of Professional Journalists (SPJ) Code of Ethics, provides a clear, structured set of principles: Seek Truth and Report It, Minimize Harm, Act Independently, and Be Accountable and Transparent (Society of Professional Journalists, 2014). These ethical principles are enacted through the practical skills of information literacy, which the Association of College and Research Libraries (2016) defines as the ability to "locate, evaluate, effectively use and ethically apply the needed information". Yet, journalism education is in a reactive race to adapt. Current research predominantly focuses on professional workflows (Diakopoulos et al., 2024) or prompt engineering (Nishal and Diakopoulos, 2024), leaving a gap in our understanding of the subjective learning experiences of emerging journalists.

This paper reports on the first phase of a two-phase study designed to explore this gap by investigating students who have already completed foundational journalism courses. We adopt a stance of experiential plurality, arguing that a GenAI system is co-created in the moment of interaction. This study investigates these emergent GenAIs through the following research questions:

RQ1: How do communication students with prior journalism training approach collaborating with a GenAI tool?

RQ2: What are the key challenges students encounter during this collaboration?

RQ3: What emergent archetypes of engagement can be identified based on how students' pre-existing dispositions mediate their critique of the GenAI tool?

2. Theoretical Framework: From Stable Tool to Subjective Encounter

To understand how emerging journalists engage with GenAI, a purely technical analysis is insufficient. We argue that a GenAI's function is co-constructed in the unique context of each user's interaction. This framework synthesizes phenomenology, post-structuralist thought, and the philosophy of technology.

We begin with the concept of the lifeworld (Schutz and Luckmann, 1973), the taken-for-granted reality that shapes our perception. For a journalism student, the lifeworld is not just a generic personal background but is profoundly shaped by their professional training and internalization of journalistic principles. Each student enters the task from a unique lifeworld that pre-figures the kind of phenomenon the GenAI can become (Hamamra et al., 2025). This is particularly salient when confronting the black box problem—the inherent opacity of AI systems (Misri, Blanchett and Lindgren, 2025). In the absence of technical transparency, users project their own lifeworld onto the machine. When a student confronts the black box of the AI, their interaction is an attempt to reconcile their developing professional ethics with the affordances and limitations of the tool.

We advance this by framing the user as a bricoleur (AI Inquiry Garden, 2025), creatively assembling a solution from whatever is at hand. An LLM, with its vast repository of textual fragments, is the ultimate bricoleur's toolkit. The student must actively assemble a coherent story by sifting through and re-contextualizing the probabilistic pieces the AI provides. This process constitutes a hermeneutic relation (Ihde, 1990), where one reads the world through a technology. Students interpret the dataset through the AI's language while simultaneously interpreting the AI's capabilities through the lens of journalistic values. This dynamic sense-making becomes observable through Schön's (1983) model of the reflective practitioner. Reflection-in-action is the real-time bricolage of tweaking prompts. Reflection-on-action, captured in our post-task survey, is the retrospective moment where the student makes sense of the unique, subjective GenAI.

3. Study Design

This paper reports on the preliminary findings from the first phase of a two-phase sequential case study. This phase was conducted with nineteen (N=19) undergraduate communication students who had completed foundational journalism courses. The three-step procedure involved: (1) a pre-study questionnaire capturing demographics, news habits, and prior AI perceptions; (2) a 60-minute experiential task where students used a custom RAG-style GenAI tool (GPT-4o-mini API) to produce a data-driven news story from a provided dataset, with all interactions logged; and (3) a post-study qualitative survey prompting reflection on their process and challenges. A reflexive thematic analysis (Braun and Clarke, 2006) of the qualitative data was systematically triangulated with the pre-study data and interaction logs to develop a holistic typology of student engagement.

4. Findings: A Typology of Co-Created GenAIs

Our analysis revealed that students, despite using identical software, interact with GenAI by using diverse approaches, motivations, and ethical frameworks. We identified four emergent relational patterns, or archetypes, that describe their engagement, as seen in Table 1.

Table 1: An Emergent Typology of Co-Created GenAIs

Archetype	Core Motivation	Characteristic Behavior (from Logs)	Illustrative Quote (from Post-Study Survey)	Dominant Journalistic Principle (SPJ Code of Ethics)
The Director	Efficiency & Control	Issues precise, multi-step, and technically specific prompts (e.g., "inverted pyramid," 5N1K).	"My relationship with the AI was like boss-employee." (P12)	Be Accountable & Transparent: Demands precision and verifiable outputs, taking responsibility for the final product
The Collaborator	Co-construction & Exploration	Engages in conversational, iterative dialogue; uses anthropomorphic language.	"I tried to be kindly to it, because I felt it did better that way." (P01)	Minimize Harm / Engage the Public: Focuses on framing and tone to make information accessible and engaging for the audience.
The Delegator	Task Offloading & Simplicity	Starts with vague, minimal prompts (e.g., "write a news story") and engages in repetitive refinement.	"The part about copying the table was difficult, the system couldn't deliver it properly." (P13)	Failure to Seek Truth: Abdicates the core responsibility of verification and critical inquiry, leading to potential inaccuracies.

Archetype	Core Motivation	Characteristic Behavior (from Logs)	Illustrative Quote (from Post-Study Survey)	Dominant Journalistic Principle (SPJ Code of Ethics)
The Antagonist	Skepticism & Scrutiny	Encounters critical technical failures (crashes, hallucinations) or interrogates the AI's ethical capacity.	"AI has no *şiar* (guiding principle)... its absence of depth of meaning... is a deficiency." (P14)	Seek Truth & Report It / Act Independently: Upholds the primacy of human ethical judgment and skepticism toward unverified information.

4.1 The Director: AI as an Embodiment of Accountability

This archetype's core motivation for Efficiency & Control can be reframed as an expression of the journalistic principle of Be Accountable & Transparent. The Director's use of precise, technical prompts like inverted pyramid format and 5W1H technique is not just a sign of high AI skill; it is an attempt to hold the AI accountable for producing content that meets professional standards. This behavior directly mirrors the ethical mandate to "Take responsibility for the accuracy of their work" and to "Verify information before releasing it". By treating the AI as a boss-employee, the Director is asserting their ultimate responsibility for the final product, refusing to cede control over journalistic form and structure to an algorithm. For the Director, success is defined by the tool's ability to adhere to their commands, reflecting a professional's need for reliable and verifiable outputs. Their position aligns with research identifying a request-driven AI assistance pattern, where the user maintains control (Gomez et al., 2024)

4.2 The Collaborator: AI as an Effort to Minimize Harm and Engage

The Collaborator's approach of Co-construction & Exploration can be linked to the principle of Minimize Harm and the broader journalistic goal of serving the public by making complex information engaging and accessible. Their conversational and anthropomorphic style ("I tried to be kindly to it") and their focus on making a headline more punchy can be interpreted as an intuitive understanding that tone and framing are crucial journalistic tools. The principle to Minimize Harm involves treating subjects with respect and compassion, a value the Collaborator appears to project onto the AI itself. Furthermore, their exploratory dialogue reflects the journalistic purpose of not just cataloging facts but of telling a story with a purpose, striving to make the significant interesting and relevant for the audience. This interaction can be seen as a form of AI-guided dialogic user engagement, to diversify the ideation process. However, research suggests AI can increase the collective diversity of ideas but not necessarily their individual creativity (Meincke, Mollick and Terwiesch, 2024).

4.3 The Delegator: AI as a Failure to Seek Truth

The Delegator archetype provides a clear example of a deviation from core principles. Their motivation for Task Offloading & Simplicity should be framed as a failure of the fundamental principle to Seek Truth and Report It. This approach resonates with the *passive believer* archetype, which describes users who have high trust but low engagement (Stocker, 2025 Starting with vague prompts like write a news story represents an abdication of the journalist's core responsibility to actively gather, assess, and verify information. This behavior demonstrates poor information literacy, specifically a failure in the initial, critical step of defining and articulating the information need. Their subsequent frustration with the AI's generic outputs and limitations is a direct consequence of this failure. The Delegator's experience highlights the danger of viewing GenAI as a replacement for journalistic labor rather than a tool to be wielded with professional rigor. This experience was frequently defined by friction with the AI's limitations, a common source of user frustration in human-computer interaction when a system fails to meet expectations (Ceaparu et al., 2004; Lazar et al., 2007).

4.4 The Antagonist: AI as an Expression of Independence and Skepticism

The Antagonist is perhaps the most potent example of journalistic principles in action. Their Skepticism & Scrutiny should be framed as the purest embodiment of the principles to Seek Truth and Report It and Act Independently.2 For the student who experienced technical failures, their antagonism reflects the non-negotiable demand for accuracy. For Participant 14, the antagonism was philosophical. Their profound statement that the AI has no "şiar" (a guiding principle or ethos) is a direct ethical critique rooted in the core of journalism. Their interaction was filtered through a deep professional skepticism, mirroring the *hesitant sceptic* or *critical user* archetypes, characterized by low trust in the system (Stocker, 2025). It also reflects a broader ethical resistance to AI in professional workflows (Gutiérrez-Caneda et al., 2024). For the Antagonist, the AI is not a tool to be optimized but a deficient obstacle—either technically broken or ethically bankrupt. This use of the Turkish word *şiar*—denoting a guiding ethos—is telling. For this student, the AI's failure was not a technical

bug but a moral and philosophical void. The GenAI they constructed was a soulless mimic, capable of syntax but devoid of the principled substance that defines journalism.

5. Discussion and Conclusion

Our primary findings demonstrate that journalism students do not merely use generative AI; they actively co-create it through the lens of their developing professional ethics, which we operationalize via the Society of Professional Journalists (SPJ) Code of Ethics. The emergent archetypes are expressions of this co-creation: the Director's precise commands reflect a commitment to Accountability, while the Antagonist's scrutiny embodies the principles of Seeking Truth and Acting Independently. Conversely, the Delegator's uncritical offloading of tasks represents a failure of these same principles. The primary challenge this reveals is not technical, but ethical: ensuring that AI collaboration aligns with, rather than subverts, the core values of journalism. This requires experiential learning spaces where students confront complexities directly, addressing calls for ethical guidance (Djokic et al., 2024 This has profound implications for pedagogy that moves AI literacy beyond operational skills to include an understanding of AI's societal and ethical dimensions (Goodlad and Stoerger, 2024). Our findings suggest AI literacy must also include a *phenomenological* component that facilitate to recognize how students' subjective dispositions and interactional stances are actively shaping a unique 'GenAI' into being.

To address this challenge, our findings suggest the need for experiential learning environments, or ethical labs, designed to move students from passive interaction to principled practice. A tangible model for such a module could involve a three-stage process. Stage 1 (The What) would use the study's archetypes as a tool for metacognitive self-awareness, where students identify their own interaction patterns from logs. Stage 2 (The So What) would apply formal ethical models like the Potter Box to analyze case studies of AI failures, building structured reasoning skills. Stage 3 (The Now What) would then operationalize this learning through *principled prompting,* tasking students with crafting prompts explicitly guided by the SPJ Code of Ethics. This approach transforms prompting from a technical input into a deliberate act of professional practice.

The central contribution of this work in progress is a typology of engagement that reframes AI literacy not as a technical skill, but as a reflective, ethical practice. Experiential models, such as the ethical lab concept, are offered as a concrete way to foster this competency. While the specific AI tools used in this study will inevitably become obsolete, our findings focus on the enduring patterns of human-professional adaptation. The archetypes represent fundamental relational stances—reconciling human principles with algorithmic processes—that will persist as technology evolves.

Ethics Declaration: Ethical clearance for this study was obtained from the Institutional Review Board (IRB), and all participants provided informed consent, with their data being fully anonymized to ensure confidentiality.

AI Declaration*:* Gemini, a large language model from Google, was used for the limited purpose of proofreading the text to identify grammatical errors and suggest phrasing to improve clarity.

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Late Submissions

Integrating Ethical, Legal, and Technological Safeguards in Space-Focused Cyberbiosecurity: AI, Cloud, and Crew Considerations

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Abstract: Long-duration crewed missions and orbiting habitats such as the International Space Station (ISS) present unique intersections of biological and cybersecurity risks. Cyberbiosecurity, a hybrid field that combines biosecurity and cybersecurity in the investigation of system vulnerabilities, is being addressed across multiple domains of Earth but remains underexplored in space environments. The closed-loop life-support, modular robotics, and telemetric control systems aboard space stations create novel attack surfaces, while microgravity and radiation alter microbial behavior in ways that could exacerbate bio-contamination risks. Additionally, the use of artificial intelligence (AI) for equipment health monitoring, autonomous robotics, and crew support introduces new vulnerabilities, as adversarial inputs or model poisoning could compromise critical diagnostics and decision-making aids. Cloud-based infrastructures used for off-board data storage, analytics, and command relay further expand the threat surface, requiring rigorous cloud security, encryption, and isolation protocols to prevent unauthorized access or data exfiltration. This paper explores potential attack vectors in both cyber- and bio-informed arenas across launch, transit, and orbital habitats, and proposes forward-looking countermeasures for these proposed attacks. We outline a framework that incorporates ethical and legal considerations, including crew privacy rights and compliance with international space treaties and biosafety regulations. By combining AI-robust design principles, secure cloud architectures, and clear legal guidelines, our approach aims to present ideas to safeguard space-based biological operations, uphold crew well-being, and ensure mission resilience against emerging cyberbiological threats.

Keywords: Space, Space station, Cyberbiosecurity, Biocybersecurity

1. Introduction

Human presence in space (from government ventures) to emerging commercial habitats depends on the tight integration of life-support, command-and-data handling, robotics, and biomedical research modules (Everroad et al, 2024). Space-station systems are highly interdependent and are projected to become more intertwined: novel proposed systems include encrypted telemetry of experimental samples with specialized hardware, remote maintenance using robotic arms, and crew health parameters fed through environmental controls (Putz, 1999; Fink et al, 2014; Mora et al, 2016; Khodadad et al, 2021; Overbey et al, 2024). While these systems face significant implementation challenges, the evaluation of their security is underdiscussed in the literature. Conventional cyber threats could disrupt environmental or command systems, and biological risks may be expedited by an attacker maliciously manipulating life-support protocols (Skopik et al, 2012; Elgabry, 2023; Sreejalekshmi, 2024; Khan et al, 2024; Oh et al, 2025). For instance, a fungal bloom caused by airflow stagnation on a hypothetical mission in space could allow *Cladosporium* to accumulate near avionics panels, and if an attacker alters filter replacement schedules via a compromised digital or cyber-physical interface, both crew health and critical systems could be jeopardized.

This interface between biosecurity and cybersecurity has been extensively discussed, but their use is over-represented in terrestrial environments since 2018 and under-discussed in the context of space (Elgabry and Johnson, 2024; Potter & Palmer, 2023). Considerable amounts of literature treat space cybersecurity and biological control separately, and incident reports (e.g., software resets, environmental-control failures) may find themselves operating with an insufficiently unified vulnerability assessment. This work bridges that gap by exploring cyberbiosecurity in a representative space habitat environment and proposes practical mitigations and policy recommendations. We conclude with directions for future research and operational practice. This work is by no means fully inclusive, but it aims to offer a conversation starter; we cannot assume that these matters are not already being discussed, after all. Simplified versions of terms will be used to increase

accessibility among our audience, which we expect to be diverse among those in aerospace, biology, and cybersecurity. This position paper emphasizes both the practice and law of biocybersecurity relevant to the theater of space, and provides appropriate practical preparation as well as proposed legal frameworks to guide the development of this exciting, nascent field.

2. Space-Station Biocybersecurity: The Architecture and Vulnerabilities of an Integrated Cyber-Biologic Threat Landscape

The central feature of cyberbiosecurity is that biological assets are used as intermediaries or targets in attacks that involve computerized systems (Murch et al., 2018; Elgabry & Johnson, 2024; Potter & Palmer, 2023). Space stations are an excellent example of high-risk, high-value cyberbiosecurity targets: they are significantly automated, long-duration human biological habitats used in the hostile environment of space and are fundamentally cyberbiological. One essential space habitat feature that exemplifies this cyberbiological nature is the Environmental Control and Life Support System (ECLSS) (Traweek & Tatara, 1998; Berger, 2008; Sorokin & Markov, 2008; Messerschmid & Bertrand, 2013). The ECLSS is the combined on-board hardware, software, and biochemical support system used to simulate Earth's natural, regenerative life-sustaining resource supply - it predominantly recycles water via waste reclamation and filtering and revitalizes air using flow through filtration chambers and oxygen generation by electrolysis (Cowan et al, 2022). However, the elegance of the ECLSS belies its risk as a high-value target: it is an essential automated biophysical network where any lapse in security can be exploited by attackers. For example, an ECLSS operating on legacy *command and data handling (CDH)* protocols, using firmware updates that do not have a verifiable origin and without encryption, may prove deadly for the crew: sophisticated air and water control systems could be modified or halted outright, and astronauts could be held hostage for ransom payment or political motives (Asaju et al, 2024; Hazra et al, 2024; Ivey, 2024; Badke et al, 2025). Even miscommunication of resource status, biomass, waste, atmosphere stabilization, or improper utilization could be disastrous, as significant planning and coordination is required to maintain closed-loop regeneration onboard a space habitat (Caraccio et al, 2014). An attacker may seek to exploit insufficiently protected CDH protocols while disguised as an approved user, either by repeating prior commands at an inappropriate time (replay attack) or inputting their own malicious commands (uplink spoofing) (Torabi et al, 2021; Lai et al, 2022; Martínez et al, 2023). Limited time to fix software errors, especially for space missions far from Earth, and stringent reliability requirements further magnify these risks, as solutions can be delayed despite immediate mission-critical needs.

Consequences of an attack may not be immediately obvious: over days, closed-loop habitats can dramatically expedite genetic drift and small-scale evolution. If not closely monitored, microbial genetic selection pressure may increase virulence, favor one species over another, and increase biofilm formation (Nnaji et al., 2024; Osta-Ustarroz et al., 2024; Onofri et al., 2025). This has implications for automated water-processing filters on space stations; scheduled biocidal treatments, necessary for regular filter cleaning, can be targeted in an attack to delay or cease function. This would allow many known contaminant microbes aboard space biohabitats to multiply out of control, as many form biofilms that increase their virulence and decrease their vulnerability to conventional biocidal products (Vance et al., 2022; Justiniano et al., 2024; Beitle et al., 2024; Herrera-Jordan et al., 2024). Similarly, maliciously reprogrammed automated microbial monitoring systems could suppress contamination alerts, promote resistant strains of microbes, or skew biomass estimates, delaying crew interventions until risks become unmanageable. For example, human immune system dysregulation is a well-known consequence of space travel (Lv et al, 2023). Fecal-oral transmission of endemic diseases can spread rapidly among crew if filtration of reclaimed wastewater is tampered with, and an entire crew affected by a diarrheal disease when potable water is scarce could prove lethal (as was common among terrestrial expeditions in the past) (Barrila et al, 2021). The same goes for any undetected upper respiratory infections in a crew member, whether already on a team or joining a space station from Earth: tampered air filtration could render quarantining ineffective, and the aforementioned immune weakening could put astronauts at increased risk of life-threatening pneumonia (Mermel, 2013). Reprogrammed robotic manipulators in astrobiology experiments may mishandle containment units, releasing engineered or opportunistic microbes into the habitat's air or water systems. Unauthorized access to sequencing devices further enables exfiltration and tampering with genomic data, masking emerging infections, or facilitating the engineering of novel biothreats. Another attack vector exists along maintenance of microbial populations essential for broader life support function: altering micro-environmental controls may so dramatically disrupt microbial ecology that populations become unstable and ultimately collapse, leaving a broken link in the ECLSS recycling chain. In addition to crew safety, mission success is at risk, as numerous experiments could be

compromised: an attacker intercepting encrypted sensor data could spoof readings, altering experimental results in a way that may not be detected until after the mission is over.

Emerging commercial habitats may create new security issues if they use third-party payload racks and specialized interfaces without proper interoperability, governance, and security. Vulnerabilities may emerge from undiscovered flaws in programming that are found by malicious actors; the mix of connected, disparate electronic and biocentric hardware presents unique risks, especially within microgravity. This includes personal devices like smart inhalers and glucose monitors, especially if they connect to station systems. The supply chain poses risks, as well: third-party hardware or firmware may hide dangerous payloads that could activate once in orbit. For example, insiders might change microbial monitoring schedules or system settings to conceal a biothreat or cause system malfunction (Zafar et al, 2021; Panunzio et al, 2021; Nahar et al, 2022; Pietraru et al, 2023; Seiden et al, 2023). Each part of the network can be a potential entry point for attacks (Babajide et al, 2025; Babcinschi, 2025; Saroka et al, 2025). Together, these cyber and biological threats form a deeply intertwined attack landscape that demands unified, layered defenses combining cryptographic hardening, network segmentation, anomaly detection, supply-chain attestation, and bio-containment protocols to protect both the digital and biological integrity of space habitats.

3. Cloud Infrastructure in Space Habitats: Threat Surfaces and Resilience

Cloud computing enables remote analytics, telemetry processing, and data sharing across sensors and servers (Aderinto, 2025; Kua et al., 2021; Wang et al., 2025). In space habitats, onboard computers can collect and perform lightweight preprocessing on critical data, then transmit to Earth-based cloud platforms for more intensive computations. Insights gleaned from the terrestrial processing can then be sent back to the space habitat for interpretation. Yet all transmissions hold the potential for man-in-the-middle attacks, sensor spoofing, data exfiltration, and artificial intelligence (AI) model poisoning (Ahmed & Kashmoola, 2021; Bajcsy et al, 2025; Korada, 2024).

For instance, adversarial interference in microbial sensor data could suppress contamination alerts, delaying mitigation (Usynin et al, 2025). Cloud-based environmental monitoring algorithms utilizing compromised inputs can place crew safety at risk. In the current commercial cloud infrastructure environment, this risk is compounded due to the sharing of computational resources among several independent users, a cost-saving measure known as “multitenancy.” Multitenancy becomes a risk when sensitive mission data is stored and processed on servers also used by independent (and possibly malicious) users. Sophisticated attackers could erode barriers within virtualized tasks, expose data that may lead to inferring mission operations, extract restricted data, or sabotage hardware operation by feeding automated controls incorrect information for their function (Javeed et al, 2023; Lou et al, 2024). Of course, the collection and processing of health-related information in cloud systems raises legal and ethical challenges related to patient privacy, data sovereignty, and regulatory compliance (Chakilam et al, 2025; Shafik et al, 2025).

To mitigate the risks associated with terrestrial cloud integration in space operations, encouraging continuous authentication is essential, ensuring that every interaction, from onboard subsystem communication to remote mission controller contact, undergoes permission validation, encryption, and authorization. By incorporating federated learning, model training can be distributed across platforms without centralizing sensitive data, preserving the confidentiality of crew health, genomic, and environmental telemetry while reducing transmission exposure. Audit trails that cannot be altered, supported by systems based on distributed, but cryptographically linked, data structures used to record events (such as those seen in blockchain-based ledgers) can further strengthen accountability. This can provide tamper-evident tracking of system access and configuration changes; the choice of blockchain ledger would need to be developed with space-based stakeholders in mind. Next, quantum computing has potential to undermine existing encryption standards; the adoption of cryptographic algorithms that are quantum-resilient must become standard for all mission-critical communications. Accompanying this concern is the fact that most cloud infrastructure is physically located on Earth. Both jurisdictional and geopolitical concerns in terms of data sovereignty and state-sponsored interference present additional challenges for the deployment of the technology mentioned here. Further, mismanagement of privilege escalation during mission transitions, where users retain unnecessary access across cloud environments, can exacerbate vulnerabilities. Despite these risks, cloud computing remains invaluable for its scalability, redundancy, and ability to alleviate onboard processing demands. Its secure implementation depends on dynamic access management, real-time auditing, and adherence to stringent, jurisdiction-aware governance frameworks that balance operational agility with uncompromising biocybersecurity.

4. Countermeasures and Resilience Strategies

Having discussed how an attacker might exploit space habitat systems, it is worthwhile to turn our attention to methods of preventing such an intrusion. First, communications channels must be secured: data transmission to and from the spacecraft must be cryptographically hardened to prevent snooping by unauthorized parties or timing delays, as either opens the space crew to harm by way of malfunctioning equipment. Additionally, firmware images must carry digital signatures that are verified by hardware-rooted, ID-based, system-specific bootloaders. Critical on-board networks must be sandboxed with firewalls, so that life-support and bio-monitoring systems are isolated from payload and crew internet; this reduces the ability for attackers to gain unprivileged access to sensitive systems. To this end, biological analysis platforms (whether scientific or clinical) should operate using only necessary network connectivity, and any removable storage should undergo fingerprinting that checks against corruption before analysis. Any introduction of third-party modules needs clear, consistent digital watermarking and hardware attestation, with an immutable ledger of component provenance and firmware hashes that tracks all physical and digital components allowed to join any (isolated) network. Following good security practice includes that physical and digital third-party components are not installed or enabled without a clear rationale and appropriate permissions.

Besides securing and isolating avenues for an attack, an addition security can be provided by active surveillance of networks: lightweight machine-learning monitors (or even simple activity thresholds) can establish baseline telemetry patterns for ECLSS, robotics, and bio-sampling subsystems, flagging deviations that suggest sensor spoofing or schedule manipulation. Insider-threat management relies on multi-person authorization for critical commands, such as filter-change scheduling and tamper-evident audit logs, which can only be accessed by independent safety officers.

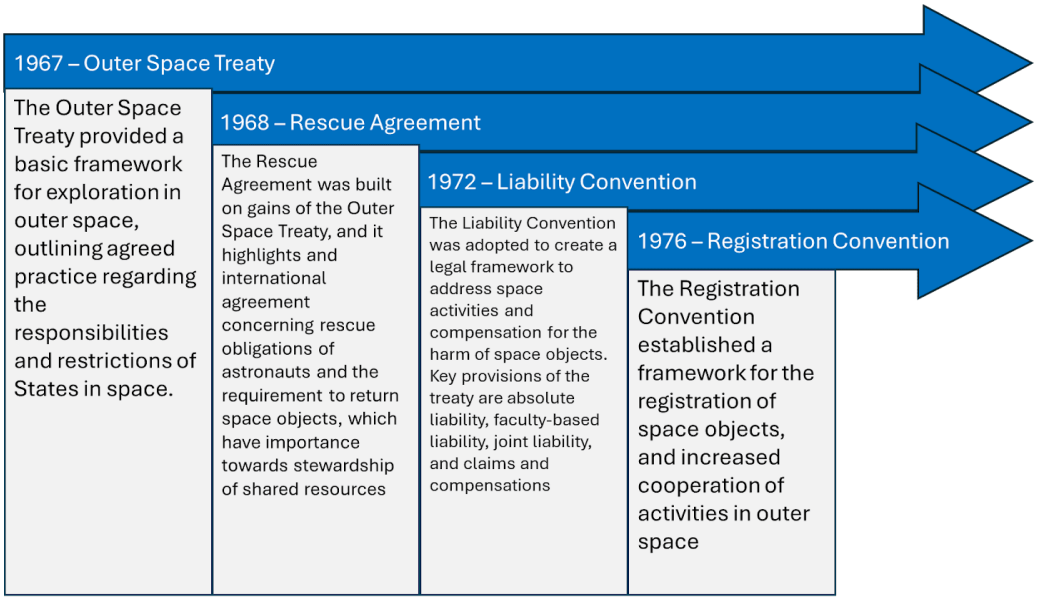
In the event of a breach or intrusion, one last line of defense is preparing a crew to operate a space habitat under a compromised network. For example, subsystem redundancy and manual override capabilities, such as mechanical valve bypasses for life support, ensure that the crew can maintain essential functions without network connectivity.

5. Limitations

A thorough discussion of cyberbiological threat assessment and preparation is incomplete without acknowledging the limitations of our analysis. Several factors constrain our understanding of spaceflight cyberbiological risks: first is data availability. Both private and public space programs restrict access to their data under proprietary agreements or classified status. This makes open analysis of cyberphysical system architecture, incident investigations, and even interoperability queries difficult. The rapid pace of system evolution through hardware upgrades, software patches, and architectural overhauls also means that any known vulnerability solution can become outdated within months.

6. Ethical and Legal Implications

Space activities are expected to grow tremendously within the next few years: this is bolstered by both the emergence of new cost-effective satellite systems and the incorporation of automated systems control (Gal et al, 2020). The use of automated systems in space highlights a series of important ethical considerations, considering the shift from “computer-assisted human choice and human-ratified computer choice” to non-human analysis, decision, and action selection (Gal et al, 2020). We previously described the physical and ethical risks of automated system control in space, recommending scrutiny of all deployed systems, and highlighted the rapid and varying development timelines such automated systems possess. An advanced legal framework is recommended to match with the emerging developments of AI. (Soroka & Kurkova, 2019). Space law, the branch of law that governs the activities and technologies relating to space, can be used to establish this framework; in particular, multiple international laws were put forth from 1967 to 1979 to guide conduct in space, including The Outer Space Treaty of 1967, The Rescue Agreement of 1968, The Liability Convention of 1972, The Registration Convention of 1976, and the Moon Agreement of 1976 (Dempsey, 2015; Pagallo, Bassi, & Durante, 2023). Four treaties are noteworthy and are highlighted in this paper. The agreements mentioned within Figure 1 were significant in developing not only the responsibilities of States' obligations regarding astronauts but also in addressing the complexities of space tourism (Dempsey, 2015).



(Dempsey, 2015; Pagallo et al, 2023)

Figure 1: A Primer on Space Law

The increasing use of purely autonomous AI systems to analyze and make decisions in space is controversial. Additionally, there are several issues concerning AI in space which includes fault liability, due diligence, and several other legal standards and should all be revisited (Lyall & Larsen, 2017; Pagallo et al, 2023). However, most state parties have developed their own regulatory frameworks regarding space-related activities. However, two issues arise from allowing States to regulate themselves. First, there is no coordination nor autonomy in the development of the legal framework. Second, there will be varying levels of accountability for private organizations based on where they are incorporated. Therefore, the law should reinforce strict liability regulations with an extension of current tortious liability to "tackle compensation gaps in accidents" caused by AI. Furthermore, the unique challenge of outer space lends the recommendation of the adoption of specific standards, e.g. standards implemented for every space mission (Pagallo et al, 2023).

6.1 Suggested Legal Framework

The suggested legal framework for AI in space, in Figure 2, mirrors the framework established by NASA. Any AI developed for space should be fair, explainable and transparent, accountable, secure and safe, human-centric and societally beneficial, and scientifically and technically robust. Our focus, for this paper, is the accountable aspect of the framework. (McLarney et. al. 2021). AI deployment in space systems needs clear attribution of fault, paired with scrutiny of design and deployment; legal framework selection benefits stakeholders when weighted heavily towards the impact of the developed and deployed system (Walia, 2024). Organizations should be legally required to: respect intellectual property rules; develop AI systems that have a documented framework; develop monitoring systems and report their findings; and register the AI system with applicable space agencies. Helpful areas of development that can strongly serve humanity as we step boldly into the stars include (1) advocating for policy changes that declassify non-critical incident data and mandate standardized reporting frameworks, (2) developing open-source terrestrial testbeds that replicate station subsystems to enable public security research, (3) convening interdisciplinary working groups of cybersecurity specialists, biologists, and aerospace experts to co-develop integrated guidelines, and (4) implementing adaptive monitoring regimes that continuously update risk assessments in step with system upgrades (Murch et al, 2018; Guise et al, 2023; Zimmerman et al, 2025).

IP and Health Rule Compliance	Ensure all deployed AI systems and data usage comply with applicable Health and IP laws.
Documented Framework Development	Parties should create and maintain formal records outlining AI system goals, risks, and safeguards. Risks to life should be emphasized.
Monitoring & Reporting	Parties should implement for continuous evaluation and the means to submit findings to applicable regulatory authorities.
AI Registration with Applicable Space Agencies	AI systems deployed in or for space missions should be registered, and this should be mandated.
Continuous Policy Evolution	Periodically revise legal and technical frameworks as AI technology and their reach into life outcomes for life aboard spacecraft advances.

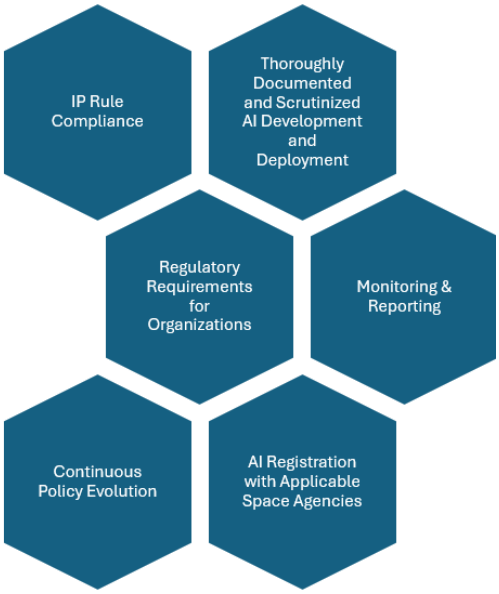


Figure 2: Suggested Framework

7. Conclusion

We have outlined several cyberbiological attack vectors, from remote tampering of on-board environmental monitors to unauthorized critical systems access via Earth-linked cloud computing infrastructure. To counter these threats, we proposed a suite of multilayered controls tailored for spaceflight: cryptographic hardening of communication, network, and biological segmentation to isolate critical networks, active surveillance of telemetry data, and a legal framework to ensure proper development and utilization. Despite significant gaps in understanding arising from government security, vendor non-disclosure restrictions, and the rapid evolution of station configurations, advancing space cyberbiosecurity will demand coordinated efforts. As humanity ventures beyond low-Earth orbit to lunar bases, Mars transit habitats, and eventually to deep space exploration, embedding robust cyberbiosecurity measures from the design phase will be essential to safeguarding crew health, ensuring mission success, and recruiting confidence towards building the exhilarating future of humans exploring beyond Earth. The pathway to that secure future begins today.

Ethics declaration: Not Applicable.

AI declaration: AI was not used in the final product of this paper. Use was limited to organization of initial drafts.

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Android Malware Detection (AMD) Based on Shallow Feature and Permission Correlation

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Abstract: There are apps for everything, from online banking, social software to shopping. They have become one of the most important tools in our daily lives. This even implies that a mobile device has stored most of personal information, including photos, credit cards, and communications. If an intruder succeeds in hacking into the mobile device, all private properties must suffer from the leakage threats. Undoubtedly, a malware is the commonest tool used by an attacker to compromise a mobile phone. In particular, it is often disguised as a popular application through an obfuscated or packed form. That is the main reason why it is difficult to distinguish a malware from the legal ones. In this article, we have adopted machine learning technique to develop a static analysis mechanism for Android malware detection based on shallow feature and permission correlation (AMD). AMD first analyses the Application Programming Interfaces of the target to detect all possible and hidden privilege threats. It then filters this obfuscation information using permission correlation to eliminate noise and identify meaningful malicious indicators. The proposed approach leverages the correlation patterns between permissions and API calls to distinguish suspicious behaviours from legitimate ones. Thus, AMD can extract all the representative shallow features to achieve the high detection rate. Simulation results have shown that AMD can outperform related works under the datasets of CICAndMal2017 and CICMalDroid2020, which confirms the effectiveness of shallow features and permission correlation.

Keywords: Machine learning, Malware detection, Static analysis, Shallow features, Permission correlation

1. Introduction

With the explosive development of the Internet, thousands of apps have been designed for enriching people daily lives, including social media, communications, online banking and shopping. This clearly indicates that a mobile device has recorded most of personal information, including photos, credit cards, and communications. The popularity of these applications not only brings convenience to the public, but also shows how people rely on them. According to the Statcounter statistics, the open source adoption enables Android operating system to reach a 71.96% occupation in the global smart phone marketing at the end of 2024 [1].

The high coverage rate of Android operating system has brought smart phones the extremely diverse and numerous apps developments. Nevertheless, subsequently malicious attacks for Android mobile devices have occurred all the time, such as ransomware, adware, and spyware. They have caused a serious and great threat to user privacy and property. The Kaspersky statistic from 2021 to 2022 [2] points out that the continuous price decline of virtual currency has led to the increase of malware. But the numbers of detected malware have lowered down, as shown in Figure 1. It is due to that hackers who create malware have actively enhanced the concealment and infection attributes. A distribution of various malware has been depicted in Figure 2 [2]. Obviously, the number of Trojan-Dropper which is able to escape from malware detection to infect users lacking of security awareness has highly increased.

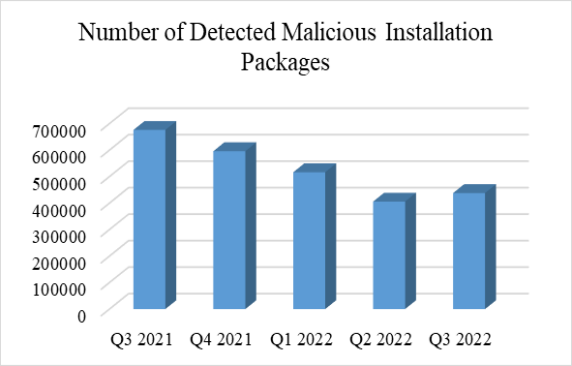

Figure 1: The numbers of detected malware

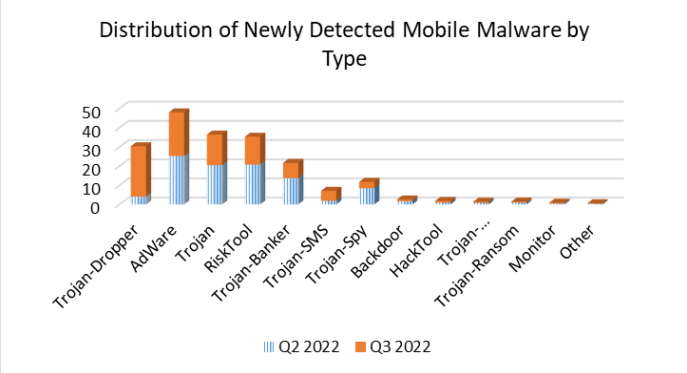

Figure 2: The distribution of mobile malware

The techniques of detecting malware could be classified into two types, including static analysis and dynamic analysis. Actually, hackers are of course familiar with these methodologies, which implies that they might be able to make up the malware to be a legal Apps through a serial of confusion or camouflage. That is the crucial challenge to malware detection. Without loss of generality, it takes the integrity verification and source code reviewing to achieve the determination, concerning the first category [3, 4]. The static features could be extracted from a malware without executing [5, 6]. For instance, researchers could confirm the integrity of APK (Android Package) or dig out the APK signature to classify whether the API (Application Programming Interface) or permission used are exceeded. However, Apps developers often obfuscate or pack the program before the APK is put on the online store to prevent from being illegal pirated. These additional operations usually lead to the detection ineffectiveness of static analysis. In 2021, Ateeq and Moreb have applied the neural network to design a malicious URL detection method [7]. Actually, it is easy to counterfeit a malicious URL through replacing some letters or digits by resembling symbols so that the length of malicious URL is often longer than that of a legal one. Therefore, it verifies whether an URL is valid or not via semantic analysis in [7]. Later on, Amenova et al. adopted convolutional neural network (CNN) and long short term memory (LSTM) to detect malicious Apps [8]. CNN is used to analyse the API to extract feature, while LSTM is applied to enhance the accuracy via correlation. Nevertheless, the prediction accuracy remains a crucial challenge in the category of static analysis.

As to the category of dynamic analysis, it retrieves the behaviour signature of a running malware. Due to the executing characteristics, behaviours of the obfuscated and packed malicious process can still be recorded to conclude illegal features. The obtained signature, however, relies on the length of analytic period, which is an extremely time-consuming task and becomes the main constraint on malware detection in this category. In 2020, Mahdavifar et al. have applied semi-supervised deep learning technique to develop a dynamic malware analysis model [9]. Here, fake levels and true labels are input into the training model to enhance the prediction accuracy. After that, Luo et al. further designed a DCGAN_1D-CNN (Deep convolution generative adversarial networks one-dimensional convolutional neural networks) model to distinguish encrypted malicious streams from normal ones [10], which also belongs to the dynamic type. To eliminate the problem of imbalance category distribution, authors have used 1D-CNN to increase the number of samples for those with a small number. By this way, the determination accuracy for new malware and those with a small number could be effectively enhanced. Whether the static or dynamic analysis is used, it is extremely inefficient to manually

analyse each malware. That is the reason why the technique of machine learning has been widely introduced into the malware detection.

Actually, the determination result of machine learning is often affected by the malware characteristics. In particular, lots of features may lead to the overfitting phenomenon; thus, increasing the computation overhead and lowering down the accuracy rate. To address these two issues, eliminating parts of unnecessary features while figuring out significant characteristics are very critical in the training model. In [11], it has demonstrated that removing seldom performing benign process is helpful to accuracy and efficiency enhancement. Regarding [12], it has tuned the machine model to dig out malware after being shuffled and noised. As to [13], all the programs are categorized according to the corresponding actions; thus, a pre-processing framework for machine learning is imperative.

So far, there exist lots of challenges in the detection of malware. Among them, how to increase the detection accuracy is the most crucial and emergent one. No doubt that the malware is constantly evolving thanks to the rapid development of Internet technology. Specifically, it is hard to dig them out as the stealth has become more serious. Therefore, we aim to design a static detection framework based on the API and program access privilege provided by Android. One of the main contribution of the new framework is that it is able to analyse the APK to filter out the necessary features for training model even though many meaningless APIs and access rights have been appended to the target program. Taking the trade-off between analysing time overhead and detection accuracy into consideration, the main target of this work is to fully dig out the malware as it has caused serious damage for general systems. According to the simulation results, the new method outperforms related works in terms of efficiency and accuracy based on the concept of shallow features and access right analysis.

The rest of this article is listed as follows. Related works and preliminary are described in section 3, followed by the detail of new method in section. Discussions on the simulation outcomes and comparisons are explained in section 4, while conclusions are made in section 5.

2. Related Works

Technology of machine learning has been well-developed, and sufficient models have been produced according to individual needs, which have been applied in various fields with satisfactory results. Actually, it also plays an important role in the detection of malware. Traditional expert analysis cannot approach the explosive development of malware anymore. More precisely, rule-based detection has come out to replace conventional methods to fulfil the real demand. Undoubtedly, the incredible increasing of malware variety and number have become an unbearable burden on traditional detection methods. That is the reason why the solution of machine learning model is urgent to be imported to this field. To achieve a higher detection accuracy, researchers have applied machine learning models to classify malware based on specific features. As to the new method, multi-layer perception (MLP) and random forest are applied to figure out the connection between distinct features, which is able to ensure the malware classification correctness and practicability.

2.1 Multilayer Perceptron (MLP)

In MLP, neurons of each layer are fully connected and transferred to the next layer. Multi-layer adoption has been used to expand or compress features, and neurons of each layer obtain specific feature through individual neuron weight. During the training process, the backpropagation algorithm has been applied to gradually tune a better weight to increase the prediction accuracy; thus, mitigating the difference between the real value and the predicted one. The structure of multi-layer perceptron is depicted in Figure 3.

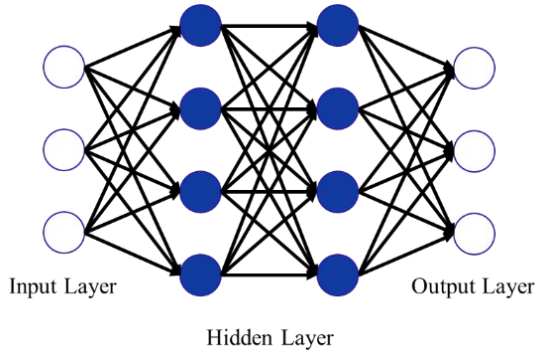

Figure 3: The model of multi-layer perceptron

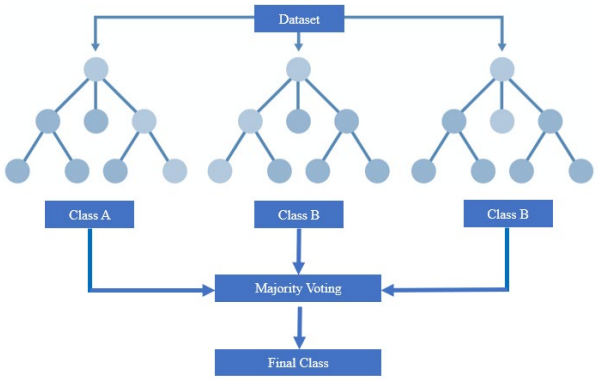

Figure 4: The model of random forest

Generally, the numbers of hidden layer and neuron could be adjusted to extend or compress the features according to the user demand. The weight of each neuron is applied to determine the significance of target feature. No matter in the hidden or output layer, the neuron value is derived from the previous layer neurons based on Eq. (1), where y_i represents the output of the *i*-th neuron, *p* is the number of previous layer neuron, w_{ji} denotes the weight between the *j*-th neuron of previous layer and the *i*-th neuron of the current layer, and x_i is the value of previous layer neuron.

$$y_i = \sum_{j=1}^{p} w_{ji} x_j \tag{1}$$

2.2 Random Forest (RF)

The model of RF consists of one or multiple decision trees, and each decision tree is constructed through the random feature selection of data cluster. After completing the training process of decision trees, the majority rule has been employed to determine the prediction type in RF. As the feature selection is random, the results predicted by each decision tree are different. Thus, the ensemble learning mechanism can increase the prediction stability and accuracy, while the structure of RF model is displayed in Figure 4.

Without loss of generality, RF can help lay out a satisfactory various prediction due to the adoption of random sampling along with the majority rule of decision trees. Meanwhile, the over-fitting problem could be mitigated effectively through the strategy. The eventual prediction outcome is determined according to the majority vote of decision trees, as shown in Eq. (2),

$$p = arg \max_{n} \sum_{i=1}^{n} w_i I(f_i(x) = n) \tag{2}$$

where *p* denotes the final outcome, *n* means the number of decision trees, w_i displays the weight of the *i*-th tree, *I* is the indicator function, and $f_i(x)$ depicts the prediction on the input *x* from the *i*-th tree.

3. Proposed Scheme (AMD)

Here AMD imports two significant behaviours, shallow feature and permission correlation, to determine the legality of a suspicious App. Androguard [14] is used to analyze all possible and hidden privilege threats, while Axplorer [15, 16] is applied to dig out the permission correlation. The flowchart is illustrated in Figure 5. The feature analysis of APK is described in Subsection 3.1, the permission estimation of APK is explained in Subsection 3.2, the feature correlation is examined in Subsection 3.3, while how to extract the shallow feature is introduced in Subsection 3.4.

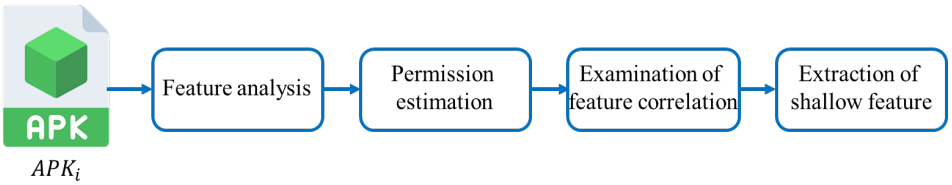

Figure 5: The flowchart of AMD

3.1 The Feature Analysis of APK

Step 1. Aggregate all the dataset applications into $APKs$, where

$APKs = \{APK_1, APK_2, \dots, APK_n\}$, n is the total number of applications.

Step 2. Apply Androguard [14] to analyze each APK_i, where $APIs^{APK_i}$ and $Permissions^{APK_i}$ denote the application interface and permission, respectively, $i \in \{1, 2, \dots, n\}$.

Step 3. Repeat Steps1 to 2 until all application analyses are completed.

3.2 The Permission Estimation of APK

Actually, parts of APIs can occupy a higher permission to complete a specific operation without advance authority, and such feature cannot be dug out through previous analysis. Here AMD concentrates on figuring out these additional information, called Extra_Permissions, using the tool Axplorer [16].

Step 1. Apply the Axplorer [16] to extract the hidden permission of ${API_j}^{APK_i}$,$Extra_Permissions^{API_j^{APK_i}}$, where $i \in \{1, 2, \dots, n\}$, $j \in \{1, 2, \dots, m\}$.

Step 2. Concatenate $Extra_Permissions^{API_j^{APK_i}}$ with $Permissions^{APK_i}$ to form $ALL_Permissions^{APK_i}$, and integrate the result with $APIs^{APK_i}$ to obtain the total feature of APK_i.

Step 3. Repeat Steps 1 to 2 until all additional information are retrieved to layout a feature set $Features$ containing all APKs and APIs permissions.

3.3 The Examination of Feature Correlation

Here is to reserve the uncommon features of BAPKs and those used by malware.

Step 1. Refine $APIs$ by removing API_j which does exist in API_{ALLOW}, such that $APIs \in API_{ALLOW}$.

Step 2. Calculate the frequency of $Feature_j$ occurring to $BAPKs$ based on Eq. (3).

$$Feature_rate_j = \frac{1}{n}\sum_{i=1}^{n} {Feature_j}^{BAPK_i}, j \in \{1, 2, \dots, m-1, m\} \quad \textbf{(1)}$$

Step 3. Select $Feature_j$ according to TH=0.8 and Eq.(4).

$$\begin{cases} \text{Remove } Feature_j, TH \le Feature_rate_j \\ \text{Keep } Feature_j, otherwise \end{cases} \quad \textbf{(2)}$$

3.4 The Extraction of Shallow Feature

After the correlation analysis, AMD further extracts the shallow feature through APIs with the same classification.

Step 1. Generate $Package_k^{APK_i}$ by extracting the same $APIs^{APK_i}$ of $Features^{APK_i}$, $k \in \{1, 2, \dots, l-1, l\}$.

Step 2. Repeat above procedure until all extraction have been done and concatenate the results to form $Packages^{APKs}$.

Step 3. Train AMD model with $Packages^{APKs}$ and $ALL_Permissions^{APKs}$.

4. Experimental Result and Analysis

Here we used the Python language to conduct the simulation and ensure that the detection system can support the latest Android version 14. Furthermore, we applied Scikit-learn [19] to perform the classification with the kits of MLP and RF. The simulation environment is equipped with Windows 10 64bit, Intel i7-7700HQ 2.8GHZ CPU, 8GM RAM, and NVIDIA GTX 1050 GPU. The testing dataset is discussed in Subsection 4.1, the detection outcomes under different THs are shown in Subsection 4.2, while the analyses and comparisons are explained in Subsection 4.3.

4.1 Dataset Selection

The paper uses two Android malware datasets, including CICAndMal2017 [18] and CICMalDroid2020 [9]. The CICAndMal2017 dataset consists of 2125 APK files, containing 426 malicious APKs and 1699 benign ones, where malicious APKs comprise advertising, ransomware, intimidation, and SMS malware. As to CICMalDroid2020, it covers more APK files and types of malicious APKs, including 9803 malicious APKs and 1795 benign ones, whereas malicious APKs include advertising, banking, SMS, and risky malicious APKs.

We analysed and preprocessed the two aforementioned datasets, resulting in 218 features. Among these, 183 features were Packages integrated by the API used, and the remaining 35 features were Permissions used in the dataset. To evaluate the detection effectiveness of AMD, we divided the datasets based on the Pareto principle, using 20% as the test set and the remaining 80% as the training set. The distribution is shown in Table 1.

The valuation indicators in this research are composed of True positive (TP), False positive (FP), True negative (TN), and False negative (FN).

- TP: The actual number of samples that are malicious APK and are determined to be malicious APK.
- FP: The actual number of samples that are benign APK but are determined to be malicious APK.
- TN: The actual number of samples that are benign APK and are determined to be benign APK.
- FN: The actual number of samples that are malicious APK but are determined to be malicious APK.

Using the four evaluation metrics above, we calculate *Accuracy*, *Precision*, *Recall*, and F_β according to Eq. (5) to (8). Here, β is set to 1, representing the weight of *Precision*, indicating that *Precision* and $Recall$ have the same importance in the classification of benign and malicious APK.

$$Accuracy = \frac{(tp+tn)}{(tp+fp+fn+tn)} \quad (3)$$

$$Precision = \frac{tp}{(tp+fp)} \quad (4)$$

$$Recall = \frac{tp}{(tp+fn)} \quad (5)$$

$$F_\beta = (1+\beta^2) * \frac{Precision*Recall}{(\beta^2*Precision)+Recall} \quad (6)$$

Table 1: Dataset distribution

Name of Dataset / APK Class	CICAndMal2017 [18]		CICMalDroid2020 [9]	
	Training Set	Test Set	Training Set	Test Set
Benign	1359	340	1436	359
Adware	83	21	1002	251
Ransomware	81	20	-	-
Scareware	90	22	-	-
SMS Malware	87	22	3123	781
Banking	-	-	1680	420
Riskware	-	-	2037	509
Total	1700	425	9278	2320

4.2 The Detection Outcomes Under Different *TH*s

The AMD employs machine learning to identify benign or malicious APKs, achieving high accuracy and stability the heavily relies on the quality of the data used for training the model. If too many features are provided, it can lead to overfitting, increasing the time consumption and reducing the classification effectiveness. Conversely, too few features are provided can lead to underfitting, rendering the model ineffective in classifying malicious and benign APKs. This study proposes a method based on feature correlation analysis to reduce the features required for detecting malicious APK under different thresholds (*TH*). This approach reduces the training time for machine learning and improves *Precision* and *Recall*. The experimental process places greater emphasis on *Precision* and *Recall*. *Precision* represents the proportion of benign APKs

misclassified as malicious among those identified as malicious APKs. Conversely, *Recall* represents the proportion of actual malicious APK among those identified as malicious. Hence, a higher *Recall* indicates a stronger ability to identify malicious APK.

Table 2: Result of CICAndMal2017 based on different *TH*

Metrics	*Accuracy*		*Precision*		*Recall*		$F1-score$	
Model / *TH*	MLP	RF	MLP	RF	MLP	RF	MLP	RF
0.5	87.32	86.15	87.43	87.07	98.24	97.06	92.52	91.79
0.6	90.14	90.14	90.93	90.93	97.35	97.35	94.03	94.03
0.7	91.78	91.31	92.24	92.20	97.94	97.35	95.01	94.71
0.8	92.72	92.49	93.28	93.02	97.94	97.94	95.55	95.42
0.9	91.08	91.31	92.42	91.97	96.76	97.65	94.54	94.72
1.0	91.08	89.20	91.71	90.38	97.65	96.76	94.59	93.47

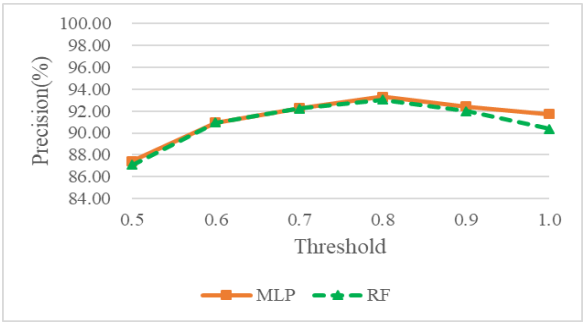

Figure 6: Comparison of $Precision$ at different TH in the CICAndMal2017

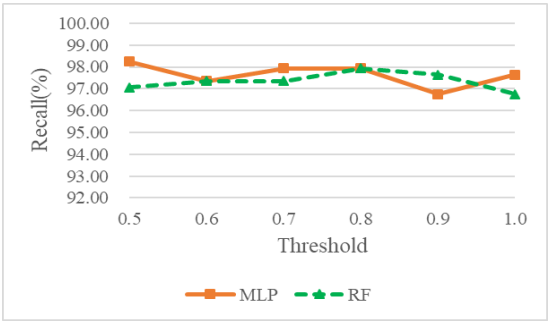

Figure 7: Comparison of $Recall$ at different TH in the CICAndMal2017

Using APIs in benign applications as features for detecting malicious APKs is insufficient for effective classification. Therefore, the number of features discarded through feature correlation analysis depends on changes in the *TH* value. In the CICAndMal2017 dataset, there are 1699 benign and 426 malicious samples. Reducing unnecessary features can improve machine learning *Precision* and *Recall*, as shown in **Table 2**. The analysis of the CICAndMal2017 dataset, shows that when the *TH* value is 1, features present in all benign APKs need to be removed. However, these features are rare since there are slight differences among different APKs. This results in only a slight improvement in detection after removing these features. When the *TH* value is continuously lowered to 0.8, both *Precision* and *Recall* achieve results, as the removal of some meaningless features effectively improves detection efficiency and accuracy. As shown in **Figures 6** and **7**, *Recall* decreases when the *TH* value is below 0.8. The lower the *TH* value, the more features are removed. Some of these removed features include important or distinctive features, affecting the accuracy of classifying malicious APKs. Therefore, AMD can avoid the overfitting problem encountered in machine learning for APK detection. It also adjusts the *TH* value according to the dataset to achieve the best classification results.

Table 3: Result of CICAndMal2020 based on different *TH*

Metrics	*Accuracy*		*Precision*		*Recall*		*F1-score*	
Model / *TH*	MLP	RF	MLP	RF	MLP	RF	MLP	RF
0.5	95.32	95.38	96.21	96.39	97.68	97.56	96.94	96.97
0.6	96.63	96.78	97.35	97.62	98.23	98.15	97.79	97.88
0.7	96.30	96.51	97.23	97.57	97.92	97.84	97.57	97.70
0.8	96.06	96.33	96.53	97.12	98.35	98.07	97.43	97.60

Metrics	*Accuracy*		*Precision*		*Recall*		*F1-score*	
Model / *TH*	MLP	RF	MLP	RF	MLP	RF	MLP	RF
0.9	96.12	96.39	96.78	97.34	98.15	97.92	97.46	97.63
1.0	96.63	96.99	97.50	97.85	98.07	98.19	97.79	98.02

As shown in **Table 3**, compared to CICAndMal2017, the CICMalDroid2020 dataset, which has more samples, demonstrates significant improvements in various metrics based on the feature correlation analysis. With the increase in sample size, *Precision* and *Recall* also achieve favourable results at different *TH* values, as illustrated in **Figures 8** and **9**. In AMD, features with high usage rates in benign APKs are removed to reduce the chance of the detector being confused. Consequently, the CICMalDroid2020 dataset, which contains more malicious APK samples, is less likely to remove important features, effectively classifying malicious APKs. Thus, *Precision* and *Recall* have outstanding performance at different *TH* values. AMD enhances classification efficiency and stability by removing unnecessary features through feature correlation analysis in datasets with more samples and a greater proportion of malicious APKs.

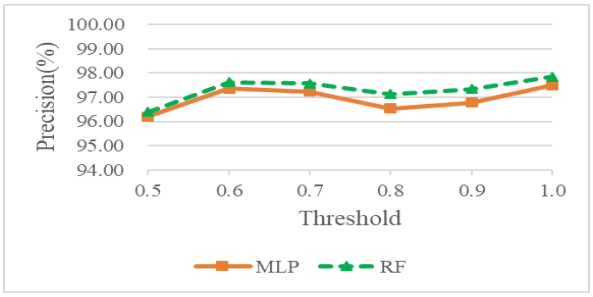

Figure 8: Comparison of $Precision$ at different TH in the CICAndMal2020

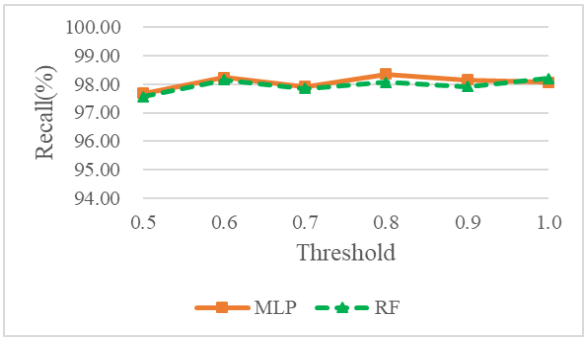

Figure 9: Comparison of $Recall$ at different TH in the CICAndMal2020

As shown in **Figure 10**, whether in the CICAndMal2017 dataset or the CICMalDroid2020 dataset with a larger sample, AMD avoids poor classification due to model overfitting by setting the *TH* value to 0.8, thereby effectively improving the accuracy of classifying malicious APKs. This indicates that adjusting the *TH* value according to different datasets and sample sizes can further enhance the detection rate of malicious APKs. Regarding the choice of model, although the *Precision* of RF in CICMalDroid2020 improved by 0.59 compared to MLP, the *Recall* decreased by 0.28. This suggests that RF might misclassify some benign applications in the CICMalDroid2020 dataset, which has many malware samples but is more accurate in identifying malicious APKs. Conversely, in the CICAndMal2017 dataset, which has fewer malware samples, both MLP and RF maintain better classification results. Therefore, we adopt MLP as the classification model.

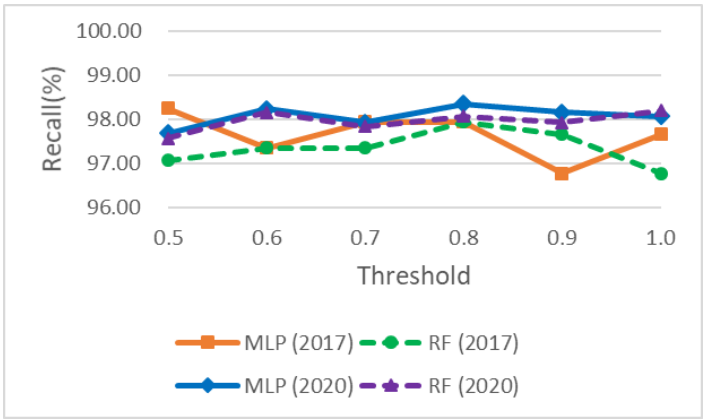

Figure 10: Comparison of $Recall$ between CICAndMal2017 and CICAndMal2020

4.3 The Analyses and Comparisons

The AMD classifies API calls and APK permissions through static analysis. To evaluate classification performance on different datasets, we use the CICAndMal2017 dataset proposed by Lashkari and Rahali et al. [18] and the CICMalDroid2020 dataset [9]. The proposed AMD method is compared with the static analysis method [8] and dynamic analysis methods [9, 10], focusing on the detection of malicious APKs. Misclassification of benign softwares has relatively minor impacts, whereas misclassifying malwares leads to issues like data leakage. Therefore, this paper aims to achieve higher *Recall*, improving the detection accuracy of malicious APKs. As shown in **Table 4**, *Recall* indicates the proportion of malicious that are accurately detected.

Table 4: Comparison between related works

Dataset	CICAndMal2017 [18]			CICMalDroid2020 [9]		
Metrics	*Precision*	*Recall*	*F1-score*	*Precision*	*Recall*	*F1-score*
[8]	-	-	-	93.30	94.45	95.78
[9]	-	-	-	99.16	96.54	97.84
[10]	95.87	97.23	96.55	-	-	-
AMD (*TH* = 0.8)	93.28	97.94	95.55	96.53	98.35	97.43

AMD uses static analysis, which takes less time than dynamic analysis and avoids wasting time due to malicious APKs deliberately hiding their overprivileged behaviours. For example, malicious APKs intentionally hide their malicious behaviours until certain conditions are met to evade detection [20]. In the CICAndMal2017 dataset, although this method's *Precision* is slightly lower than the method in DCGAN_1D-CNN [10], its Recall is 0.71 higher, and static analysis is more efficient than dynamic analysis. In the CICMalDroid2020 dataset, which has many malicious APK samples, AMD shows significant improvements in various metrics compared to the static analysis method [8]. Malicious APKs have minor correlations but continuously evolve to evade detectors, making them difficult to detect. Compared to the dynamic analysis method [9] and the CICMalDroid2020 dataset they proposed, although AMD has lower *Precision*, it improves *Recall* by 1.81. While our method may misclassify benign softwares, it is more effective in detecting softwares in a dataset with more malicious samples. These results demonstrate that AMD is better at identifying malicious softwares and effectively blocking malicious behaviours. Additionally, AMD surpasses dynamic analysis time, making it superior in time efficiency and detection effectiveness. Since our primary concern is detecting malicious APKs, we should focus on detecting malicious programs. Misclassifying a malicious APK as benign can lead to users downloading malicious APK, resulting in potential asset loss.

5. Conclusions

This paper proposes a machine learning-based static malware detection method, which primarily relies on the correlation between shallow features and APK permissions. It conducts an in-depth analysis of the relationships between applications and their features. Experimental results show that AMD detects malicious APKs accurately. Even when malicious softwares hide their behaviours within various APIs, our method effectively analyses and detects them. Moreover, in feature correlation analysis, our method can effectively prevent hackers from interfering with security analysts' detection processes. Extracting shallow features allows our method to focus on identifying representative behavioural features without being affected by commonly used but non-informative data. Our research results indicate that, compared to related works, our method detects malicious APKs more accurately, demonstrating its feasibility in practical applications. Users can enjoy the convenience of mobile devices while ensuring a secure environment with AMD.

Ethics Declaration: This research involves no human subjects and uses only publicly available malware datasets. All experiments were conducted in isolated environments following ethical cybersecurity research standards.

AI Declaration: AI tools were used solely for grammar checking and language polishing. All research methodology, analysis, and findings are entirely human-generated.

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Artistic Intelligence: Distinguishing Human From Ai-Generated Art Through Perception

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Abstract: With the new advances in technology, the ability of AI to produce human-like art questions established notions of creativity, authorship, and artistic value. This study explores the differences between human-created artwork and AI-generated artwork using human experience. We analyze whether or not AI-generated art can be distinguished from human-created art consistently based on qualities such as emotional effect, aesthetic depth, and originality. Our methodology involves a perception study where people rate and attempt to classify images as human or AI-created. The rating criteria are emotional effect, perceived beauty, detail richness, and subjective creativity. We also ask participants to see if they can identify common signs of AI-generated images, such as over-smoothing transitions, blurred details, and unnatural or flat viewpoints. We measure the accuracy of human classification, comparing the degree of consistency or inconsistency in their judgments. This transdisciplinary project aims to shed light on core differences in perception and structure between AI and human creativity. It also raises broader ethical and philosophical questions about creativity, ownership, and cultural value in this AI age. In particular, we question whether AI art models that have been trained from copyrighted content can produce original images that are just as good as human artwork. By comparing subjective human judgments, this research will seek to shed light on how AI art is understood, evaluated, and possibly distinguished from traditional human imagination. The results of this research will contribute to current discussions at the intersection of technology, art, and ethics, providing a foundation for more open and ethical AI art production.

Keywords: AI-generated art; human perception; artistic intelligence; art authenticity; ethics in AI; digital art.

1. Paper Overview

1.1 Conceptual Framework

Our framework is structured around two analytical layers:

- **Perception Layer – Human and AI Art Convergence**: Our perception study integrates human ratings of both AI and human-created art. This establishes a baseline for how humans distinguish art origins based on subtle perceptual cues.
- **Ethical and Philosophical Layer – Societal and Conceptual Views**: The reliance of AI art on vast, often copyrighted, datasets raises questions about intellectual property, ownership, and the value of human creativity. This layer reframes the art world as a critical ethical and philosophical space.

2. Problem Background

2.1 Review of Prior Events

The increasing integration of AI into creative fields has demonstrated both efficiency gains and security challenges. Prior incidents show how AI art systems are vulnerable to disruption. For example, generative AI models are susceptible to prompt injection and data poisoning, enabling attackers to create biased or malicious outputs that undermine artistic integrity (Perez & Ribeiro, 2022; Greshake et al., 2023). Research also shows how AI-generated images can mislead public perception, causing confusion about authorship and the value of human art. These findings indicate that digital art, while technically effective, is exposed to adversarial manipulation.

The digitization of creative assets has created a second vulnerability frontier. Cloud-hosted repositories of human art are sensitive targets, and models trained on these uncredited datasets raise critical questions about copyright and fair use. The public backlash against the Guess campaign in Vogue, which used a hybrid human-in-the-loop and AI workflow, illustrates how public perception is heavily influenced by prior knowledge of the content's origin (Chitrakorn, 2025). This incident shows that disclosing AI involvement can trigger public skepticism and reframe creative work as an ethical problem.

Beyond art, the ethical implications of AI extend to other domains. The work done in "AI-Driven Cybersecurity Strategies for ISPs" (Singh & Kumar, 2025) explores how AI is used for threat mitigation and monetization. Similarly, the research in "Impact of AI in Social Media" (Kumar et al., 2025) addresses how AI on social media platforms is used in cybercrime and influences gender dynamics. These studies, like ours, underscore the necessity of a nuanced understanding of AI's societal role.

2.2 Limitations in Existing Approaches

Most current approaches to AI art prioritize technical functionality over a holistic understanding of its societal impact. While generative AI models produce aesthetically pleasing images, they often lack transparency regarding their training data, making them vulnerable to intellectual property disputes and ethical challenges that threaten the livelihoods of human artists.

A second limitation is the minimal consideration of how human perception is influenced by non-visual information. With AI art's increasing use in commercial campaigns, its exposure to public backlash is a significant blind spot. The work of Kumar, Crowe, & Gu (2025) on the perception gap between designers and practitioners in security standards highlights a similar issue.

3. Methodology

3.1 Research Design

The core of this study is a quantitative human perception study combined with computer image analysis. Our architecture includes a diverse collection of AI-generated and human-created images. Participants rate these images on several dimensions, including visual appeal, emotional impact, and perceived originality.

3.2 Data Collection and Analysis

The study uses a varied collection of images. We produced 10 unique images with popular generative AI models like Midjourney and DALL-E 3, and selected 10 human-created artworks from online platforms and museums that match the AI styles.

For the human perception study, we will recruit at least 25 participants from Texas A&M University. Participants will view a random sequence of 20 images and perform two tasks for each:

- **Perceptual Rating**: Rate each image on a 5-point scale for visual appeal, emotional impact, and originality.
- **Source Identification**: Identify the art's origin (Human, AI, or Unsure) and provide qualitative feedback.

We will analyze the human perception data using statistics, including descriptive stats for ratings and confidence. **Correlation analysis** will check the link between ratings and correct identification rates. Qualitative answers will be analyzed by coding common themes.

4. Results and Analysis

4.1 Evaluation Criteria

The evaluation of human perception outcomes was based on three criteria: accuracy of classification, consistency of ratings, and perceptual tells. Preliminary pilot data from a small group of 8 participants showed humans correctly classified AI art just above 60% of the time, revealing the difficulty of correct identification. Analysis of emotional impact and originality ratings revealed a more strategic set of cues: human art consistently scored higher on both. Qualitative comments from participants revealed common “AI tells” such as “too perfect,” “unnatural smoothness,” and “blurry details.”

4.2 Observations and Outcomes

Preliminary pilot data revealed that even advanced AI-generated art can be undermined by adversarial human perception. The finding that participants correctly identified AI art just over 60% of the time underscores that prototypes optimized for visual appeal remain fragile when subjected to human judgment.

Expanding the analysis to emotional impact and originality illustrated a strategic vulnerability. Human art consistently scored higher for emotional impact (3.9/5) and originality (3.5/5) compared to AI art (2.7/5 and 2.9/5, respectively). This highlights a critical escalation—the inability of current AI models to replicate the subjective depth of human creativity—which transforms a technical achievement into a perceptual gap.

At the societal level, preliminary results showed a strong preference for labeling AI art, with 84% of participants saying "Yes." This outcome highlights a critical need for clear attribution, reflecting broader concerns about intellectual property and the value of human creative work. The mixed answers about AI's ability to genuinely replicate human creativity offer a nuanced view of public thinking.

5. Discussion

5.1 Interpretation of Results

Our findings reveal that AI art, despite being technologically advanced, has introduced vulnerabilities across aesthetic, emotional, and ethical domains. At the visual level, "AI tells" like unnatural smoothness can undermine the perceived authenticity of an image. This suggests that humans don't need to be art experts; they only need to identify subtle weaknesses that disrupt trust.

The analysis of emotional impact and originality highlights a second escalation of risk. The perceived lack of emotional depth in AI art creates a global perceptual gap. The inability to truly replicate human creativity collapses the boundary between technical generation and authentic creation, leading to AI art being seen as a hollow imitation. This underscores that artistic intelligence must evolve beyond visual appeal.

At the societal level, the strong preference for labeling AI art reframes the discussion as an ethical security challenge. By demonstrating a collective desire for transparency, participants revealed that a work's origin is as important as its appearance. This finding suggests that AI art can be judged based on the ethics of its creation, transforming a technical achievement into a societal debate.

5.2 Limitations and Lessons Learned

While comprehensive, this research has limitations. The preliminary pilot study was small (N=8) and non-diverse. A larger, more varied group might reveal additional complexities. The specific set of 20 images might not cover the full range of artistic expression. The self-reported nature of demographic data is also a limitation.

Despite these limitations, the lessons learned are significant. Security considerations—in this case, ethical and perceptual ones—must be embedded at the earliest stages of AI art design. Deploying models without clear ethical guidelines or a robust understanding of human perception creates blind spots. The art world must be understood as a cyber-human-ethical system where technical vulnerabilities can cascade into perceptual and ethical destabilization.

6. Conclusion

6.1 Key Takeaways

This research shows that while AI-generated art is promising, it also introduces critical vulnerabilities. Preliminary findings, even from a small sample, reveal that human perception is effective at distinguishing AI from human art based on a combination of visual, emotional, and conceptual cues. This confirms that aesthetic appeal alone cannot ensure authenticity.

The analysis of societal views highlighted a strategic ethical risk. Participants' strong desire for labeling AI art underscores that transparency is a critical factor in how art is valued. This suggests that artistic integrity is inseparable from ethical transparency.

At the philosophical level, the analysis of AI's ability to replicate human creativity raises broader questions about the very definition of creativity. This reframes the AI art debate as a matter of philosophical resilience and societal values.

Ethics Declaration

This research did not involve human participants, animal testing, or the use of sensitive biological samples. The human perception study was initially conducted with a small group of friends and family for preliminary data collection and will expand to a formal study with university students. All image datasets used were either self-created through generative AI models or publicly available from museum digital collections. Therefore, no formal ethical clearance was required for this study.

AI Declaration

Artificial intelligence tools were used in this study for literature synthesis, drafting, and editing. The AI was not involved in conceptual contributions, system implementation, or data analysis. It was used exclusively as a writing support system, and the final responsibility for accuracy, integrity, and originality rests with the authors.

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Could AI Podcasts Improve Students' Academic Performance AND Engagement?: An Empirical Assessment

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Abstract: In recent years, podcasts have emerged as a significant educational tool that influences students' learning, academic performance, and retention, particularly within the context of business education. This study investigates the potential of Artificial Intelligence (AI)-generated podcasting as an innovative instructional tool to enhance student academic performance in business education. Leveraging generative AI to create short, topic-specific audio summaries, we integrated podcast episodes into an undergraduate business analytics course and evaluated their impact on student outcomes. Using a quasi-experimental design, we compared performance metrics between students who received AI podcast supplements and a control group with traditional materials. Survey and focus group data were also collected to assess engagement, comprehension, and perceived value. The study highlights how tailored, on-demand audio content can support student success in data-driven, concept-heavy business courses. The impact of podcast listening on students' learning, academic performance, and retention in business education is multifaceted. The integration of podcasts into educational practices offers distinct advantages, including enhanced listening skills, greater engagement through relatable content, and accessibility that support self-directed learning. Nevertheless, educators must navigate potential challenges in implementation to fully leverage the benefits of this dynamic learning tool. Future research should continue to explore innovative podcast applications and best practices to optimize learning outcomes in business education.

Keywords: AI, AI-generated podcasting, podcasts, business analytics, survey, undergraduate business education.

1. Introduction

Conventional podcasts originated in the early 2000s and gained popularity in educational settings around 2005, following their integration into Apple's iTunes platform. This advancement provided wide reaching access and subscription to educational audio content for both educators and students. The next stage of podcasting emerged when instructors began recording and sharing their own material; however, this was often challenging due to the significant time commitment and technical expertise required, which were difficult to balance with already busy academic schedules. More recently, AI- generated podcasts have surpassed their conventional counterparts as a major teaching resource, offering students flexible, on-demand access to more course specific content. Unlike traditional lecture formats, these podcasts allow students to revisit material repeatedly and integrate learning into everyday activities such as commuting or exercising. Research suggests that this accessibility supports improved listening skills, fosters independent study, and enhances content retention (Harvard Business Publishing, 2024).

In business education, however, AI-generated podcast applications remain relatively limited and underutilized (Engzell, Norrman, Norberg, & Lundvall, 2025). Podcasts have been increasingly used in general management, marketing, and other business disciplines (Harvard Business Publishing, 2024; AACSB Insights, 2024), but few studies (to researchers' knowledge) have explored their role in more quantitatively intensive courses, one being business analytics. The latter is frequently identified as challenging, especially for undergraduate students due to its abstract content and the extensive use of statistics and spreadsheet application. The potential of AI generated podcasts to improve comprehension and reduce cognitive barriers in this context remains underexplored.

Conventional podcasts, while highly respected for their authenticity and emotional connection, require instructors to record, edit, and distribute episodes, an often time consuming and restrictive task. Numerous developments in generative artificial intelligence now make it possible to automate much of this process by producing short, topic or chapter specific podcasts that are tailored to course materials. AI generated podcasts can draw directly from lecture slides, test banks, quizzes, or other instructional resources, producing high quality, targeted content intended to reinforce course or program learning outcomes. One example is Google's NotebookLM, which allows instructors to upload course documents and produce AI-generated content in an audio form. Recent discussions highlight how tools like NotebookLM are being applied in academic settings to produce podcast style learning resources, providing

students with new avenues for engagement (AI Goes to College, 2024). This marks a possible transition using podcasts as an extra instructional resource to their role as an AI driven tool for content delivery.

Academic performance and student engagement in undergraduate business analytics courses are often influenced by the ability to understand and retain abstract material. Especially, asynchronous online courses in particular present additional challenges, as reduced direct interaction can weaken student motivation and comprehension. AI-generated podcasts may help address these challenges by offering clear, concise, and accessible explanations of key topics aligned with assessments. Emerging evidence suggests that podcasts can enhance engagement and comprehension when integrated with traditional instruction (Harvard Business Publishing, 2024). By aligning AI-generated episodes directly with quizzes and other evaluations, instructors may also foster greater retention and performance. Thus, podcasts, particularly those created through AI platforms, have the potential to improve both engagement and measurable academic outcomes in data-intensive business courses.

2. Literature Review

Over the past ten years, podcasts have become increasingly prominent in business education. As a digital medium, they offer distinctive learning advantages by delivering content that is both accessible and adaptable to various schedules. This review brings together recent research on the educational value, benefits, and evolving use of podcasts within business learning environments. Podcasts offer a modern content medium for sharing knowledge, allowing students to interact with educational material in ways that traditional lecture formats may not offer, especially in online education. Their convenience enables learners to absorb information during everyday tasks, a point emphasized by Shaw and McNamara, who found that users favored realistic and easily digestible content while multitasking (Shaw & McNamara, 2021). This supports earlier findings by Singh et al., who noted that short, flexible podcast episodes can enhance learning by fitting into individual routines (Singh et al., 2016).

Studies such as those by Wang et al. highlight the growing role of podcasts in fields like nursing education, reinforcing the idea that digital tools are transforming how students learn (Wang et al., 2023). Evidence from Cho et al. suggests that incorporating podcasts into academic programs can boost student engagement and retention (Cho et al., 2017). The blend of storytelling and instruction found in podcasts creates a more immersive learning experience, as demonstrated by McNamara et al., whose research on Content Acquisition Podcasts showed improved comprehension of complex topics (McNamara et al., 2020). The effectiveness of podcasts in business education is increasingly supported by empirical data. Educational strategies that include podcasting have been linked to better test performance and heightened learner involvement, though Katz and Nandi caution that more studies are needed to confirm these outcomes across diverse curricula (Katz & Nandi, 2021). Despite promising results, challenges persist—particularly the need for robust evaluation methods to accurately assess podcast impact, as noted by Raupach et al. (Raupach et al., 2015).

Current trends show that business and educational podcasts are integrating sophisticated teaching models and promoting collaborative learning. Research indicates that podcasts can foster communities of practice, encourage interaction among learners, and enrich shared understanding (Zumach & Portillo, 2020). The emergence of student-created content is especially significant, shifting the dynamic from instructor-driven delivery to a participatory model that empowers learners and deepens their engagement (Barney & Bunda, 2024).

Although the literature is abundant with integration of podcasts into higher education curricula, Artificial Intelligence (AI) - generated podcasts have recently been used in education industry thus only a handful of works focused on investigating the impact of AI generated podcasts, while the business education focus is still lacking in the recent literature. For instance, Chaikovska et al. (2024) found that AI-based podcast listening activities undertaken by engineering students outside the classroom significantly enhance their listening comprehension skills, while also fostering curiosity and motivating them toward further personal and academic development (Chaikovska et al.,2024).

Moreover, Lydia Kilz's (2024) study explores how students perceive the use of AI in higher education through an analysis of podcasts created during a Virtual Collaborative Learning course. The qualitative findings reveal that students view AI tools as helpful for enhancing learning efficiency and personalization, particularly for tasks like text improvement. However, they also express concerns about overreliance on AI, emphasizing the importance of human

interaction, ethical use, and maintaining critical thinking. The study highlights the need for a balanced integration of AI that supports autonomy and intellectual engagement in academic settings.

Furthermore, Hobson and McGinnis (2023) investigate the use of AI-generated podcasts as a pedagogical tool in media education, focusing on how such technology can enhance student engagement and creativity. Using a qualitative case study method, the researchers analyzed reflections from a cohort of 12 undergraduate media students who created podcasts with AI voice synthesis and content structuring tools. The project allowed students to concentrate on scripting and conceptual development while interacting with emerging media technologies. Findings revealed that students experienced increased motivation, deeper learning, and greater creative confidence, suggesting that AI tools can democratize media production and enrich educational practices.

In another work, Trevor Brown's chapter, *No Podcast Ever Gets Made*, presents a qualitative case study exploring human-AI collaboration in storytelling podcast production. Using AI tools like large language models for scriptwriting, ElevenLabs for voice synthesis, and Ableton Live for sound design, Brown documents the creative process of developing a single podcast episode. The study highlights both the potential and limitations of AI in creative audio work, emphasizing that while AI can assist with technical and generative tasks, human input remains essential for emotional depth and narrative coherence. The title reflects the paradox that despite technological advances, meaningful podcast creation still demands human artistry.

Moreover, Lee et al. (2024) focuses on exploring how AI-generated podcasts can support older adults in learning about artificial intelligence. Using a co-creation methodology, researchers collaborated with 14 older adults over a series of workshops to design and evaluate podcast content tailored to their interests and needs. The podcasts were generated using AI tools and refined through participant feedback. Key findings reveal that older adults appreciated the conversational and narrative style of AI podcasts, which helped demystify complex AI concepts and fostered engagement. The study underscores the value of participatory design in making emerging technologies more accessible to aging populations.

In another study from nursing education, Desmedt et al. (2025) focuses on evaluating the effectiveness of an AI-generated podcast as a tool to enhance patient education and reduce anxiety among individuals with heart failure. Conducted as a randomized controlled trial, the researchers enrolled 100 patients who were divided into two groups: one received standard care, while the other accessed an AI-generated podcast tailored to heart failure education. The podcast was developed using natural language processing and machine learning techniques to deliver personalized, engaging content. The key finding revealed that patients who listened to the AI podcast showed significantly improved knowledge about their condition and experienced reduced anxiety levels compared to the control group.

Furthermore, Smith (2023) investigated the educational potential of AI-generated podcasts in higher education, focusing on their impact on student engagement and learning outcomes. Using a mixed-methods approach with surveys and interviews involving 60 participants, the study compares podcast-based learning to traditional reading materials. AI-generated podcasts were created using text-to-speech and summarization tools. Findings suggest that while podcasts enhance engagement, especially auditory learners, they do not significantly outperform traditional formats in comprehension or retention.

In summary, podcasts offer a dynamic, accessible, and effective tool for self-guided learning in business education. Nonetheless, further investigation is needed to measure their impact precisely and to refine best practices for their use. As education continues to evolve, podcasts are poised to play an influential role in shaping how business knowledge is delivered and absorbed.

3. Methods

3.1 Study Design

An undergraduate-level business analytics class was used for this investigation. This course consists of comprehension-oriented and application-oriented assessments. Quizzes, midterm and final exams were comprehension-oriented assignments, where multiple choice, true-false, and essay type of questions were used. On the other hand, weekly homework assignments and term projects require practical application of analytics methods. The course is being offered in both online-asynchronous and on-ground (in person) modalities. Historically, students

enrolled in online sections seem to have lower engagement due to the asynchronous (no live lectures) format and the abstract concepts covered in the course such as optimization, simulation, statistical analysis, etc. To increase course engagement and overall course performance, AI-generated podcasts were developed and offered to students, accompanied by a quiz study guide summarizing topics covered and offering study tips. Quiz assignments served as the focal point of this paper, where students are typically given a set of 10 to 15 randomly drawn questions from a test bank. Students were given 2 attempts per quiz, where the final quiz score was the average of both attempts if the 2nd attempt was taken. The primary objective was to assess how AI-generated podcasts impacts students' academic performance and course engagement in the online learning environment.

We employed a mixed methods approach. Quantitatively, we compared quiz performance across students who had listened to the podcasts and/or used study guide versus those who did not within the same class. The quizzes included a question asking whether a student listened to the podcast (without point incentives) and reviewed the study guide to be used in statistical comparison (Mann Whitney U Test). Additionally, another online section was used as a control group, where students took the same quizzes but were not offered podcasts nor study guides. Secondly, we administered a post-course survey (via Qualtrics) in Week 7 (online modality) and conducted voluntary interviews to explore student perceptions of AI podcasts, patterns of use, engagement, and suggestions for improvement. The combined methods intend to shed light on both the effect of size and the mechanisms of impact. The intervention section (where AI podcasts were integrated) included 26 students, while the control section (without AI podcasts) consisted of 28 students.

3.2 AI Podcast Generation

Although many platforms can generate AI podcasts, researchers in this study chose Google's NotebookLM, a Gemini 2.0 powered research and writing assistant. The selection was driven primarily by its ease of use, availability of a free version, and speed of podcast generation. As shown in the flow chart below (Fig. 1), the process begins by visiting notebooklm.google.com and signing in with a Google account. Users then create a new notebook and upload their sources, which may include PDFs, websites, YouTube videos, audio files, Google Docs, text files, or Google Slides. In our application, the entire pool of quiz questions and answers were provided along with the detailed chapter slides as the main resource prior to podcast generation.

After uploading the resource documents, users can engage with their sources through the Chat Panel by asking questions or generating summaries, or move directly to the NotebookLM Studio, which offers several output options such as interactive or non-interactive podcasts, mind maps, video overviews, reports, flashcards, and quizzes. The final step is to save and share the selected materials with students, enabling a seamless and interactive learning experience.

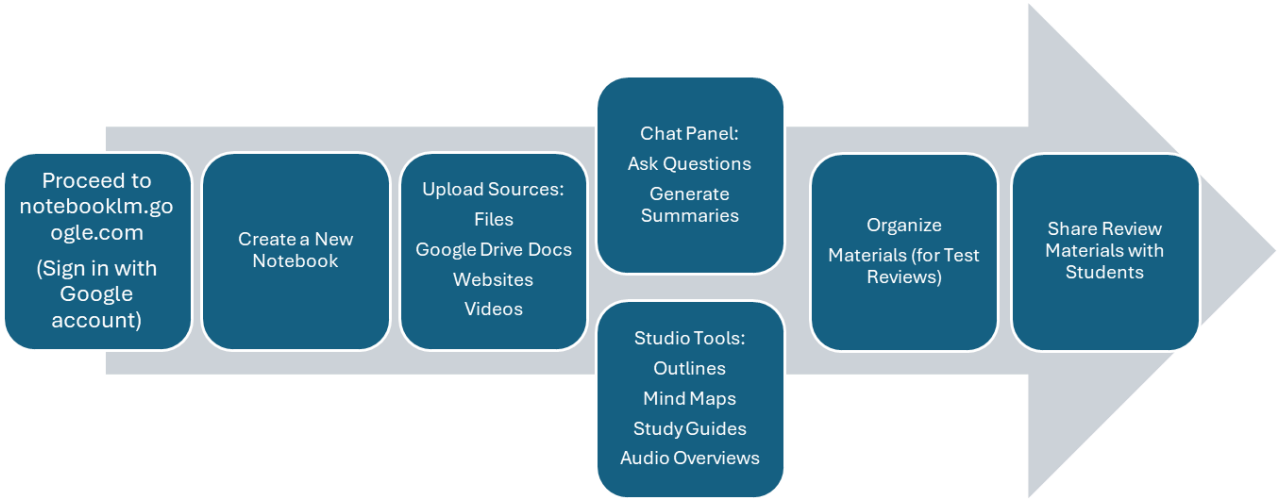

Figure 1. Podcast Generation with NotebookLM

4. Results

4.1 Statistical Analysis

Initially, the lead investigator conducted a normality check of the quiz performance (grades) data by groups (whether a student reviewed the study guide before and whether a student listened to the podcast). Grades were previously normalized between 0 and 1. Weekly quizzes were assigned. 6-week quiz data was collected for statistical analysis and comparison. Depending on the normality check results, a parametric or non-parametric statistical comparison would be conducted. Histograms of quiz performance results by groups are provided in Figure 2, and results of normality check conducted with Shapiro Wilk test are provided in Table 1. Both visual (Fig. 2) and statistical (Table 1) results indicate that the quiz grades data is partially non-normal. Therefore, Mann Whitney U test was used to conduct statistical comparisons within the intervention section. Furthermore, to compare the intervention (AI podcast integrated section) with the control group (no podcast was used), paired t-test (parametric) and Wilcockson (nonparametric) tests were conducted.

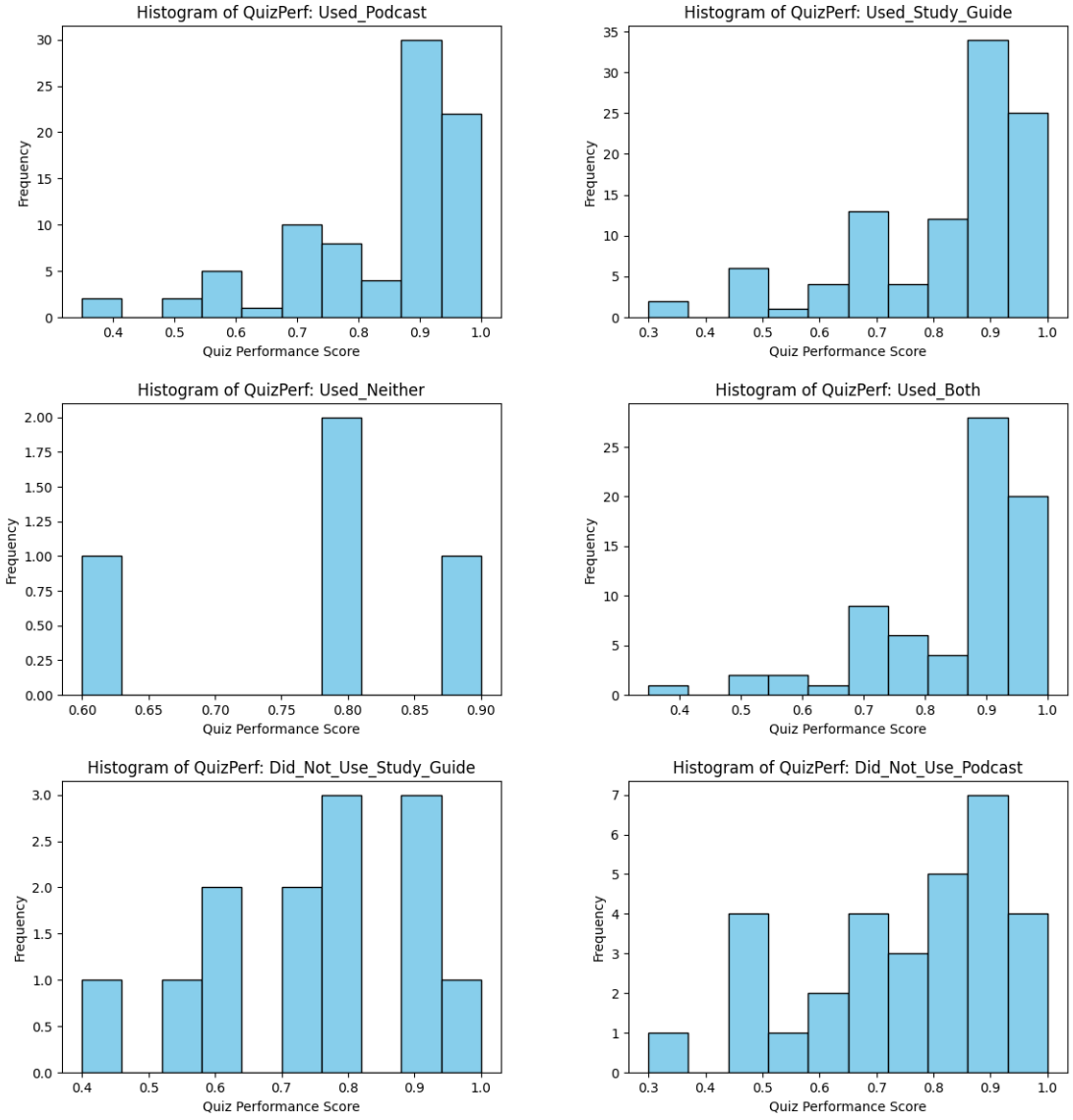

Figure 2. Normality Check (Histograms of Quiz performance (0,1))

Table 1. Normality Check (Shapiro Wilk Test)

Group	Statistic	p-value	Sample Size	Normality Conclusion
Used Study Guide	0.8614	2.84e-08	101	Not normal
Did Not Use Study Guide	0.9524	0.0636	13	Normal
Used Podcast	0.8503	9.64e-08	84	Not normal
Did Not Use Podcast	0.9389	0.0753	31	Normal
Used Both Study Guide & Podcast	0.8329	1.28e-07	73	Not normal
Used Neither	0.8949	0.4066	4	Normal (small n)

4.1.1 Statistical Comparison within the course

Within the intervention section, students were grouped based on whether they used the study guide before taking the quiz, listened to the podcast before the quiz, or used both the study guide and the podcast. Among these groups, students who listened to the podcast performed significantly better on the quizzes than those who did not (See Table 2).

Table 2. Statistical Comparison of Podcast and Study Guide's Impact

Comparison Group	Test Type	Statistic	p-value	Significance
Study Guide Usage vs. No Study Guide	Mann-Whitney U test	868.5000	0.0536	Not significant
Podcast Usage vs. No Podcast	Mann-Whitney U test	1719.0000	0.0072	Statistically significant
Both Study Guide & Podcast vs. Neither	Mann-Whitney U test	212.5000	0.1167	Not significant

4.1.2 Statistical Comparison against a previous section

Additionally, a prior section of the same course which was taught in Spring I 2025 was used as a control group, and compared statistically with the intervention group (the section which was taught in Fall I 2025). Results of quiz performance (grades) were visually depicted in Figure 3 as well as the statistical comparison results were summarized in Table 3. Even though the intervention group (AI podcast use) yielded higher quiz scores, the difference was found to be statistically insignificant (See Table 3) in both Paired t-test and Wilcoxson tests. It is important to note that the intervention group included 26 students, and the control group included 28, resulting in a relatively small sample size.

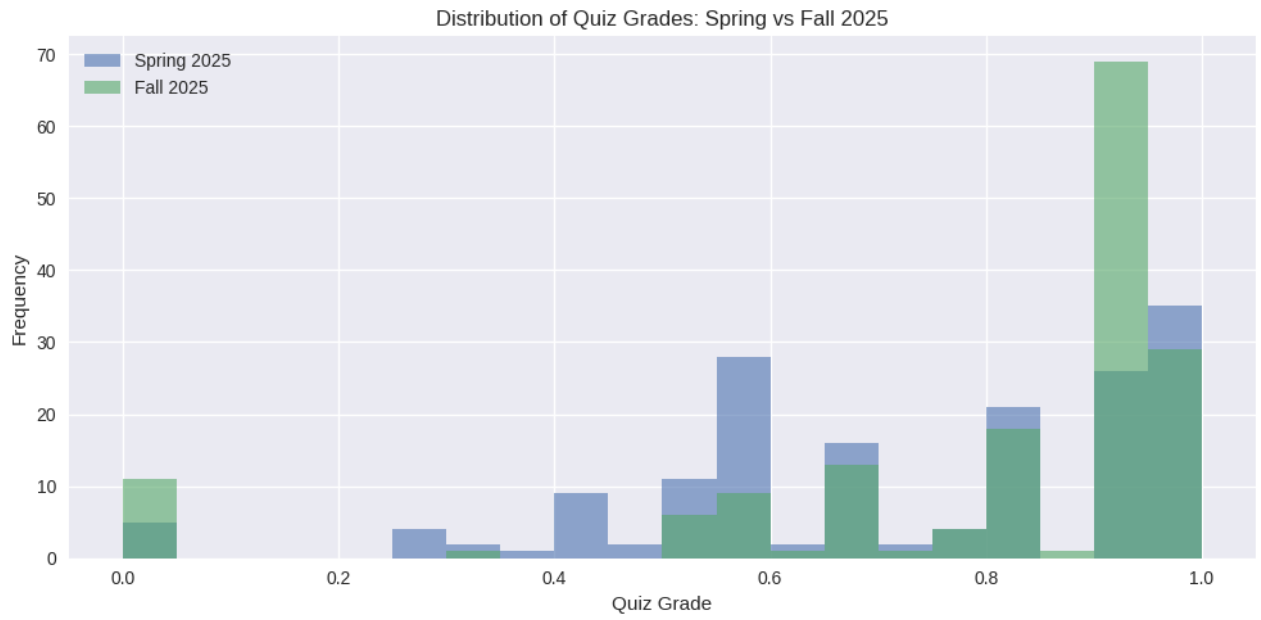

Figure 3. Graphical Comparison of Fall 2025 (Intervention with AI Podcast) vs. Spring 2025 (Control) Cohort

Table 3. Statistical Comparison of Fall 2025 (Intervention) vs. Spring 2025 (Control) Cohorts

Quiz ID	Paired t-test Statistic	Paired t-test p-value	Wilcoxon Statistic	Wilcoxon p-value	Significant Difference
Q1	-0.3589	0.7227	142.0	0.5808	No
Q2	-1.0713	0.2951	73.0	0.0822	No
Q3	-0.1517	0.8809	101.0	0.8810	No
Q4	-1.0458	0.3088	54.0	0.2861	No
Q5	-0.9057	0.3777	47.5	0.2881	No
Q6	0.0000	1.0000	57.0	0.8644	No

4.2 Survey (n=17 students)

4.2.1 Quantitative Analysis

Demographic Trends

In terms of majors, the most common was Business Administration (41%), followed by Accounting (18%). All in all, there was a diverse representation across 9 majors including Data Science, Sport Management, and Economics.

In terms of Academic Year Classification: Seniors (41%) and Juniors (29%) made up the majority. Freshmen were the least represented (6%).

Prior Podcast Use: Mirrors academic year distribution, suggesting prior exposure increases with academic progression.

Familiarity with AI-generated content: 65% had moderate to very high familiarity and only 6% were not familiar at all.

Race/Ethnicity: Predominantly White or Caucasian (76%). Minority representation included Asian, Black or African American, and American Indian/Native American (each 6%).

Gender Identity: Male (47%), Female (41%), Non-binary/Third gender (6%).

Age Group: Majority ranged 18–24 (65%). The remaining respondents spanned 25–64, indicating a mix of traditional and non-traditional students.

Podcast Usage:

In terms of listening frequency, 53% listened most weeks or every week, 29% rarely or occasionally listened, while 12% never listened.

Average listening time: 41% spent 10–20 minutes. 18% spent >30 minutes. 18% spent <10 minutes. 6% preferred not to say.

Academic Performance:

Preparedness for quizzes: 47% felt more prepared (Somewhat or Strongly agree); 29% were neutral, while 24% disagreed.

Improved quiz performance: 59% agreed podcasts helped, 29% were neutral, and 12% disagreed.

Understanding chapter concepts: 59% agreed, 29% neutral, 12% disagreed.

Retention of key concepts: 71% agreed, 24% neutral, 6% disagreed.

Compared to traditional study methods, 53% found podcasts more effective; 35% said they were about the same, while 6% found them less effective.

Course Engagement: Most students found the AI-generated podcasts beneficial for engagement. About 71% said the podcasts made the material more engaging, and 65% felt more motivated to study after listening. Additionally, 56% would recommend using podcasts in other courses, though a third remained neutral, while a small minority expressed disagreement.

4.2.2 Qualitative Analysis

Convenience & Flexibility: Many appreciated being able to listen during commutes, work hours, or walks. Podcasts offered a way to study when traditional methods weren't feasible.

Engagement & Variety: Students found the format refreshing and more interactive than reading notes or slides. The audio format made learning feel more dynamic and enjoyable.

Content Quality & Relevance: Podcasts were praised for summarizing key chapter topics effectively. Their timing, being available before quizzes, was especially helpful.

Ease of Use: The simplicity and accessibility of the podcasts made them a practical study tool.

Mixed Usage: A few students noted they didn't fully engage with the podcasts or didn't use them at all.

4.3 Interviews

In an interview conducted via Microsoft Teams, a total of 15 structured questions were discussed to explore student perceptions of AI-generated podcasts. The responses highlighted that the podcasts were clear, concise, and effective in supporting understanding complex topics such as regression analysis. The interviewee noted that listening to episodes before quizzes improved confidence and performance, and that the flexibility to listen while commuting or multitasking made learning more accessible and less burdensome. The podcasts were described as helping to strengthen connection with the course material and encouraging greater engagement in class discussions. While the overall format and structure were seen as focused and easy to follow, it was suggested that adding short, real-world examples could make future episodes even more engaging and relevant. Overall, the podcasts were regarded as a valuable and motivating supplement to traditional learning materials.

5. Conclusion & Future Remarks

This study explored the use of AI-generated podcasts in fields that place heavy emphasis on both concepts and quantitative analysis. It addressed gaps in the current research while offering practical guidance for instructors who may want to incorporate audio supplements into their teaching. By looking specifically at business analytics and other similar disciplines, the study highlighted how generative tools can support learning in higher education. The findings of this study can guide recommendations on when and how these tools are most useful, and for which groups of students they may work best. As a future work, the study's sample size is limited; therefore, it will be expanded to have at least 30 students' sample size in both control and intervention groups. Moreover, the AI podcasts were integrated into the asynchronous online section. It will be integrated into the on-ground sections, and experiments will be repeated. Lastly, other podcast generation platforms along with more resources could be used to implement innovative, student-friendly, engaging pedagogical approaches in business education.

Ethics Declaration

The necessary IRB process was conducted prior to survey distribution and IRB approval was obtained on October 13, 2025.

AI Declaration

Generative AI (MS CoPilot & ChatGPT OpenAI) was used to summarize the interview transcripts and generate Figure 1. Furthermore, SciteAI was used to collect relevant papers in literature review. Grammarly, an AI-powered writing tool, was used to enhance clarity, flow, and overall language quality of the work. All references were individually checked and verified during the preparation of literature review.

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