Integrating GenAI into Corporate Knowledge Management: A Socio-Technical Approach to Overcoming Knowledge Management Challenges

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Abstract: The growing importance of Artificial Intelligence (AI), especially Generative AI (GenAI), is revolutionising the way knowledge is handled and opening up enormous potential for corporate knowledge management (KM). The rapid development of Large Language Models (LLM) and complementary technologies such as Retrieval Augmented Generation (RAG) or knowledge graphs opens up new opportunities for corporate KM, but also presents companies with complex challenges and barriers. This study examines the integration of genAI into corporate KM, taking into account a holistic socio-technical approach. A AI4KM survey was designed to capture the current state of AI use by asking companies about their use of AI technologies. The survey aims to gain insights into the practical implementation of AI solutions, particularly in relation to KM challenges. Based on the results of the AI4KM survey, a socio-technical TOP approach (Technology - Organisation - People) for the introduction of AI-based KM will be developed, which takes into account not only technical, but also organisational and people-related aspects. By addressing these three factors, the study aims to provide a comprehensive framework that ensures the successful adoption of AI technologies in diverse business environments. Specific recommendations for the development of an effective, holistic AI strategy in KM are developed for the various barriers. Among other things, the importance of human-machine interaction will be emphasised in order to create a seamless link between human expertise and machine intelligence. The results of these studies should help companies, especially small and medium-sized enterprises (SME), to effectively use genAI technologies for their KM, to counteract the loss of knowledge due to demographic change and to increase their competitiveness. The combination of theoretical findings and practical recommendations will build a bridge between research and business practice, contributing to the successful integration of AI into corporate KM and equipping companies for the challenges of the future.

Keywords: Generative AI (GenAI), Corporate knowledge management, Knowledge management challenges, Socio-Technical approach, Human-Machine interaction

1. Introduction

In the context of increasing digitalisation, demographic change, and mounting competitive pressure, the ability of organisations to manage knowledge effectively has become more critical than ever. Knowledge is widely acknowledged as a key strategic resource and a core enabler of organisational performance, innovation, and resilience (Nonaka & Takeuchi, 1995; Spender & Grant, 1996). However, many companies still struggle to operationalise knowledge management (KM) in a way that ensures long-term availability, accessibility, and productive use of organisational knowledge.

At the same time, the emergence of generative artificial intelligence (GenAI), driven by rapid advancements in large language models (LLMs), Retrieval-Augmented Generation (RAG), and knowledge graphs, is profoundly transforming how knowledge is created, structured, and shared. Technology has long been a core enabler of KM. Traditional KM technologies such as knowledge repositories, collaborative platforms, and document management systems have shaped the way knowledge is stored and accessed. More recently, GenAI tools like ChatGPT or Microsoft Copilot have added powerful new capabilities such as contextual search, summarisation, and automation of routine knowledge tasks (Liu et al., 2023; Nazeer et al., 2023). These technologies offer new possibilities for solving long-standing KM challenges – such as knowledge silos, fragmented documentation, or the loss of critical expertise – but also introduce new risks and uncertainties (Davenport & Mittal, 2022). Understanding how these technologies affect KM effectiveness is crucial to leveraging their full potential.

Despite the increasing popularity of GenAI tools, their integration into enterprise knowledge processes remains largely experimental. Many organisations, especially small and medium-sized enterprises (SMEs), lack clear strategies for embedding GenAI in their operational and knowledge ecosystems. In addition to technological issues such as data quality and system interoperability, organisational and human factors often hinder adoption. These include unclear roles, resource limitations, lack of AI competencies, and low user acceptance (Märkel & Lundborg, 2020; BMWi, 2021; Bughin et al., 2018).

The existing literature on KM and AI integration tends to focus either on theoretical models or on specific technologies. Holistic, practice-oriented SME-applicable frameworks that address the socio-technical interplay between technical aspects (technology) and social aspects (organisation & people) remain scarce (Grüneke et al., 2024). To bridge this gap, the present study explores how companies approach the integration of GenAI in their knowledge environments. The study is based on the AI4KM survey, which captures both current practices and perceived barriers from a socio-technical perspective.

The aim of this paper is twofold: First, it presents key findings from the AI4KM survey on the current use and challenges of GenAI in corporate KM. Second, it introduces a practical framework – the TOP approach (Technology – Organisation – People) – designed to support the effective and responsible implementation of GenAI tools in knowledge-intensive settings. By offering both empirical insights and actionable recommendations, the study seeks to support organisations – particularly SMEs – in leveraging the potential of GenAI while addressing critical implementation challenges. In doing so, it contributes to building a conceptual and practical bridge between AI innovation and KM strategy.

2. Knowledge Management and its Challenges

In today's dynamic and knowledge-intensive environments, the ability to manage knowledge effectively has become a key factor for organisational success (North & Gueldenberg, 2011). KM encompasses the structured processes of developing, preserving, sharing, applying and continuously improving asset knowledge so that it contributes to the achievement of the organisation's objectives, value creation and long-term competitiveness (ISO 30401:2018). Especially in times of demographic shifts, increased complexity, and accelerating digitalisation, KM plays a vital role in preserving know-how, facilitating collaboration, and ensuring continuity.

While KM is a strategic issue across all sectors, its relevance is particularly pronounced in SME. These companies often depend heavily on the expertise of individual employees, yet they frequently lack the formal structures, dedicated resources, or technological support to implement comprehensive KM systems. As a result, knowledge remains undocumented, is difficult to access, or is lost when people leave the organisation. Studies show that SMEs are especially vulnerable to such losses, as informal communication channels and role overlaps dominate daily operations (Orth et al., 2011; Durst & Edvardsson, 2012; Voigt et al., 2016).

In addition to structural limitations, organisations also face a number of persistent challenges in managing knowledge effectively. Fraunhofer IPK conducted a survey of companies and knowledge-intensive organisations on typical KM challenges (e.g. Orth et al., 2011; Orth et al., 2023). The results show that the five biggest challenges are 1) the (re-)use of existing knowledge for new projects and services, 2) the fast integration of new employees into the organization (e.g. systematic onboarding process), 3) the use of knowledge to optimize processes and products as well as 4) the capturing and communicating the knowledge in people's heads and 5) a lack of transparency regarding the internally available competences.

Recent meta-analytical research confirms that knowledge management technologies (KMT) are not merely supportive tools but strategic enablers of organisational performance, particularly in knowledge-intensive environments (Liu et al., 2023). In this context, GenAI technologies offer new possibilities for overcoming persistent KM challenges. Based on large language models, these tools can synthesise content, support classification and retrieval tasks, and generate knowledge artefacts like summaries or documentation. They can, for instance, support onboarding, reduce information silos, or help capture and reuse tacit knowledge (Davenport & Mittal, 2022). As Sumbal et al. (2024) argue, such AI-driven capabilities are reshaping KM from static repositories into dynamic, interactive ecosystems.

However, the integration of GenAI into organisational KM is not without its challenges. Besides technical questions around data quality and system compatibility, issues such as user acceptance, trust, and responsible use are central to successful adoption. The use of AI tools for knowledge work must therefore be embedded not only in IT infrastructures but also in organisational routines and human workflows (Märkel & Lundborg, 2020; Grüneke et al., 2024) – highlighting the need for socio-technical integration.

Although KM and AI have been widely discussed in the literature, research has predominantly concentrated only on statistical surveys, technological architectures, or abstract management models. What is lacking are empirically grounded, practice-oriented frameworks with concrete recommendations for action that acknowledge the complex socio-technical dynamics of GenAI implementation. In this context, the present paper aims to provide both empirical insights and a structured approach to guide the adoption of GenAI in KM settings. The following section presents the design and key findings of the AI4KM survey, which provide the empirical foundation for the recommendations developed in this study.

3. AI4KM-Study: Survey Design and Findings

In light of the growing relevance of GenAI for corporate KM, the AI4KM survey was developed to investigate current application practices, perceived potential, and implementation barriers. The study particularly focuses on capturing how organizations approach GenAI within knowledge processes, what challenges they encounter, and which expectations they associate with its use. Adopting an exploratory, practice-oriented perspective, the study aims to provide empirical insights into the integration of AI technologies in KM. The standardized online questionnaire was implemented using LimeSurvey and made available in both German and English to ensure accessibility across different organisational contexts. Designed to be concise and user-friendly, the survey takes approximately ten minutes to complete. Participation is anonymous and voluntary. The questionnaire comprises four thematic sections: (1) the current state of AI adoption within the company, (2) the anticipated value of GenAI for organization's most pressing KM challenges, (3) perceived barriers to GenAI implementation, and (4) Application Areas for GenAI Solutions. A detailed analysis of the content and findings of these sections is presented in the following sections.

Data collection began in June 2024, with the survey disseminated via professional and academic networks, conferences, and relevant newsletters. Due to its open distribution, the study follows a non-probabilistic, self-selection sampling approach, which is common in exploratory research on emerging technologies where early empirical orientation is prioritized over statistical representativeness. As the survey remains open at the time of writing, data collection is still ongoing, and no definitive response rate can be reported. Rather than targeting a fixed population, the study seeks to gather diverse perspectives from various sectors and organisational types. This methodological setup enables the identification of both common patterns and contextual differences in how companies engage with GenAI in their knowledge environments. It should be noted that the AI4KM survey exhibited a relatively high dropout rate across the questionnaire. As a result, the number of valid responses varies between individual questions. For each question analysed, the corresponding number of respondents (n) is indicated in parentheses. Due to these variations in the base sample, percentages may not always be directly comparable across all questions. Nevertheless, the results provide valuable exploratory insights into the current use, perceived potential, and barriers related to AI and GenAI adoption in corporate KM. They serve as a foundation for the development of actionable recommendations and a socio-technical framework that addresses the interplay between technological, organisational, and human dimensions of GenAI adoption in KM.

3.1 Status quo

The AI4KM survey shows a heterogeneous landscape regarding the current use of AI and GenAI technologies in companies (n = 64). Overall, 39% of participants reported having multiple AI solutions operational, while 17% stated that they had implemented a single solution. Another 17% have conducted pilot tests without operational deployment, and 14% are in the planning stage. Only a small share has decided against AI adoption or has yet to engage with the topic. Focusing on GenAI specifically (n= 63), 36.5% of respondents indicated that GenAI applications are already in operational use. Among those planning adoptions, around 33% expect implementation within the next 12 months, while 20% consider GenAI currently irrelevant to their organisation. These findings suggest that, although early operational use of AI is relatively widespread, GenAI adoption is still emerging, with companies either actively moving towards integration or remaining cautious due to strategic uncertainties.

3.2 GenAI for KM Challenges

Participants were asked to assess the extent to which they expect GenAI tools to support various KM activities (n = 45). The highest expectations were recorded for *fast search and identification of knowledge*, *reuse of existing knowledge for projects and services*, and *optimisation of processes and products*. Also highly rated were *structuring and networking of data repositories* and *knowledge transfer within and between projects*. Expectations were slightly lower – but still clearly positive – for *capturing tacit knowledge*, *knowledge transfer between generations*, and *supporting onboarding*. All average ratings remained above *rather agree* (4) on the six-point scale – ranging from *strongly disagree* (1) to *strongly agree* (6), indicating that companies broadly expect GenAI to contribute meaningfully across a wide range of KM tasks (see Figure 1).

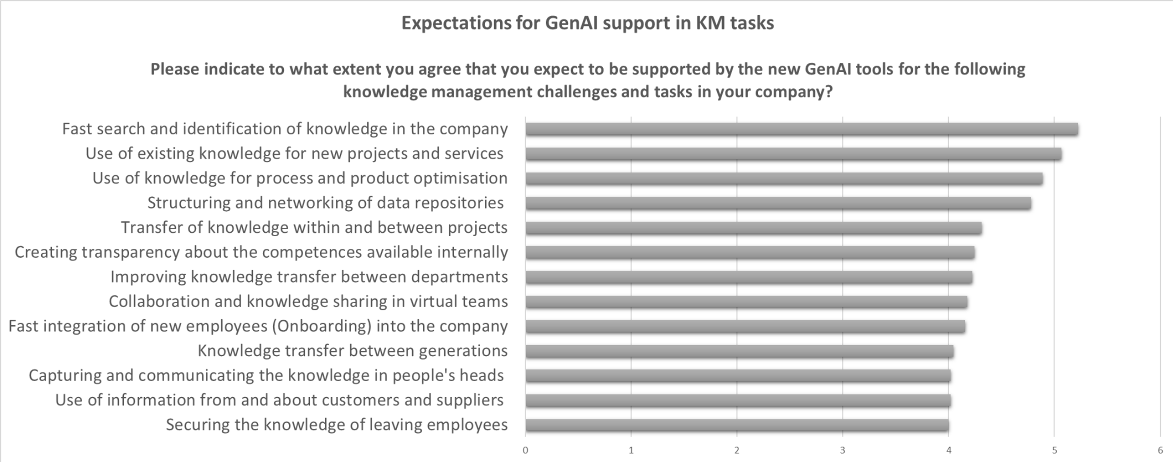

Figure 1: Expectations for GenAI support in KM tasks

Independently of GenAI use, participants ranked their three most pressing KM challenges (n = 42). The most frequently selected issues were *structuring and networking of data repositories*, *reuse of existing knowledge for new projects and services*, and *fast search and identification of knowledge*. Challenges related to *capturing and communicating tacit knowledge*, as well as *knowledge use for process and product optimisation*, also ranked highly. These results underline a strong operational need for better knowledge organisation, retrieval, and reuse mechanisms across organisations.

A comparison of expected GenAI support and current KM challenges reveals a remarkable degree of alignment. Organisations primarily expect GenAI to address exactly those areas where they perceive the most urgent KM challenges. Minor differences are observable: *knowledge transfer between projects*, while highly expected as a GenAI-supported activity, was not prioritised among the top current challenges. Overall, the findings suggest a realistic understanding among organisations regarding both the capabilities and the limitations of GenAI in KM, particularly in socially complex tasks like tacit knowledge capture.

3.3 Barriers to the Implementation of GenAI Solutions

The AI4KM survey also examined the barriers companies face when implementing GenAI solutions for KM (n = 35). Participants rated their level of agreement with several potential barriers on a six-point scale, ranging from *strongly disagree* (1) to *strongly agree* (6). The results show that concerns about *data quality and quantity* were rated highest across all categories, achieving the strongest agreement (see Figure 2). This highlights the critical dependency of GenAI applications on clean, comprehensive, and reliable datasets. Organisational challenges such as the *development of a company-specific AI strategy*, *legal and regulatory issues*, and *the provision of resources* were also identified as major barriers. Respondents indicated significant concern regarding the lack of strategic alignment, compliance risks, and insufficient investment in AI initiatives. Among people-related factors, *competence and skill development* emerged as a substantial hurdle. Many organisations reported gaps in employee capabilities to work effectively with GenAI systems, particularly in areas such as prompt engineering and critical evaluation of AI outputs. Technical barriers, notably the *integration of GenAI into existing IT infrastructures*, were likewise rated high. Additionally, *employee acceptance* and *ethical considerations* – while still relevant – were perceived as slightly less severe barriers compared to other issues. Overall, the findings indicate that companies face a complex mix of technological, organisational, and people-related challenges in embedding GenAI into their KM processes.

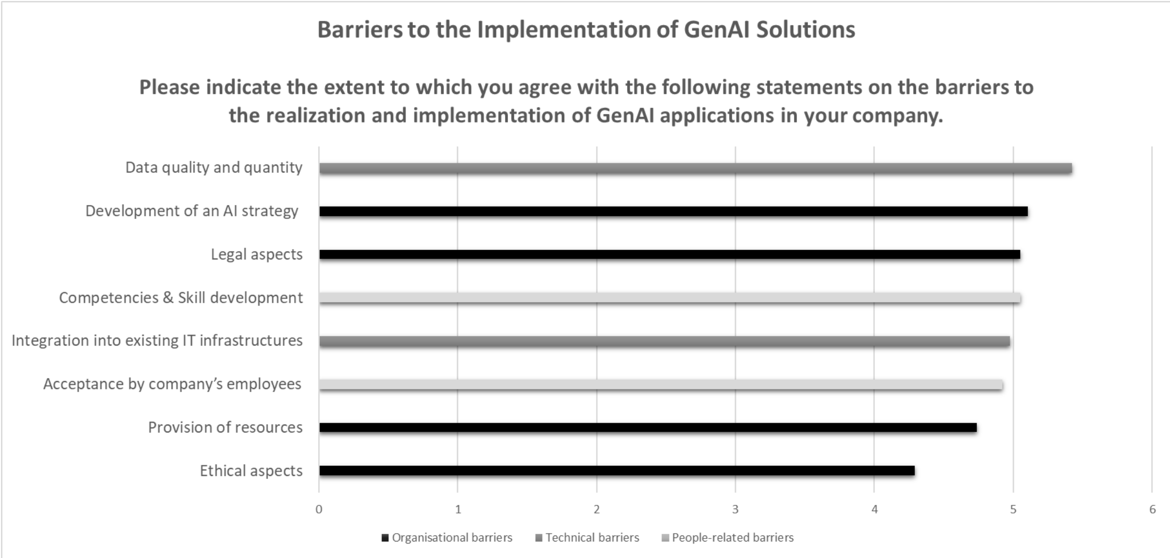

Figure 2: Barriers to the Implementation of GenAI Solutions

3.4 Application Areas for GenAI Solutions

The AI4KM survey also explored how companies assess the potential of GenAI technologies to improve various business processes and functional areas (n = 35). Respondents rated the perceived improvement potential on a scale from *no improvement potential* (1) to *very high improvement potential (6)*. The results indicate that *information technology* and *research and development* are perceived as the areas with the greatest improvement potential (see Figure 3) Companies expect GenAI to enhance IT processes, accelerate research activities, and drive innovation. Other functions, such as *logistics*, *production/service delivery*, and *marketing and sales*, were also rated highly, suggesting that organisations increasingly view GenAI as a tool for operational optimisation and customer engagement. In contrast, functions like *human resource management*, *customer service and after-sales*, *procurement*, and *controlling and finance* received moderate ratings. These areas may present additional challenges for GenAI adoption due to regulatory, relational, or process-specific complexities. Overall, the findings reveal broad optimism regarding the role of GenAI in business processes, with particularly strong expectations in technology-intensive and innovation-driven domains.

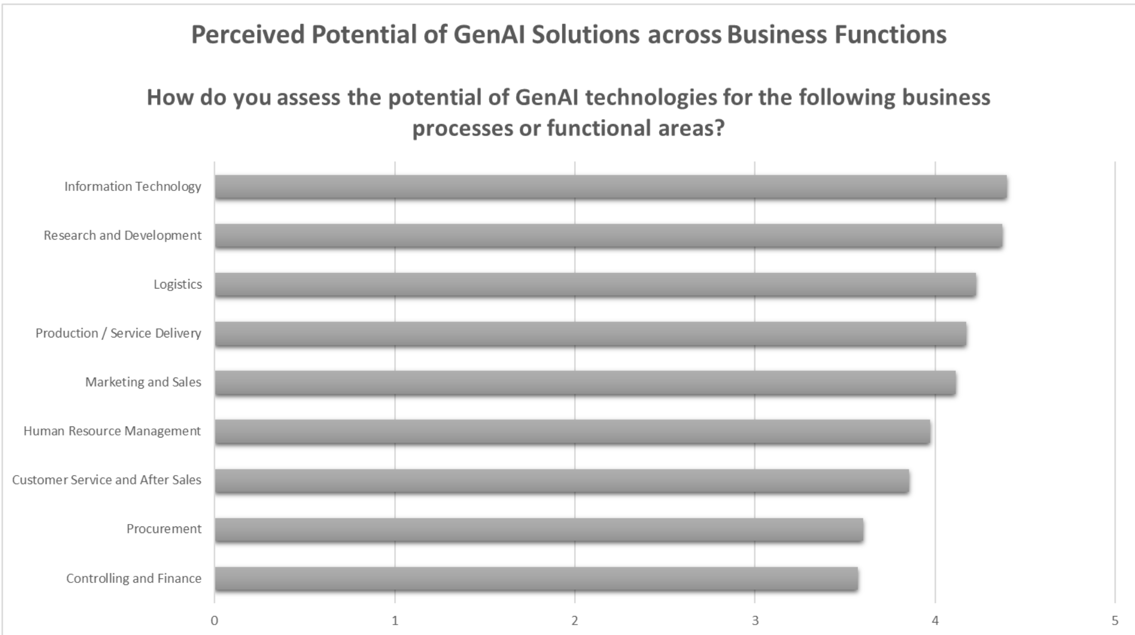

Figure 3: Perceived Potential of GenAI Solutions across Business Functions

The AI4KM survey highlights strong interest in leveraging GenAI for KM and broader business processes. Organisations primarily seek support in knowledge retrieval, reuse, and data structuring, while facing barriers related to data quality, strategy development, and employee competencies. Overall, the findings suggest a cautiously optimistic view: GenAI is seen as a key enabler, yet its successful integration depends on addressing technical, organisational, and human factors simultaneously.

4. Towards Socio-Technical Integration: The TOP Framework for GenAI in Knowledge Management

The integration of GenAI technologies into KM presents both unprecedented opportunities and complex challenges for organisations. While technical innovations such as LLMs and RAG systems offer powerful tools to enhance knowledge processes, their successful and responsible implementation requires more than technological readiness alone. The findings of the AI4KM survey underline that technological, organisational, and human factors all play critical roles in enabling or hindering the adoption of GenAI solutions for KM. To address these interdependent dimensions systematically, this chapter proposes a socio-technical integration framework based on the principles of the established TOM model (Technologie–Organisation–Mensch) and tailored to the specific challenges of GenAI. The adapted *TOP framework* (Technology – Organisation – People) serves as a structured orientation for practice and provides actionable guidance for overcoming identified barriers and achieving sustainable GenAI-supported KM.

4.1 Deriving the Socio-Technical TOP Framework for GenAI Integration in Knowledge Management

The theoretical foundation for the integration framework proposed here draws on the socio-technical TOM model, originally developed by Bullinger, Wörner, and Prieto at the Fraunhofer IAO in 1997 (Bullinger et al., 1998). TOM established that successful KM initiatives depend on the simultaneous and balanced consideration of technological infrastructures, organisational structures, and human factors.

Building on this tradition, researchers at Fraunhofer IPK, including Heisig and Orth further advanced the socio-technical perspective by operationalising TOM principles in practice-oriented frameworks such as GPO-WM® and ProWis (Heisig & Orth, 2005; Orth et al., 2011). These models showed that sustainable KM cannot be achieved through IT solutions alone but requires organisational alignment and human-centred strategies.

In the context of GenAI integration, this socio-technical view gains even greater relevance. While GenAI technologies can automate content generation, support knowledge retrieval, and accelerate knowledge structuring, their full potential can only unfold if embedded in appropriate processes, supported by user competencies, and governed by responsible organisational practices.

The AI4KM survey results confirm the necessity of this integrated approach. Respondents identified major barriers across all three dimensions – technology (e.g., poor data quality, IT integration issues), organisation (e.g., lack of AI strategy, legal uncertainties, lack of resources), and people (e.g., skills gaps, employee resistance).

Against this background, the **TOP framework** is proposed as an adapted, practice-oriented extension for the specific case of GenAI-supported KM:

- **Technology (T)** addresses the deployment, integration, and quality management of GenAI solutions. The focus lies on improving data infrastructures, ensuring interoperability, and embedding GenAI systems seamlessly into existing IT landscapes.
- **Organisation (O)** focuses on strategic alignment, AI governance, regulatory compliance, and resource planning. It ensures that GenAI initiatives are aligned with KM and business objectives and that legal and ethical standards are met.
- **People (P)** targets the development of user competences (e.g., AI literacy, prompt engineering) and the facilitation of change management processes that foster acceptance, trust, and human-machine collaboration.

This three-dimensional framework forms the conceptual basis for deriving targeted recommendations for action, which are detailed in the following section.

4.2 Addressing the Barriers: Recommendations for Practice

The barriers analysed in the AI4KM survey demonstrate that organisations must adopt a holistic, coordinated approach to realise the benefits of GenAI technologies for KM. Based on the adapted socio-technical TOP framework (Technology – Organisation – People), the following recommendations provide actionable guidance for overcoming the key obstacles identified.

Technology

Ensuring and continuously improving data quality is a foundational requirement. Organisations should establish structured processes for data cleansing and maintenance to guarantee that GenAI systems are trained and operated on clean, representative, and up-to-date datasets (BMWi, 2021; PwC, 2019; Davenport & Ronanki, 2018). In addition, it is crucial to provide sufficient data volumes for GenAI applications. Researchers highlight that the generation and augmentation of synthetic data can significantly enhance training datasets, especially when real data is scarce (BMWi, 2021; Davenport & Ronanki, 2018; Goodfellow et al., 2016; Shorten & Khoshgoftaar, 2019). Building modular and scalable GenAI architectures that ensure seamless integration into existing IT infrastructures is essential. Such architectures should prioritise interoperability, data security, and scalability from the outset (Grüneke et al., 2024).

Organisation

Developing clear legal compliance frameworks is essential to manage risks related to data use and AI-generated content, particularly regarding data protection, liability, and transparency (Ogolla et al., 2020; BMWi, 2021). In parallel, organisations are advised to define ethical guidelines that prioritise fairness, transparency, and non-discrimination (BMWi, 2021; Ogolla et al., 2020). Strategic planning and early securing of resources – both financial and human – is a key success factor for sustainable GenAI initiatives. (Grüneke et al., 2024; BMWi, 2021). The inclusion of interdisciplinary teams, particularly those with domain-specific knowledge, and a proactive resource strategy significantly enhance implementation feasibility (Ogolla et al., 2020). Finally, a company-specific AI strategy is needed that aligns GenAI efforts with overarching business and knowledge management goals to ensure long-term value creation (Grüneke et al., 2024; Liebowitz, 2001).

People

To address skills gaps among employees, companies should launch targeted training programmes focused on AI fundamentals, media competence, and prompt engineering. Such measures build AI literacy and enable confident tool usage (Grüneke et al., 2024; BMWi, 2021). Structured change management processes should accompany the rollout of GenAI solutions to foster acceptance. Transparent communication, participation formats, and support services are critical to reducing employee fears and building trust (Ogolla et al., 2020; Grüneke et al., 2024; Osterloh & Frey, 2000). Establishing human-machine interaction (HMI) as a guiding principle is essential. Organisations should emphasise augmentation rather than substitution of human capabilities, enabling creative collaboration between employees and GenAI systems (Ogolla et al., 2020; Brynjolfsson & McAfee, 2014; Daugherty & Wilson, 2018).

In line with the socio-technical TOP framework and based on the AI4KM survey findings, the following table summarises the key barriers to GenAI integration in KM. Each identified barrier is mapped to the corresponding TOP dimension and paired with specific recommended actions and their anticipated impacts (see Table 1). The recommendations are intended to support organisations in systematically addressing technological, organisational, and people-related challenges, thereby creating the conditions for a responsible, sustainable, and human-centred deployment of GenAI in KM contexts.

Table 1: Actionable Recommendations along the TOP Dimensions

TOP Dimension	Barrier	Recommended Action	Expected Impact
Technology	Poor data quality and availability	Establish structured processes for data cleansing and maintenance; enrich datasets through synthetic data generation where needed	Higher reliability and performance of GenAI systems
	Integration challenges with existing IT infrastructures	Build modular, scalable, and interoperable GenAI architectures with early focus on interfaces, data security, and scalability	Seamless integration and scalability of GenAI solutions
Organisation	Lack of a company-specific AI strategy	Develop a coherent GenAI strategy linked to KM and business objectives	Strategic alignment of GenAI initiatives with organisational goals

TOP Dimension	Barrier	Recommended Action	Expected Impact
	Legal and ethical uncertainties	Create clear compliance frameworks for data usage and content generation; define ethical principles (e.g., fairness, transparency) for GenAI use	Reduced legal risks; enhanced organisational trust and ethical integrity
	Resource bottlenecks	Plan and secure interdisciplinary expertise and financial resources early	Feasibility and sustainability of GenAI implementation projects
People	Skills gaps regarding GenAI usage	Launch targeted training programmes on AI literacy, media competence, and prompt engineering with practical learning scenarios	Increased employee capabilities and confident GenAI tool use
	Employee resistance to GenAI adoption	Implement structured change management initiatives with transparent communication and participative formats	Higher acceptance, reduced resistance, strengthened collaboration culture
	Lack of a human-machine collaboration culture	Establish augmentation as the guiding principle for human-machine interaction, promoting collaborative and complementary working models	Enhanced creative collaboration and meaningful division of tasks between humans and GenAI

The overview illustrates that successful GenAI integration into KM requires coordinated interventions across all three TOP dimensions. While technological readiness remains crucial, strategic governance structures, legal and ethical safeguards, competence development, and a culture of human-machine collaboration are equally important for achieving long-term effectiveness and organisational acceptance of GenAI-supported knowledge systems.

5. Conclusion and Outlook

GenAI offers unprecedented opportunities for transforming KM, especially for SMEs with limited resources. By automating content generation, enhancing knowledge structuring, and improving information retrieval, GenAI technologies can help SMEs overcome traditional challenges related to scalability, knowledge retention, and accessibility.

The results of the AI4KM survey show that companies are well aware of the potential of GenAI for enhancing their knowledge processes. High expectations were recorded for tasks such as the reuse of existing knowledge, the structuring of data repositories, and the acceleration of internal knowledge flows. However, the practical implementation of GenAI in KM remains hesitant. Many organisations are still in pilot stages, with limited operational experience, and only a small share has developed strategic, large-scale initiatives for GenAI integration. The analysis of barriers confirms that technology is only part of the equation. In addition to technical obstacles such as data quality and IT integration, organisational challenges (e.g., lack of AI strategies, insufficient resource planning) and human factors (e.g., skills gaps, resistance to change) present significant hurdles. These findings underscore the necessity of adopting a comprehensive, socio-technical perspective when implementing GenAI in KM.

The TOP framework (Technology – Organisation – People) developed in this study provides a structured orientation for addressing these challenges. It highlights that successful and sustainable GenAI integration requires balanced attention to technological infrastructures, organisational strategies, and human competencies alike. By systematically addressing these three dimensions, organisations can better manage the complexity of GenAI adoption and enhance the chances of achieving meaningful improvements in knowledge practices.

This paper contributes to the discourse on AI in KM by proposing an empirically grounded socio-technical framework, that offers practitioners actionable guidance to overcome implementation barriers and align AI with business goals. By combining theoretical insight and managerial relevance, the study strengthens the link between academic research and organisational application.

Future research should focus on systematically operationalising the individual dimensions of the proposed framework across diverse organisational contexts. This entails developing concrete tools, methodologies, and support mechanisms to translate the elements of *Technology*, *Organisation*, and *People* into practical, context-sensitive interventions. A key initiative in this regard could be the development of a GenAI-specific readiness assessment (AI-Readiness-Check). Based on the TOP framework, such an instrument could help organisations assess their current level of preparedness for GenAI-supported KM initiatives, identify gaps in their technological, organisational, and human capabilities, and prioritise actions accordingly. A tailored readiness assessment would offer a valuable starting point for companies aiming to move from experimentation to systematic, large-scale GenAI integration. Overall, GenAI holds immense promise for reshaping KM. However, its full potential can only be realised through holistic, well-coordinated approaches that bridge technology, organisation, and people.

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