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CHALLENGES OF APPLYING GENERATIVE AI IN KNOWLEDGE MANAGEMENT: INSIGHTS FROM A SYSTEMATIC LITERATURE REVIEW

Introduction

In recent decades, with the emerge of the digital era, we have witnessed an unprecedented transformation in the way knowledge is created, stored, and used in organizations. This era is characterized not only by a rapid increase in available data, but also by the evolution of tools and technology for processing and analyzing this data [Alavi, Leidner, Mousavi, 2024]. A pivotal moment is the arrival of GenAI which, by using advanced machine learning algorithms and natural language processing, can generate new content, respond to complex queries, create realistic images, and even compose music [Korzynski et al., 2023].

Scholars are increasingly discussing the use of GenAI in different business domains and the potential challenges arising from its application. However, the specific implications of GenAI for knowledge management (KM) systems and processes remain underexplored. While there is growing interest in risks related to GenAI in organizational contexts, a clear research gap exists concerning how this technology affects the acquisition, validation, sharing, and storage of knowledge within organizations [Naqbi, Bahroun, Ahmed, 2024]. This lack of focused attention is particularly significant given the central role that knowledge management plays in innovation, learning, and strategic decision-making.

In the context of the knowledge economy, where information is considered as a key resource, the role of KM is evolving to become the core of strategic thinking

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in organizations [Jashapara, 2011]. Knowledge management, traditionally focused on gathering, organizing, and sharing knowledge to improve efficiency and foster innovation, must now adapt to the new challenges presented by GenAI [Benbya, Strich, Tamm, 2024]. On the one hand, integrating AI with KM systems can significantly accelerate decision-making processes, personalize tools, and enhance an organization's innovation capabilities [Korzynski et al., 2023]. On the other hand, the rapid development of AI and its generative capabilities raise concerns about reliability, data security, and ethical aspects of knowledge automation [Wach et al., 2023].

Despite the widespread popularity of GenAI tools in business, most existing studies rarely link these implementations directly to structured KM frameworks. As a result, there is insufficient academic insight into how GenAI disrupts or enhances core KM principles. Addressing this gap is crucial for both researchers and practitioners seeking to understand how to best leverage these emerging technologies to gain a competitive advantage [Wach et al., 2023, Quan et al., 2023, Stoykova, Shakev, 2023].

Taking these concerns into account, a deeper understanding of the challenges emerging from the implementation of GenAI into KM practices seems to be crucial. Therefore, the aim of this research is to identify and categorize the key challenges associated with using GenAI in the context of KM. By conducting a systematic literature review, this study seeks to map current academic discussions, highlight emerging problem areas, and propose directions for future research.

The article begins with a theoretical introduction to KM and GenAI, laying the foundation for the discussion that follows. Then, through a systematic literature review, existing research in this field examining the influence of GenAI on KM is analyzed. This is followed by a review of the challenges that organizations may face when implementing GenAI. The final section presents a discussion and recommendations for future research, aiming to support researchers and practitioners in navigating this fast-evolving area.

2. Literature review

2.1. Knowledge management

KM, as both a scientific discipline and a management practice, has evolved over the years to become a key element in the operation of modern organizations. As early as the 1990s, Peter Drucker [1992] drew attention to the transformation of society into a knowledge society, in which knowledge – rather than traditional resources such as capital, labor, or land – becomes the most important asset of an organization. In this context, KM emerges as an essential process for managing this key resource. The variety of definitions and approaches to KM is due to its interdisciplinary nature and its close relationship with other fields, such as information management. Jashapara [2011] notes that while KM has its roots in various disciplines, it is sometimes confused with information management, making it challenging to define the field precisely. Different researchers approach the topic of KM from diverse perspectives, leading to a multiplicity of definitions and frameworks. Swan, Scarborough and Preston [1999] emphasize the human aspect of KM, considering it as the process of creating, acquiring, capturing, sharing, and using knowledge to improve organizational performance and support learning processes. Mertins, Heisig and Vorbeck [2000] highlight the importance of information management systems, defining KM as the use of methods and tools to promote knowledge throughout key organizational processes in a holistic manner. Newell, Robertson, Scarbrough, and Swan [2009] focus on strategy, defining KM as a set of activities aimed at improving the use of knowledge within an organization to ensure continuous innovation in a dynamic and rapidly changing environment. As Jashapara [2011] points out, KM encompasses several dimensions – such as strategy, organizational culture, organizational learning, and systems and technology – highlighting its complex and multifaceted nature.

2.2. GenAI

GenAI is the subject of intense research in computer science, defining itself as a field concerned with the fully automated construction of intelligence [van der Zant, Kouw, Schomaker, 2013]. It is a complex machine learning system that relies on training on large datasets, including text, images, videos, audio, or a combination of all [Accenture, 2023]. With this ability to process and generate multiple forms of content, GenAI creates new possibilities for knowledge creation and distribution. Chatbots, such as ChatGPT, use large language models trained on massive amounts of data from the Internet and other sources. They generate responses to given commands (prompts) using statistical inferences learned during training [Dempsey, 2023]. In the early stages of development, these systems focused on generating textual content. However, technological advances have enabled them to process and generate other types of content beyond text as well [García-Peñalvo, Llorens-Largo, Vidal, 2024]. Over time, GenAI tools have gained prominence, acquiring the ability to create not only text but also images, sounds, and videos, indicating their growing versatility and application potential [OpenAI, 2024]. With these advances, GenAI is beginning to play a key role in fields ranging from education and entertainment to business or medicine.

2.3. GenAI in the context of KM

Technology plays a key role in the entire KM process, being not only a tool that facilitates the flow and availability of information, but also a catalyst for new forms of collaboration and knowledge sharing within the organization. The use of these modern technologies enables not only faster and more efficient processing of large amounts of data but also supports learning and innovation by facilitating access to expertise, enabling personalization of content, and promoting interdisciplinary knowledge connections [Milton, Lambe, 2020]. In this context, the prospect of implementing GenAI appears highly promising.

2.4. Literature review process and methodology

This study adopts a systematic literature review (SLR) approach based on methodology proposed by Webster and Watson [2002]. As emphasized in their work, systematic reviews are essential for theory building, clarifying constructs, and charting new research directions – especially in emerging research areas. Since the intersection between GenAI and KM remains relatively underexplored, the goal of this review is not only to summarize the existing body of knowledge, but also to identify, categorize, and map key research themes and associated challenges. This SLR aims to highlight conceptual gaps that can serve as the basis for future model development, as the small number of directly relevant articles reflects an emerging research field of inquiry rather than a fully developed area of study.

The database search took place from February 1 to 10, 2024, using five academic databases widely recognized for their scope and relevance in the fields of management, technology, and information systems: Scopus, Web of Science, EBSCO, ProQuest, and Emerald Insight. Search terms were constructed using keywords: "Knowledge management" AND "Generative AI". To account for the diversity of terminology related to generative AI, the terms "Generative Artificial Intelligence" and "Large Language Model" were used in addition to the phrase "Generative AI," which are often used interchangeably in scientific literature.

The phrase "knowledge management" was selected as the fundamental keyword due to its well-established status as structured domain in both management studies and information system research. On the other hand, to capture the evolving and often inconsistent associated with GenAI, the search included not only "Generative AI", but also "Generative Artificial Intelligence" and "Large Language Models" (LLM). This combination was based on a review of resent academic publications, which frequently use these terms interchangeably despite subtle technical differences. Considering short and extended forms of GenAI terminology was intended to maximize the number of potential results without any significant loss for precision. This approach ensured that relevant research papers were not excluded due to variations in keyword usage.. What is more, the decision to include the term “large language model” reflects the dominance of LLMs, such as ChatGPT or Gemini, in the context of using GenAI in organizations.

To ensure adequacy and credibility of selected papers, predefined inclusion and exclusion criteria were established. The inclusion criteria required that the research be published in peer-reviewed journals, written in English, and clearly linked to the relationship between GenAI and KM – either directly or within the organizational context. Simultaneously, the exclusion criteria eliminated non-academic sources, such as information papers, opinions, as well as studies discussing artificial intelligence in general without reference to generative capabilities. Additionally, research that did not address either the theory or practice of KM was also excluded from the final selection.

Among the databases, Scopus had the largest share, presenting 434 records. However, it should be noted, that despite the use of varied search terms and databases, many results were duplicated – both across databases within the same database when different terms for generative AI were used. This indicates a significant thematic overlap in the literature, suggesting that the actual number of unique and relevant sources is substantially lower than the initial 714 records.

The filtering process was divided into three phases, conducted by a single reviewer:
1. Examination of article titles to exclude clearly irrelevant papers.
2. Evaluation of abstracts to assess their alignment with the topic of GenAI and KM.
3. Full-text analysis in cases deemed ambiguous or borderline.

Finally, after careful review and evaluation, 14 articles were selected that focus directly or indirectly on the role of generative artificial intelligence in the field of knowledge management. These selected papers provide a solid foundation for further consideration and reflection, enabling a deeper understanding of the potential that generative artificial intelligence offers for knowledge management processes, as well as the challenges it presents.

3. Challenges connected to GenAI in knowledge management – research results

Seventeen potential challenges in the context of GenAI and KM were identified. These challenges were organized into four thematic clusters: technological and functional limitations, trust and social acceptance, organizational and cultural impact, and legal or strategic risks. This categorization enables a more structured understanding of how GenAI affects various dimensions of knowledge management. GenAI tools such as ChatGPT represent a breakthrough in the way organizations collect, process, and use knowledge. These solutions offer promising prospects for KM by enabling the automation and streamlining of many processes that previously required intensive human involvement. Nevertheless, as Wach et al. [2023] point out, the advent of GenAI – while accompanied by great expectations – is not without challenges. The number of concerns, limitations, and unresolved issues is steadily increasing.

3.1. Technological and functional limitations of GenAI

The generation of responses by LLMs is characterized by a certain degree of randomness, meaning there is no guarantee that the output will always be completely correct. In industries, where a high level of precision and rigor is required, knowledge-based question-answering systems (KBQA) need to use semantic query analysis to ensure that answers generated from unstructured or semi-structured databases are reliable [Hu, Zhang, Zhang, 2023]. One major risk associated with GenAI is the phenomenon known as *hallucination* – the generation of information that is not grounded, often resulting from incomplete, inadequate, or biased training data [Ghimire, Kim, Acharya, 2024]. Over-reliance on AI-generated responses without verification can lead organizations to use false, inaccurate, or even falsified data [Alavi, Leidner, Mousavi, 2024]. Therefore, organizations should implement data verification procedures to ensure accuracy and adapt GenAI tools to support the reliable presentation of information during their use. It should also be emphasized that OpenAI, the developer of one of the most popular GenAI's services, has acknowledged that ChatGPT can create content that is convincing but factually incorrect [OpenAI, 2023].

The inaccuracy of data presented by LLMs is a significant challenge, which becomes even more problematic when users lack expertise in each domain. In such situations, there is an increased risk of generating entirely fictitious or inaccurate information. These deficiencies may omit key factors, which can negatively affect the success of the project at hand [Ghimire, Kim, Acharya, 2024].

Bias in GenAI is a significant challenge highlighted by Ferrara [2023]. This problem can arise from various factors, such as the nature of the data on which the model is trained, the algorithms used in the learning process, the terminology used to describe the datasets, the target user group, and decisions made by the organizations developing the models. Referring to previous research, Ferrara [2023], emphasizes that bias can manifest in multiple areas, including demographics, politics, and culture. This may potentially affect the reliability of data presented in the KM process. To reduce the risk of bias, Wach et al. [2023] suggest implementing measures such as regular model audits, re-training with revised datasets, involving diverse AI development teams, and applying a human-in-the-loop approach, where human intervention and oversight play a key role in monitoring AI performance. These measures aim to ensure greater objectivity and fairness in AI-generated content, thereby enhancing the quality of KM in organizations.

The introduction of GenAI into organizations' KM processes is changing the dynamics of control over data quality and relevance. In traditional systems, organizations had direct control over what information was considered important and how it was processed and used. In contrast, in the context of GenAI, where models are trained on broad data sets from a variety of sources, this control becomes less direct and more complex [Alavi, Leidner, Mousavi, 2024]. Adapting GenAI models to specific organizational needs and contexts can be a challenge, due to the vastness and diversity of the data on which these models are trained. This raises questions about the effectiveness of such systems in assessing the quality and relevancy of knowledge extracted from organizational members. Being able to tailor GenAI to organization's specific data quality requirements and standards requires time, resources and expertise, which can be difficult, time-consuming and expensive. One solution to this problem may be to train GenAI models on specially prepared, pre-validated datasets that reflect the specifics and needs of a given organization. Such an approach increases the reliability and usefulness of AI-generated answers, as the model is "sensitive" to the context and requirements specific to the organization [Wach et al., 2023]. To effectively implement GenAI in KM processes, organizations must therefore not only adapt technologies to their needs but also develop data management strategies that ensure the high quality and security of the information processed by these systems.

Despite continued advances in GenAI, technology can still face difficulties in accurately understanding context, project nuances, industry specifics and legal issues. Thus, a deep understanding of the organization's current situation, market environment, and historical factors affecting operations at the operational level becomes crucial [Benbya, Strich, Tamm, 2024], yet AI is not always able to adequately process such information. In specific sectors, such as construction, it can be a challenge to structure and properly combine complex data from diverse sources. Appropriate analysis and processing of this information requires GenAI to have not only advanced technical capabilities but also the ability to interpret complex data relationships [Ghimire, Kim, Acharya, 2024].

Another challenge is the risk of relying on outdated models that no longer reflect current trends and market needs. This can lead to stagnation and hinder innovation processes within the organization. Benbya, Strich, and Tamm [2024] emphasize that GenAI's inadequate use of historical data may result in actions that not only fail to deliver the expected results but can also work against the organization, reversing intended outcomes and slowing adaptation to changing realities.

3.2. Trust, acceptance, and social factors

Technology adaptation is the foundation for effective implementation of artificial intelligence in organizations, including within the sphere of KM. An important factor influencing the success of such adaptation is the attitude of users toward new technologies. Studies indicate generational differences in the perception and willingness to use innovative solutions such as virtual advisors. Younger users show significantly more enthusiasm and openness to using these tools compared to older generations [Korzynski et al., 2023]. In addition, trust in GenAI technology is crucial, as it directly affects its adoption and use. Analyses show that there is a clear correlation between users' trust and their willingness to use tools such as ChatGPT. Therefore, when designing systems based on GenAI, such as chatbots, it is important for companies to focus on building trust and transparency from the early stage of development [Choudhury, Shamszare, 2023].

Transparency of the acquired data and its sources is an important aspect affecting the reliability of GenAI. This is particularly important when the tool is external and not created specifically for a given organization. A lack of transparency in these areas can undermine users' confidence in AI-generated content, which is essential for the effective use of these technologies in KM [Nazeer et al., 2023].

Over-reliance on GenAI can lead to employees neglecting the process of acquiring knowledge for future projects, instead depending on repeatedly retrieving information from external sources rather than developing their own expertise (i.e., internalization). Such reliance on GenAI can also affect the decline in creativity among employees [Alavi, Leidner, Mousavi, 2024]. Over-reliance on GenAI technologies can also result in the loss of valuable human input in the process of dealing with complex problems and responding to new challenges, which negatively impacts an organization's ability to innovate and adapt [Benbya, Strich, Tamm, 2024]. In addition, users often do not have a full understanding of the mechanisms of GenAI tools and, without critical evaluation, may rely on information that does not actually exist [Nazeer et al., 2023]. In this context, the challenge of using GenAI in the KM process is the issue of determining responsibility for the decisions made. When decisions are based on data extracted using GenAI, there is the problem of identifying who is responsible for those choices – whether or not it is the person who decided to use the AI-generated data [Benbya, Strich, Tamm, 2024]. Addressing this issue is key to ensuring clarity in decision-making and avoiding conflicts over responsibility, which can be especially important in situations where decisions based on AI data lead to unexpected or negative consequences.

The acceptance and willingness of users to use GenAI can significantly affect an organization's labor productivity. However, employees' perception of AI will play a key role in its successful implementation. There is a risk that workers may be skeptical, concerned that GenAI could pose a threat to their positions by delivering better outcomes than human labor. This may lead to a perceived devaluation of their work [Alavi, Leidner, Mousavi, 2024]. Additionally, reluctance to use GenAI may be reinforced by negative experiences involving erroneous or misleading information generated by AI. Such instances may discourage users from continuing to use these technologies, undermining their confidence in the reliability and usefulness of GenAI [Nazeer et al., 2023].

GenAI affects not only employees or employers but also customers. There are many benefits to using this technology in customer service; however, the lack of a human element in this interaction can be problematic, negatively affecting customers' perception of the brand. Xing, Yu, Zhang and Zheng [2023] emphasize that despite the effectiveness of GenAI, the lack of direct human contact may discourage both potential and existing customers. A human presence in customer service often translates into greater empathy and the ability to resolve complex issues that may lie beyond the scope of automated responses. Wach et al. [2023] recommend regular monitoring of AI-generated responses to identify potential errors and inaccuracies. Such verification allows for continuous improvement of GenAI models, ensuring that the support provided is as relevant and accurate as possible. This is key to maintaining high-quality customer service and building positive relationships with service recipients.

3.3. Organizational and cultural impact

Implementing GenAI in KM processes brings a significant change in the way of creating, storing and using knowledge. Traditional organizations had full control over these processes, including access to specific areas of knowledge [Alavi, Leidner, Mousavi, 2024]. The introduction of GenAI poses new challenges related to access to data and limitations on the answers provided by artificial intelligence, raising questions about the technical feasibility of implementing such solutions and their impact on the quality of the answers generated by AI. These problems become further complicated when data security risks are considered. Simple security measures may not be sufficient, due to the potential vulnerability of GenAI systems to social engineering and manipulation, just as with humans, which can lead to unauthorized disclosure of data [Benbya, Strich, Tamm, 2024]. The problem can be more complicated if an organization chooses to use GenAI systems that have not been tailored specifically to its unique needs and requirements [Renuad et al., 2023]. Sending sensitive data to external GenAI tools for transformation, such as to create reports, runs the risk of disclosing this information [Nazeer et al., 2023].

Over-reliance on GenAI can lead to a reduction in human interaction, both within and between company departments. The result could be a weakening of organizational communication, as the natural collaboration and share of experiences among employees will be reduced. The consequence of such a situation is fewer opportunities to establish relationships and get to know new people and departments within the company [Alavi, Leidner, Mousavi, 2024]. In organizations that choose to make heavy use of GenAI, there may be a tendency to marginalize traditional methods of knowledge sharing among employees, which in turn will negatively affect the culture of knowledge sharing and knowledge-based collaboration.

The dynamic development of AI is having an impact on organizational structures and work processes, for both employers and employees. The introduction of GenAI into daily operations can lead to a redefinition of job roles and, in some cases, job cuts due to the automation of tasks that were previously performed by humans [Morandini et al., 2023]. To effectively adapt to these changes, organizations must develop strategies to develop and modify the competencies of their employees.

Effective use of LLMs in daily work requires users not only to have a basic knowledge of how AI works, but also to have certain skills and thorough preparation. This understanding of the mechanisms of operation and the potential opportunities offered by GenAI will enable experts from various industries to maximize the benefits of its use [Ghimire, Kim, Acharya, 2024]. Adequate user training is a key element in the effective implementation of GenAI in organizations. Lack of such training can not only prevent expected productivity gains, but lead to a decline [Alavi, Leidner, Mousavi, 2024].

3.4. Legal issues, and strategic risks

Benbya, Strich, and Tamm [2024] highlight the copyright and ownership issues surrounding AI-generated content, as previously pointed out by researchers such as Eshraghian [2020], Avrahami and Tamir [2021], and Smits and Borghuis [2022]. There is considerable ambiguity regarding how the creator and owner of AI-generated content should be classified, which poses legal challenges in defining authorship and intellectual property in the context of generative technologies. This raises the need for new guidelines and regulations that address these issues with clarity and precision.

The final identified challenge regarding the use of GenAI in the KM process is the cost of implementation GenAI within organization. The potential expense can be a barrier for smaller organizations and could provide an advantage to larger ones with higher budgets for such investment [Wach et al., 2023]. Beyond the implementation process, there remains a need to maintain, train, and ensure the reliability of the answers provided by GenAI, which also requires a substantial financial outlay [Ghimire, Kim, Acharya, 2024]. Limited access to this technology may result in reduced competition, and innovation.

4. Discussion

4.1. Opportunities and risks of using GenAI in knowledge management

GenAI offers high automation possibilities, personalization, and scaling of knowledge management processes. Its abilities to generate, structure and search for information in real time may significantly enhance organizational learning, decision-making, and knowledge sharing. However, these advantages are associated with risk. The results of this research show that GenAI introduces several challenges, including hallucinations, outdated information, biases, and a lack of source transparency. These limitations raise concerns about the reliability of generated content and highlight the need for validation mechanisms and human oversight. Identifying potential risks areas will enable organizations to mitigate problems and harmful outcomes by not only redesigning internal processes but also adapting certain management models.

4.2. Bias, trust, and the reliability of GenAI

Baias in the results generated by AI – stemming from trainings data, model architecture, or user queries – poses a serious challenge to the credibility of the knowledge. As Ferrara [2023] indicates, demographic, political, or cultural biases embedded in LLMs may distort organizational knowledge, reinforce existing inequities, or lead to misleading conclusions. Similarly, this research identifies trust as one of the key factors influencing the success of GenAI implementation. A lack of trust, caused by untransparent decision making processes, unpredictable outcomes, or misinformation may reduce employees' willingness to use GenAI in KM tasks.

Based on previous results, this research suggests that increasing data transparency, implementing protocols to limit biases, and promoting explainability are necessary to increase the credibility of GenAI. What is more, integrating a human-in-the-loop approach may help ensure that this technology serves as a supportive tool rather than dominating the field of KM.

4.3. Organizational implementation and user acceptance

The implementation of GenAI significantly changes the way the knowledge is accessed, verified, and shared within organizations. The findings show that over-reliance on GenAI can hinder the development of employees' skills, creativity, and cooperation. Reduced interpersonal interaction between employees may also weaken organizational culture and informal knowledge exchange, both of which are crucial for the transfer of tactic knowledge.

In addition, analysis shows that the adoption and acceptance of GenAI depend on factors such as, age, digital literacy level, and perceived usefulness. Concerns about job security and fears of being replaced by GenAI further complicate implementation. These observations are consistent with previous studies [e.g. Korzynski et al., 2023; Choudhury, Shamszare, 2023] and emphasize the need for trainings programs, change management strategies, and ethical guidelines tailored to different segments of the workforce.

4.4. Legal, psychological, and strategic implications

The results highlight that the aspects related to copyrights and intellectual property generated by GenAI remain underexplored. As noted by Benbya, Strich, and Tamm [2024], the lack of clear legal frameworks makes it difficult to assign responsibility, especially when the knowledge generated by AI leads to strategic decisions. The costs of implementation and maintenance may create inequities among organizations, as only some can afford GenAI systems. This, in turn, poses a risk of limiting the diffusion of innovation.

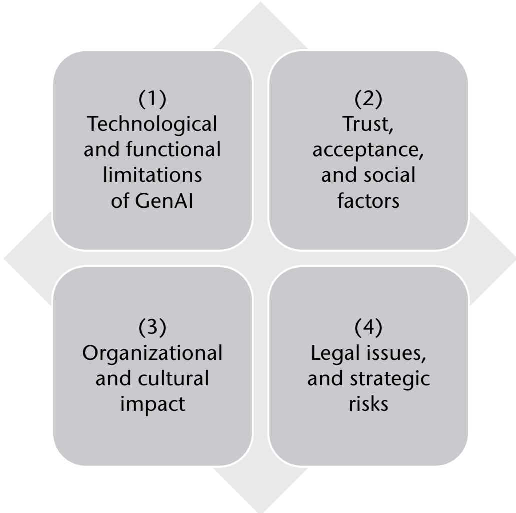
Psychological aspects such as the loss of human interaction in customer service or users' inability to verify GenAI-generated outputs, may influence on both – internal knowledge transfer and external customer perceptions. These observations support a statement that the key pillars for integrating KM modes and GenAI must align with legal provisions, ethical responsibility, and an understanding of user psychology.

4.5. Implications for KM and future research perspectives

Results of this research offer insights into possible improvements in KM within organizations by identifying and categorizing the main challenges related to the implementation of GenAI. These insights can be helpful for organizations aiming to embrace this technology in a way that improves, rather than disrupts, KM processes. From a theoretical point of view, the findings expand current understanding of GenAI in the context of KM. They underline the importance of contextual sensitivity, explainability and credibility – dimensions that are often underrepresented in technical discussions. In the case of KM, the findings suggest that traditional models of knowledge creation, validation, and sharing need to be revised in the light of dynamic and generative nature of AI. This calls for a shift from a static, document-centered approach to more adaptive and interactive systems in which AI is not merely a repository or search tool, but rather an active agent in shaping organizational knowledge.

Based on literature review and thematic clustering, a conceptual framework was developed to organize key areas in which GenAI impacts KM. This framework consists of four interconnected dimensions: (1) technological and functional limitations of GenAI, (2) trust, acceptance, and social factors, (3) organizational and cultural impact, (4) legal issues, and strategic risks.

Figure 1. Conceptual framework: Four key dimensions of GenAI challenges in KM



Source: own study.

These categories not only help to visualize where the challenges lie, but also how they interact across technical, human, organizational, and legal aspects. This model can serve as a point of reference for researchers as well as for practitioners aiming to develop holistic strategies for implementing GenAI into KM process.

5. Future research connected to GenAI and knowledge management

In the context of the rapidly expanding field of GenAI and its growing presence in business and organizational processes, it is becoming increasingly important to understand the challenges of its integration. As Alavi, Leidner, and Mousavi [2024] point out, GenAI's capabilities and versatility open new opportunities for companies. The growing interest in GenAI within the research community, especially following the rise in popularity of tools such as ChatGPT, underscores the need for further research in this area [Naqbi, Bahroun, Ahmed, 2024]. Accordingly, the following section of the article presents a table indicating potential further research directions related to the challenges associated with the use of GenAI. The issues included in table 1 are based on previous research studies and have been supplemented with the author's own concepts, providing a broader view of the future of GenAI-based KM research.

Table 1. Future research directions in knowledge management in the context of GenAI

Cluster	No.	Challenge	Potential research areas
Technological and functional limitations of GenAI	1.	Risk of hallucinations in GenAI outputs	▪ Consequences of using false or unverified data generated by GenAI
	2.	Inaccuracy of generated information	▪ Methods for verifying and validating AI-generated content ▪ Approaches to assess the reliability of GenAI output
	3.	Bias in large language models	▪ Techniques to reduce bias in LLM examining the impact of bias on the credibility of KM ▪ Development of human-in-the-loop models to mitigate bias
	4.	Lack of quality control over AI-generated content	▪ Challenges of quality assurance in GenAI ▪ Data management strategies to maintain information integrity ▪ Methods for evaluating user-provided knowledge inputs
	5.	Difficulty understanding context	▪ Sector-specific analysis of GenAI applications and the influence of organizational and market context on GenAI performance
	6.	Reliance on outdated model knowledge	▪ Analysis of methods to prevent innovation stagnation caused by outdated information
Trust, acceptance, and social factors	7.	Barriers to AI adoption	▪ Impact of AI on employee skills ▪ Role of soft skills in the AI adoption process ▪ Influence of generational differences on GenAI acceptance and usage ▪ Role of trust in organizational GenAI adoption ▪ Consequences of lacking trust in GenAI technologies on adoption and use
	8.	Lack of transparency in data and sources	▪ Influence of data transparency on KM effectiveness ▪ Assessing the role of data transparency in building trust in GenAI ▪ Determining the appropriate extent of external data usage in organizational contexts
	9.	Over-reliance on GenAI in organizational processes	▪ Investigating the impact of over-reliance on GenAI on employee skill development ▪ Assessing the impact of GenAI on creativity and innovation in organizations ▪ Analyzing the risks of over-reliance on GenAI and the issue of responsibility for decision based on AI-generated content
	10.	Low acceptance and trust in GenAI	▪ Assessing trust in chatbots across cultures ▪ Impact of GenAI use on knowledge externalization within organizations ▪ Influence of GenAI on employee motivations to share tacit knowledge ▪ Assessing employee fear of replacement by GenAI ▪ Analyzing the impact of misinformation generated by GenAI on user trust
	11.	Lack of human element in customer service	▪ Identifying risks for consumers in GenAI-supported customer service ▪ Exploring customer perceptions and expectations regarding GenAI on user trust

Cluster	No.	Challenge	Potential research areas
Organizational and cultural impact	12.	Risks of open access to sensitive data	▪ How organizations can address changes resulting from equal access to data, regardless of hierarchical roles ▪ Developing data protection strategies for KM processes using GenAI
	13.	Decline in collaboration and interpersonal interaction	▪ Analyzing the impact of GenAI on communication and collaboration dynamics ▪ Evaluating GenAI's influence on organizational culture, particularly knowledge sharing and teamwork ▪ Investigating the effect of GenAI on interpersonal relationship-building in the workplace
	14.	Organizational disruption due to GenAI	▪ Assessing the effects of GenAI on employment patterns and talent management strategies ▪ Examining the social consequences of job transformation due to GenAI implementation
	15.	Need for GenAI-related training and reskilling	▪ Developing policies for effective implementation of GenAI into organizational KM ▪ Identifying competencies required for working with GenAI and ways to acquire them a Assessing the impact of training programs on productivity in GenAI-supported environments
Legal issues, and strategic risks	16.	Legal uncertainty and intellectual property concerns	Developing new guidelines and regulatory frameworks for the use of GenAI in knowledge management
	17.	High implementation and maintenance costs	Analyzing the cost of implementing and maintaining GenAI-based in KM system Examining how limited access to GenAI technologies affects innovative potential and competitiveness

Source: original study, Morandini et al. [2023], Choudhury and Shamszare [2023], Benbya, Strich, and Tamm [2024], Alavi, Leidner, and Mousavi [2024], Ferrara [2023], Korzynski et al. [2023], Naqbi, Bahroun, and Ahmed [2024], Quan et al. [2023], Nazeer et al. [2023], Wach et al. [2023], Xing, Yu, Zhang, and Zheng [2023].

Conclusions

This study offers a comprehensive synthesis of current academic discourse on the use of GenAI in KM practices. Based on a systematic literature review, it identifies 17 key challenges, which are grouped into four main dimensions: technological and functional limitations of GenAI; trust, acceptance, and social factors; organizational and cultural impact; and legal issues, and strategic risks. The proposed conceptual framework illustrates how these dimensions influence the practical implementation of GenAI in KM systems.

Through thematic analysis, this research not only categorizes barriers but also examines their boarder implications. It shows that a successful integration of GenAI requires redesigning knowledge validation processes, investing in employee training, ensuring data transparency, and addressing legal as well as ethical concerns. These findings contribute to theory by mapping the research landscape and to practice by providing insights for organizations seeking to implement GenAI in their KM systems in an effective and responsible way.

Despite its contribution, this research has certain limitations. The final number of articles analyzed is limited, and the focus on English-language literature from selected academic databases may have affected the completeness of the data collected. Nevertheless, this study highlights potential directions for future exploration. It is also suggested that added value could be gained by unconventional sources such as social media platforms or industry discussion forums like LinkedIn, where they often share their experience openly.

In conclusion, this article underscores the significant potential of GenAI in the field of knowledge management, while also recognizing that the area remains largely unexplored and offers numerous opportunities for future research such as empirical studies, the development of conceptual models and design of implementation guidance. By extending the research out of academic scope, and incorporating the perspectives of practitioners, scholars may help bridge the gap between the potential of GenAI and its real-world application within knowledge-based environments.

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CHALLENGES OF APPLYING GENERATIVE AI IN KNOWLEDGE MANAGEMENT: INSIGHTS FROM A SYSTEMATIC LITERATURE REVIEW

Abstract

Rapid development of Generative Artificial Intelligence (GenAI) transforms the way in which organizations create, process and manage knowledge. As this technology is more and more integrated with business practices, understanding its impact on knowledge management (KM) is crucial. This paper presents a systematic literature review which aims at identification and analysis of key challenges associated with the use of GenAI in the context of KM. The review uncovers 17 challenges, which are clustered into four groups: technological and functional limitations of GenAI; trust, acceptance, and social factors; organizational and cultural impact; and legal issues, and strategic risks. The research also draws future research directions, including the need of evaluation of the long-term influence of GenAI on decision making, knowledge validation, user behavior, and organizational structures. The findings offer both theoretical insights as well as practical guidelines for researchers and practitioners, contributing to more structured and responsible approach towards integration of GenAI in knowledge-based environments.

Keywords: knowledge management, generative AI, large language models, systematic literature review

JEL Classification Codes: D83, O33, O32, L86

WYZWANIA WYKORZYSTANIA GENAI W ZARZĄDZANIU WIEDZĄ. WNIOSKI Z SYSTEMATYCZNEGO PRZEGLĄDU LITERATURY

Streszczenie

Nagły rozwój Generatywnej Sztucznej Inteligencji (GenAI) zmienia sposób, w jaki organizacje tworzą, przetwarzają oraz zarządzają wiedzą. Jako że ta technologia jest coraz bardziej zintegrowana z praktyką biznesową, zrozumienie implikacji jej wykorzystania na aspekt zarządzania wiedzą jest kluczowy. Niniejszy artykuł prezentuje systematyczny przegląd literatury, którego celem jest identyfikacja i analiza głównych wyzwań związanych z wykorzystaniem GenAI w procesie zarządzania wiedzą. Badanie wskazuje na 17 wyzwań, które zostały pogrupowane w cztery kategorie: ograniczenia technologiczne i funkcjonalne, zaufanie i akceptacja społeczna, transformacja organizacyjna i kulturowa oraz ryzyko strategiczne i prawne. Artykuł wskazuje także dalsze kierunki badań, uwzględniając takie aspekty jak długoterminowe wykorzystanie GenAI w procesie podejmowania decyzji, walidacji wiedzy, zachowania użytkownika, jak i struktur organizacyjnych. Wyniki badań dają teoretyczny ogląd oraz praktyczne wskazówki, nie tylko naukowcom zajmującym się dziedziną zarządzania wiedzą, ale także praktykom, przyczyniając się do bardziej ustrukturyzowanego i odpowiedzialnego podejścia integrowania GenAI w środowiskach bazujących na wykorzystaniu wiedzy.

Słowa kluczowe: zarządzanie wiedzą, generatywna sztuczna inteligencja, duże modele językowe, systematyczny przegląd literatury

Kody klasyfikacji JEL: D83, O33, O32, L86