Knowledge Management Systems in the age of Generative AI: Rethinking Knowledge Processes

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Abstract: The rapid advancement of artificial intelligence is fundamentally reshaping the architecture and logic of Knowledge Management Systems (KMS). Traditionally, KMS have been designed around repositories, taxonomies, and retrieval mechanisms for storing and redistributing explicit knowledge. However, in the AI era – particularly with the emergence of generative models – the role of KMS extends beyond storage and retrieval, towards active participation in knowledge processing and knowledge creation. This paper examines the evolution of KMS in the AI era through the lens of the SECI model (Socialisation, Externalisation, Combination, Internalization). It argues that AI tools can introduce a new operational dynamic within each SECI phase if properly addressed. In the externalisation process, AI systems can facilitate the conversion of tacit and loosely articulated insights into structured representations. In the combination phase, machine learning models may enable pattern discovery and synthesis across heterogeneous knowledge sources. During internalisation, AI-powered assistants can support experiential learning by contextualising and personalising information. Most importantly, socialisation can be augmented through collaborative AI-mediated environments that enhance collective intelligence, reshaping how shared meaning is constructed. The study critically explores how AI-enhanced KMS can transform from passive infrastructures to evolve into adaptive cognitive systems supporting KM. While AI may increase speed, scalability, and pattern recognition, it also introduces epistemological risks – such as bias propagation, over-automation, and erosion of human judgment. The paper discusses how organisations can mitigate these risks while developing resilient and adaptive KM practices. Adopting a conceptual and integrative approach, the research analyses current technological capabilities and conceptual KM frameworks. This research proposes an updated perspective on KMS as a hybrid socio-technical ecosystem. In such systems, AI tools do not replace human knowledge actors but extend their cognitive and organisational capacities. The paper concludes that the future of KMS lies not in more sophisticated repositories, but in intelligent systems capable of dynamic codification, contextual reasoning, and continuous organisational learning, redefining the balance between human and machine agency in organisational knowledge processes.

Keywords: Knowledge management, Knowledge management systems, AI tools

1. Introduction

Artificial Intelligence (AI), and more specifically Generative Artificial Intelligence (GenAI) and Large Language Models (LLMs), have emerged as transformative technological drivers capable of reshaping how organisations interact with knowledge. Unlike earlier forms of automation, primarily focused on efficiency and optimisation, GenAI introduces a qualitatively different paradigm - machines actively participate in the generation, interpretation, and transformation of meaningful content. These systems, built on transformer-based architectures, can produce human-like text, synthesising information across domains, and supporting complex cognitive tasks such as reasoning, summarisation, and decision support.

This evolution significantly expands the scope of human-machine interaction. LLMs and Retrieval-Augmented Generation (RAG) systems enable real-time knowledge creation, multilingual interaction, and personalised information retrieval, thereby redefining how knowledge is accessed and utilised within organisations (Pichman 2024) and knowledge work. Similarly, tools such as ChatGPT introduce unprecedented capabilities for knowledge generation and flow, positioning GenAI as a potential cornerstone of next-generation KMS (Sumbal and Amber 2024).

However, this transformation provokes many questions and concerns, and posing serious KM challenges in organisational settings. The ability of AI systems to generate content that is coherent but not necessarily accurate introduces the risk of "synthetic" or "artificial" knowledge - outputs that resemble validated knowledge but lack epistemic grounding (Brătianu and Bejinaru 2025). In addition, generated content or "artificial knowledge" by LLM and GenAI systems differs fundamentally from what human define as "knowledge" (Anshari et al. 2023). While AI content is generated through probabilistic models, it does not respond on basic philosophical mechanisms of justifications (the paradigm of "Justified True Belief"), neither support experiential or contextual understanding. This distinction raises critical concerns of organisations regarding AI content reliability, validation, responsibility and the potential propagation of bias or misinformation.

Moreover, the integration of GenAI into organisational processes introduces new dependencies beyond technical infrastructure. Organisations have to manage not only data and information, but also how the outputs of the AI systems may influence decision-making, customer service, learning, and operational workflows. The risk is not merely a technical failure, but epistemic disruption - where inaccurate or misleading AI-generated knowledge may propagate through systems and negatively impact business processes. This concern is amplified by the phenomenon of AI hallucinations, where systems produce plausible but incorrect information, potentially undermining trust and organisational effectiveness.

Consequently, the rise of GenAI results in the necessity of re-examination of the conceptual and operational foundations of KMS. Traditional KMS, designed primarily as knowledge repositories are increasingly inadequate in environments where knowledge is dynamically generated and continuously evolving. Moreover, GenAI has the potential to re-engineer knowledge-intensive processes, improving efficiency and accessibility, but also introducing challenges related to output quality, usability, and implementation complexity (Uddin et al. 2024).

The present research aims to respond on these challenges by investigating how generative AI can reshape knowledge processes within organisations. It seeks to move beyond the technological perspective of KMS and critically examine the implications of AI integration for knowledge creation, validation, and use. In doing so, it contributes to the ongoing discourse on the future of KMS in the age of generative AI.

2. Background

The rapid advancement of AI is significantly reshaping the operational logic of knowledge-intensive organisations, particularly in the context of KMS. While traditional KM technologies relied on knowledge repositories, knowledge maps and centralised knowledge documentation, recent shifts toward remote and hybrid work environments have exposed critical limitations in these approaches. Fragmented content in the knowledge repositories, delayed updates, and low user engagement have reduced the effectiveness of conventional KMS, creating a need for more adaptive and intelligent solutions. In this context, AI emerges not merely as a supporting tool but as a transformative force, capable of redefining how knowledge is generated, accessed, and utilised (Taherdoost and Madanchian 2023).

At the same time, the integration of AI into KM processes introduces new complexities. While typical KM initiatives focus on the development, transfer, storage, and evaluation of knowledge, they often fail to account for the dynamic and rapidly evolving capabilities of AI technologies (Coombs et al. 2020). This gap creates a misalignment between static knowledge infrastructures and increasingly dynamic knowledge processes. As a result, organisations must rethink how KMS are designed, moving toward models that can accommodate continuous learning and real-time adaptation.

The role of human actors also undergoes a significant transformation. Knowledge workers are required to develop new competencies to effectively collaborate with AI systems, while organisations must carefully balance automation with human oversight to maintain control over knowledge processes (Dăniloaia and Turturean 2024). This is particularly important given the reliance of AI systems on high-quality data. Issues related to data fragmentation and data silos, privacy constraints, and inconsistent data standards can significantly undermine the performance of AI models, ultimately affecting the reliability of knowledge outputs (Rezaei 2025).

Furthermore, the growing integration of machine learning into KMS highlights a broader shift toward automated knowledge processing. As organisations increasingly depend on data-driven decision-making, the activation of AI capabilities within KMS becomes essential for maintaining competitiveness and operational resilience (Anshari et al. 2023). However, this shift also raises critical questions regarding governance, validation, and the long-term implications of delegating knowledge functions to intelligent systems.

2.1 SECI Model as the Foundation of Knowledge Processes

The SECI model, introduced by Nonaka, remains one of the most influential frameworks for understanding knowledge creation within organisations. It conceptualises knowledge as a dynamic process involving four modes: socialisation, externalisation, combination, and internalisation. Central to this model is the role of the individual employee, whose interaction with both tacit and explicit knowledge drives organisational learning and innovation.

Despite its conceptual solidity, the SECI model was developed in a pre-AI context, in which knowledge processes were largely human-driven. Recent research has begun to explore how AI technologies interact with these processes. For instance, GenAI can support multiple SECI phases, particularly externalisation and internalisation, by enabling automated knowledge generation and personalised learning (Liccardo and Cerchione 2025).

However, they also highlight the ambiguous impact of AI on socialisation, where increased automation may weaken human interaction and critical thinking.

Similarly, new frameworks like SECI-MaP have emerged to bridge the gap between human insight and machine capability within a single system (Du Plessis and Britz 2025). Authors emphasise a symbiotic relationship between human and artificial agents, suggesting that knowledge creation may emerge from their combined interactions. While this perspective highlights the potential of AI-enhanced knowledge processes, it also raises questions about the extent to which machine-generated outputs can be considered genuine knowledge.

Further extending the SECI model, additional knowledge conversion modes are introduced, such as modelling, encoding, and verification (Hsu and Han 2023), resulting in a 9-square AI-based KM model. This expansion reflects the growing complexity of knowledge processes in the AI era, where machine learning and algorithmic interpretation play an increasingly central role.

2.2 KMS Evolution

KMS have traditionally been designed as infrastructures for storing, organising, and retrieving explicit knowledge. These systems rely on structured repositories, taxonomies, and document management practices, often treating knowledge as a static asset. However, this approach has been criticised for its inability to capture the dynamic and contextual nature of knowledge, particularly tacit knowledge embedded in human experience.

Recent developments indicate a shift toward more dynamic and process-oriented KMS. For example, Automated Documentation Management Systems (ADMS) (Georgiev et al. 2025) demonstrate how AI can transform static documentation into active components of business processes. These systems enable continuous updating, contextual adaptation, and integration with operational workflows, thereby enhancing the relevance and usability of organisational knowledge.

The integration of AI into KMS further extends these capabilities, proposing a knowledge-driven framework for AI-augmented business process management systems, emphasising explainability, human-AI collaboration, and dynamic adaptation (Georgiev et al. 2025). This highlights the importance of aligning AI capabilities with existing knowledge structures while ensuring transparency and user trust.

At the same time, the concept of AI-driven systems challenges traditional assumptions about knowledge within KMS (Brătianu and Bejinaru 2025). Artificial knowledge, generated by AI systems, is positioned as a complementary but distinct form of knowledge that differs fundamentally from human knowledge in its creation and validation processes. This distinction has significant implications for the design and governance of KMS, particularly for ensuring the reliability and integrity of knowledge outputs.

Despite the promising capabilities of AI-enhanced KMS, several challenges still remain. Organisations continue to face difficulties in integrating tacit and explicit knowledge, managing resistance to change, and measuring the impact of KM initiatives. These challenges are further compounded by the introduction of AI, facing new issues regarding data quality, system usability, and organisational readiness.

Moreover, while different studies demonstrate the potential of generative AI to enhance efficiency and decision-making (Uddin et al. 2024), they also underscore the importance of scalable frameworks and robust governance mechanisms. Without these, organisations risk implementing AI systems that are difficult to manage, interpret, and trust.

Overall, the literature indicates a clear transition from traditional, repository-based KMS toward more dynamic, AI-driven systems. However, this transition is accompanied by unresolved questions regarding the nature of knowledge in KMS, the role of human actors, and the risks associated with AI-generated outputs. These gaps highlight the need for a revised conceptual framework that integrates AI capabilities while preserving the epistemic integrity of organisational knowledge processes.

2.3 Research gap and Theoretical Positioning

Although prior studies examine the role of AI in KM and explore the integration of AI into SECI processes, most studies focus on technological capabilities and system functionality (Fteimi and Hopf 2021; Pichman 2024; Taherdoost and Madanchian 2023). Less attention has been paid to the epistemic implications of AI-generated knowledge and the changing role of validation, interpretation, and human oversight in AI-mediated knowledge processes. As a result, existing KM frameworks still largely conceptualise KMS as infrastructures that support knowledge processes, rather than as active socio-technical systems that participate in knowledge creation and transformation (Martino et al. 2025). This creates a theoretical gap in understanding how generative AI reshapes the logic of knowledge conversion, the nature of knowledge, and the role of human actors in knowledge validation processes.

This paper addresses this gap by developing a conceptual framework that explains how generative AI transforms SECI knowledge conversion processes and redefines the role of KMS from knowledge repositories to AI-mediated knowledge processing environments.

3. AI-Augmented Knowledge Management Systems (AIA-KMS)

The integration of GenAI transforms each phase of the SECI model by introducing automated and scalable mechanisms for knowledge conversion, while simultaneously increasing the need for human validation to ensure epistemic reliability. Across all phases, human verification is not merely a complementary activity but a necessary condition for maintaining the integrity of AI-mediated knowledge processes.

The unified analysis demonstrates that while AI enhances the efficiency and scalability of knowledge transformations, it also fundamentally alters their nature. Knowledge conversion is no longer a purely human-driven process but a hybrid interaction between probabilistic machine outputs and human judgment. This shift introduces a structural dependency on validation mechanisms, without which KMS risk transitioning from repositories of reliable knowledge into generators of plausible but unverified information.

3.1 AI-SECI Model

The AI-augmented SECI model illustrates how each phase (socialisation, externalisation, combination, and internalisation) is reconfigured through the integration of generative AI technologies (Figure 1).

- **In socialisation phase (tacit-to-tacit)**: AI systems support communication through summarisation, recommendation, and collaboration tools. While this enhances the scalability of knowledge sharing across distributed environments, it introduces a critical dependency on human actors to validate meaning and preserve contextual nuance. Without such intervention, tacit knowledge risks being reduced to oversimplified representations.
- **In externalisation phase (tacit-to-explicit)**: GenAI plays an active role by transforming unstructured insights into structured formats. This can cover automated document generation, meeting transcripts generation, schema mapping, and form population capabilities directly aligned with AI-driven knowledge extraction. However, this apparent efficiency masks a deeper issue: AI does not truly “capture” tacit knowledge but reconstructs it probabilistically. Human verification is therefore essential to ensure semantic accuracy and prevent the formalisation of misleading or incomplete representations.
- **In the combination phase (explicit-to-explicit)**: it is significantly expanded through AI-driven synthesis and pattern recognition. LLM and RAG systems enable the integration of heterogeneous knowledge sources, supporting advanced analytics, classification, and business intelligence. Yet, this phase is particularly vulnerable to hallucinations and opaque reasoning processes. The human role shifts toward epistemic validation, ensuring that generated connections between source data and generated knowledge insights are logically consistent and contextually relevant.
- **In the internalisation phase (explicit-to-tacit)**: AI enables personalised learning and decision support through adaptive assistants and contextual recommendations. This accelerates knowledge acquisition and onboarding but introduces risks of cognitive dependency and superficial understanding. Human agency remains critical, as individuals must interpret, challenge, and apply AI-generated insights within real-world contexts.

3.2 GenAI Core of the KMS

The conceptual model is further clarified by the diagram (fig.1.), which positions genAI as a central processing core that mediates between SECI processes and the operational KMS layer. Within this architecture, components such as LLMs, Generative Pre-trained Transformer (GPT), Retrieval-Augmented Generation (RAG), and virtual assistants/agents act as intermediaries that transform knowledge flows into actionable outputs. These outputs are then operationalised through four distinct categories of KMS technologies.

Enterprise Search and Discovery systems function as “finders,” enabling organisations to access knowledge distributed across multiple platforms without requiring data centralisation. By synthesising information from diverse sources, these systems enhance decision-making but depend heavily on the quality and consistency of underlying data. Their effectiveness is therefore contingent on both AI accuracy and human oversight in interpreting results.

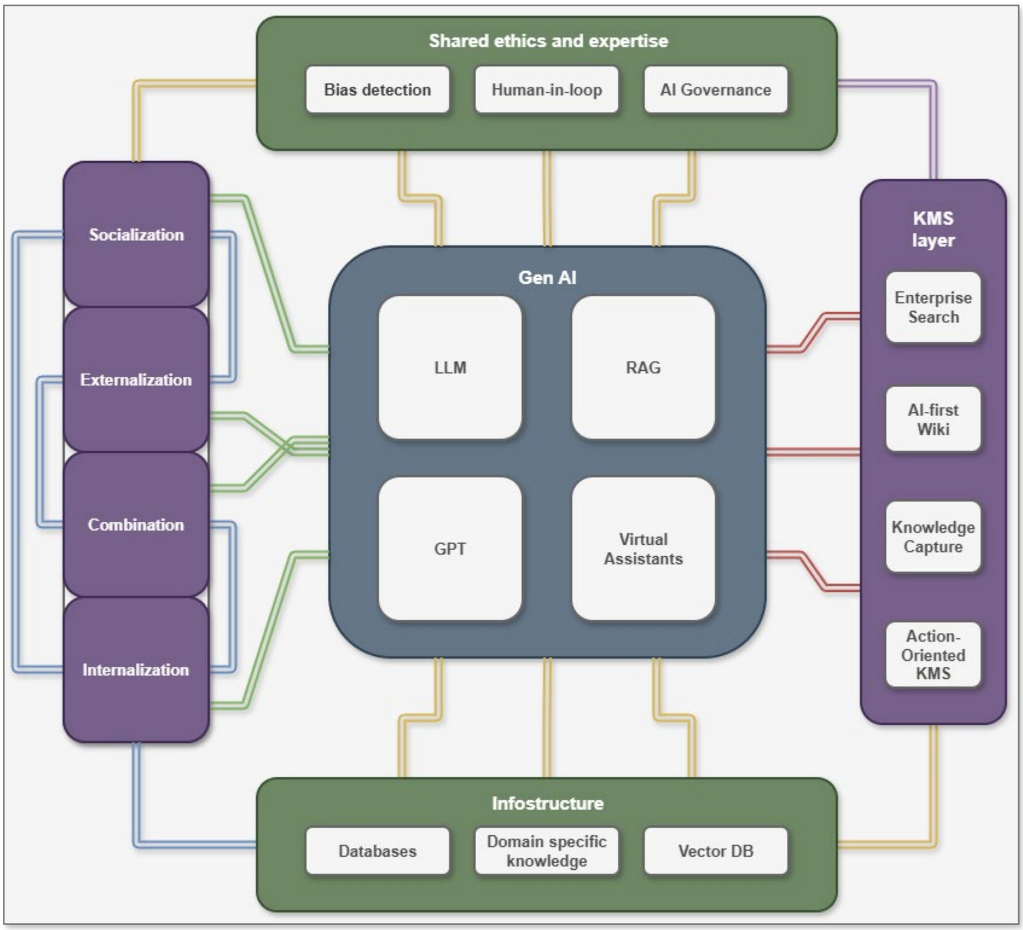

Figure 1: AI-augmented KMS model

- AI-first Wikis represent the “organisers” within the KMS ecosystem. Unlike traditional documentation systems, they actively maintain and refine knowledge through automated updates, summarisation, and conversational interfaces. This transforms documentation from a static repository into a dynamic, evolving knowledge base. However, the risk lies in the gradual accumulation of AI-generated content that may not be rigorously validated, reinforcing the need for continuous human curation.
- Automated Knowledge Capture tools address one of the most persistent challenges in knowledge management: the documentation gap. By converting conversations, meetings, and user actions into structured artefacts, these “recorders” significantly reduce the burden of manual documentation. Yet, their outputs are inherently dependent on interpretation, raising concerns about accuracy, completeness, and contextual fidelity.
- At the end, Action-Oriented Knowledge Assistants act as “doers,” directly leveraging organisational knowledge to perform tasks such as resolving support tickets or completing complex documentation. These systems mark a significant shift from knowledge access to knowledge execution. While they enhance efficiency and reduce administrative workload, they also introduce higher stakes, as errors in AI-generated actions can directly impact business processes.

Overall, the integration of these systems within the AI-augmented SECI framework demonstrates a fundamental transformation of KMS. KMS are no longer passive infrastructures for storing and retrieving information but active, AI-mediated environments that generate, transform, and apply knowledge. However, this transformation is inseparable from the need for robust human verification mechanisms. The balance between automation and control becomes the defining factor in ensuring that AI-driven knowledge processes remain reliable, interpretable, and aligned with organisational objectives.

4. Discussion

The findings of this paper suggest that the main challenge of AI-enabled knowledge management is not technological but epistemic, as organisations must increasingly manage the reliability, interpretation, and validation of AI-generated knowledge. The purpose of this paper was to explain how generative artificial intelligence transforms the functioning of KMS and the nature of organisational knowledge processes. The results indicate that artificial intelligence does not merely support knowledge management processes, but fundamentally transforms the logic of knowledge creation, transformation, and application. This is consistent with prior research suggesting that the emergence of AI transforms KMS from static knowledge repositories into dynamic and adaptive knowledge environments (Anshari et al. 2023; Coombs et al. 2020; Fteimi and Hopf 2021; Pichman 2024; Uddin et al. 2024).

4.1 The Changing Role of the KMS

One important finding of the study is that the role of KMS is changing: the focus is shifting from knowledge storage and retrieval towards knowledge processing and knowledge generation. GenAI systems are capable of creating new content, connecting different knowledge sources, and supporting decision-making, which means that KMS increasingly become active participants in organisational knowledge processes (Al Naqbi et al. 2024; Haefner et al. 2021; Sumbal and Amber 2024; Uddin et al. 2024). This shift also implies that knowledge can no longer be understood as a resource created exclusively by humans, but rather as the outcome of collaboration between human actors and artificial intelligence.

This perspective is consistent with studies that interpret knowledge creation as a human–machine collaborative process (Du Plessis and Britz 2025; Liccardo and Cerchione 2025; Parent-Rocheleau and Parker 2022). The AI-extended interpretation of the SECI model suggests that artificial intelligence appears in all phases of the knowledge conversion process; however, this does not reduce the role of humans but transforms it. The role of knowledge workers increasingly shifts towards interpreting, validating, and contextualising AI-generated knowledge (Dăniloaia and Turturean 2024; Morandini et al. 2023). Based on these findings, the SECI model should no longer be interpreted as a purely human knowledge conversion process, but as a hybrid human–AI knowledge conversion process in which artificial intelligence actively participates in knowledge externalisation, combination, and internalisation, while human actors increasingly take on roles related to interpretation, contextualisation, and validation.

The study also highlights that the application of GenAI introduces new risks into KMS. AI-generated content often appears coherent and reliable, yet it is produced by probabilistic models and may contain errors, biases, or inaccuracies. This means that one of the central issues of knowledge management becomes the validation and reliability of knowledge (Brătianu and Bejinaru 2025; Sumbal and Amber 2024). Other studies also emphasise that the implementation of AI-based Knowledge Management Systems is not only a technological issue but also a governance and organisational challenge, particularly in relation to ensuring the quality, reliability, and transparency of knowledge (Anshari et al. 2023; Braganza et al. 2021; Hsu and Han 2023).

The literature also suggests that the introduction of AI influences knowledge-sharing behaviour and organisational collaboration. In the absence of an appropriate organisational environment or trust, the introduction of AI may lead to knowledge hiding or resistance, which can reduce the effectiveness of Knowledge Management Systems (Li et al. 2025; Liu et al. 2025). This indicates that the successful operation of AI-based KMS requires not only technological development but also an appropriate organisational culture, leadership, and learning environment (Hu et al. 2025).

4.2 Theoretical and Practical Contributions

This paper makes three main theoretical contributions to the KMS literature. First, it extends the SECI model by conceptualising knowledge conversion as a hybrid human–AI process rather than a purely human-driven process. Second, it reconceptualises KMS as active, AI-mediated knowledge processing environments rather than passive knowledge repositories. Third, the paper introduces knowledge validation as a central organisational function in AI-enabled knowledge environments, thereby shifting the focus of knowledge management from knowledge storage to knowledge validation.

The theoretical contribution of this paper lies in reconceptualising KMS not simply as IT infrastructure but as hybrid socio-technical knowledge systems in which human and artificial intelligence jointly shape knowledge processes (Coombs et al. 2020; Martino et al. 2025). Based on the findings, it can be argued that the most important function of future KMS will not be knowledge storage but knowledge interpretation, validation, and application. Overall, the study suggests that the emergence of generative artificial intelligence does not simply represent a technological change in knowledge management, but requires a reconceptualisation of the nature of knowledge, knowledge creation, and the role of KMS. The key challenge of knowledge management in the age of generative AI is therefore no longer managing knowledge assets, but managing the reliability and validity of knowledge generated in hybrid human–AI knowledge processes.

5. Conclusion

This paper examined how GenAI technologies reshapes knowledge processes and the role of KMS in organisations. The paper argues that the integration of GenAI fundamentally transforms the logic of knowledge conversion by introducing hybrid human–AI knowledge processes across all phases of the SECI model. In this context, knowledge creation, transformation, and application can no longer be understood as purely human-driven activities, but rather as socio-technical processes emerging from the interaction between human judgement and probabilistic machine-generated outputs.

From a practical perspective, the findings suggest that organisations implementing AI-enabled Knowledge Management Systems should not focus solely on technological integration, but also on the development of knowledge validation mechanisms, human-in-the-loop processes, and governance structures that ensure the reliability and transparency of AI-generated knowledge. The effectiveness of AI-augmented Knowledge Management Systems therefore depends not only on technological capabilities, but also on organisational processes, managerial practices, and organisational culture that support responsible and interpretable knowledge use.

It is important to highlights several directions for future research. Further empirical studies are needed to examine how organisations implement knowledge validation mechanisms in AI-supported environments, how the roles and competencies of knowledge workers change in hybrid human–AI knowledge processes, and how AI-mediated knowledge processes influence organisational decision-making, learning, and performance. Future research may also explore the governance, ethical, and organisational implications of artificial knowledge and the long-term impact of AI on organisational knowledge ecosystems.

Overall, this paper argues that the central challenge of AI-enabled Knowledge Management is no longer knowledge storage, but knowledge validation. Understanding KMS as AI-mediated knowledge processing environments provides a new theoretical perspective for analysing knowledge processes in the age of generative artificial intelligence.

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Ethics Declaration. This study is based on a conceptual and literature-based analysis and does not involve human participants, personal data, or experimental procedures. Therefore, ethical approval was not required.

AI Declaration. AI tools were used in a limited capacity to support language refinement and editing. All conceptual development, analysis, and interpretation are the sole responsibility of the authors.

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