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A Generative AI-Driven Approach to Integrating the SECI Model for Knowledge-Based Systems

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Abstract−This study examines the potential role of Generative Artificial Intelligence (Gen-AI) in extending the Socialization, Externalization, Combination, and Internalization (SECI) model within knowledge management. Using a Systematic Literature Review (SLR) of studies published between 2024 and 2026, it maps the functions of technologies such as Large Language Models (LLMs), Retrieval-Augmented Generation (RAG), and Logic Augmented Generation (LAG) into Nonaka and Takeuchi's knowledge spiral. The findings indicate that Gen-AI can support knowledge processes such as retrieval, interpretation, structuring, and integration, which may contribute to more continuous and digitally mediated knowledge flows. Some reviewed studies report improvements in handling tacit and explicit knowledge; for example, a simulation-based study reports a tacit knowledge recall rate of up to 94.9%, although this result is derived from a specific experimental context and should not be generalized. The review also identifies challenges, including AI-generated inaccuracies, overreliance on automated systems, and data security concerns, highlighting the continued importance of human oversight. This study contributes a conceptual mapping of a Generative AI-based Knowledge Framework (GRAI) as an extension of the SECI model; however, this contribution remains theoretical and requires further empirical validation across organizational contexts.
Keywords: Generative Artificial Intelligence; Knowledge Management; SECI Model; Knowledge Conversion; Systematic Literature Review.

1. INTRODUCTION

Advances in information technology have brought Knowledge Management (KM) to a significant turning point. By 2026, the paradigm of Knowledge Management Systems (KMS) has shifted from static repositories toward more dynamic, AI-supported ecosystems. Traditional models that rely on manual processes to capture and disseminate knowledge are increasingly considered insufficient to cope with the rapid growth of digital information. This has prompted renewed attention toward adapting classical frameworks, particularly the SECI model (Socialization, Externalization, Combination, and Internalization), to remain relevant in contemporary digital environments. Generative Artificial Intelligence (Gen-AI) has been identified as a promising enabler in this context, with prior studies suggesting its potential to support knowledge creation, storage, retrieval, and application, as well as to enhance data analysis and decision-making processes [1].

However, existing research also indicates that the effectiveness of AI-driven KM systems depends on maintaining a balance between data-driven processes and human interaction. Overemphasis on technological solutions without sufficient consideration of human and social dimensions has been associated with challenges in digital transformation initiatives [2]. Despite these insights, there remains limited research that systematically examines how specific Generative AI technologies, such as Large Language Models, Retrieval-Augmented Generation, and Logic Augmented Generation, can be aligned with the SECI model to support knowledge conversion processes. In particular, the role of Gen-AI as an integrated digital knowledge infrastructure within the SECI framework has not been comprehensively conceptualized in the existing literature.

Recent developments indicate that chatbots based on Large Language Models are increasingly used beyond basic question–answering functions, supporting activities such as knowledge retrieval, interpretation, and documentation. In addition, technologies such as Retrieval-Augmented Generation and Logic Augmented Generation have been reported to assist in structuring and integrating knowledge across organizational contexts [3][4]. These developments suggest the potential for Generative AI to enhance knowledge flows within organizations, including those described in the SECI model. However, these contributions remain fragmented and have not yet been synthesized into a coherent conceptual framework.

Based on this background, this study addresses two main research questions. First, it examines how specific features of Generative Artificial Intelligence, including Large Language Models, Retrieval-Augmented Generation, and Logic Augmented Generation, may support each stage of the SECI model cycle, namely socialization, externalization, combination, and internalization. Second, it explores how Generative Artificial Intelligence, as a form of digital infrastructure, can contribute to addressing challenges in managing tacit and explicit knowledge in modern organizations.

Accordingly, this study aims to map the capabilities of Generative Artificial Intelligence within the SECI

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framework in order to identify potential points of efficiency in the knowledge management cycle. In addition, it seeks to analyze the role of Artificial Intelligence as a digital infrastructure that supports knowledge collaboration and innovation within organizational contexts.

This study contributes to the literature by providing a conceptual mapping of Generative Artificial Intelligence within the SECI model, offering an extension of the framework rather than proposing a fully developed or empirically validated model. The proposed perspective, referred to as a Generative AI-based Knowledge Framework (GRAI), is intended as a theoretical lens to better understand how AI technologies may support knowledge conversion processes. Practically, this research provides guidance for organizations in adopting AI as part of their knowledge management infrastructure, while emphasizing the importance of maintaining a balance between technological capabilities and human judgment.

2. RESEARCH METHODOLOGY

2.1 Research Design

This study adopts a Systematic Literature Review (SLR) approach to identify, evaluate, and synthesize existing research on the integration of Generative Artificial Intelligence (Gen-AI) within the SECI model. The SLR method enables a structured and transparent analysis of prior studies, ensuring methodological rigor and reproducibility. This approach is widely used to develop conceptual frameworks and synthesize fragmented knowledge across multiple sources [15].
The research is qualitative-descriptive in nature and focuses on developing a conceptual mapping of Gen-AI capabilities within the SECI framework, rather than producing empirically validated findings. The SECI model itself serves as a foundational framework for understanding knowledge conversion processes between tacit and explicit knowledge [5].

2.1.1 The Seci Model (Nonaka & Takeuchi)

The SECI model describes the process of knowledge creation through the dynamic interaction between tacit and explicit knowledge across four main phases. [5] assert that this model serves as a foundation for organizations to understand how individual experiences are transformed into structured organizational assets.

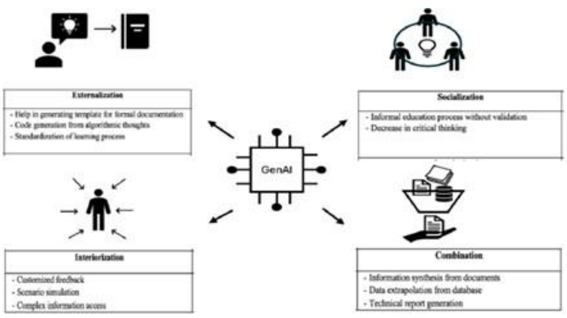

Fig 1. Gen AI on the SECI Model

1. Socialization
   The process of sharing tacit knowledge through social interaction, observation, and shared experiences without formal instruction.
2. Externalization
   The translation of tacit knowledge into concepts, metaphors, or explicit documents that can be communicated.
3. Combination
   The integration of various distinct elements of explicit knowledge into a broader and more systematic knowledge system.
4. Internalization
   The process by which explicit knowledge is understood and reabsorbed by the individual into new tacit knowledge or "learning by doing."

Based on the mapping [5], [7] the SECI model is no longer viewed as a slow, manual process but rather as a cognitive spiral whose relevance remains strong yet requires digital tools to achieve the scale and speed needed in the modern era.s

2.2.2 Generative AI in an Organizational Context

Generative AI (GenAI), particularly large language models (LLMs), are defined as a system capable of generating new, coherent content based on patterns from massive datasets. In organizational operations, AI serves

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as a "cognitive infrastructure" that not only stores but actively processes knowledge. [6] identifies five strategic roles of GenAI that support knowledge management:

1. Librarian
   Acts as a repository manager that facilitates instant access to information for organizational members.
2. Analyst
   Processes raw data or complex documents to generate summaries and strategic insights.
3. Coordinator
   Helps synchronize tasks and communication across teams to eliminate information silos.
4. Scribe
   Automates the documentation of discussions or raw ideas into structured formats (externalization phase).
5. Coach
   Acts as a personal development assistant providing personalized explanations to accelerate learning (internalization phase).

A synthesis of the views indicates that GenAI is not merely a tool, but rather a knowledge management infrastructure capable of automating knowledge-related administrative tasks so that humans can focus on high-level innovation [8].

2.2.3 The Evolution of Knowledge Management System (KMS)

The evolution of KMS reflects a shift from static data storage toward proactive and autonomous systems. Introduced the GRAI (Generative AI-based Knowledge Framework) as an evolution of SECI, where AI functions as the driving force in digital knowledge workflows [8].

1. Traditional Era
   KMS functions as a static digital library where users must manually search for information.
2. AI Agent Era
   KMS transforms into "Answer Engines" using Retrieval-Augmented Generation (RAG) technology. This system actively extracts information from organizational documents and delivers it directly to users in the form of contextual answers.
3. Human-AI Collaboration
   [7] emphasize that modern web-based systems enable interactive dialogues that accelerate the conversion of individuals' tacit knowledge into explicit organizational assets in real-time.

Drawing on the GRAI model [8] and the "Answer Engines" concept [3], today's KMS has evolved into an ecosystem of intelligent agents capable of autonomously synthesizing knowledge, thereby reducing the cognitive burden on humans in searching for and managing information.

2.2 Data Sources

The literature search was conducted across multiple academic databases, including ScienceDirect, Emerald Insight, Heliyon (Cell Press), and Google Scholar. These databases were selected to ensure comprehensive coverage of interdisciplinary research in knowledge management and artificial intelligence.
To ensure consistency and relevance, predefined keyword combinations were used in the search process, including:
1. "Generative Artificial Intelligence" AND "Knowledge Management"
2. "SECI Model" AND "Large Language Models"
3. "Retrieval-Augmented Generation" OR "Logic Augmented Generation" AND "Knowledge Creation"
4. "Digital Infrastructure" AND "Knowledge Management"

The search was limited to publications from 2024 to 2026 to capture recent developments in Generative AI technologies and their application in knowledge management systems.

2.3 Data Collection and Selection Techniques

The data collection and study selection process followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to ensure transparency and reproducibility [15]. The process consisted of four sequential stages: identification, screening, eligibility, and inclusion.

In the identification stage, articles were retrieved from selected databases (ScienceDirect, Emerald Insight, Heliyon, and Google Scholar) using predefined search strings. In the screening stage, titles and abstracts were reviewed to remove duplicate and irrelevant studies that did not align with the research focus on Generative AI and knowledge management.

During the eligibility stage, full-text articles were assessed to ensure that they discussed the SECI model, Generative AI technologies (e.g., LLM, RAG, LAG), or their application within knowledge management systems. Studies that did not meet these criteria were excluded.

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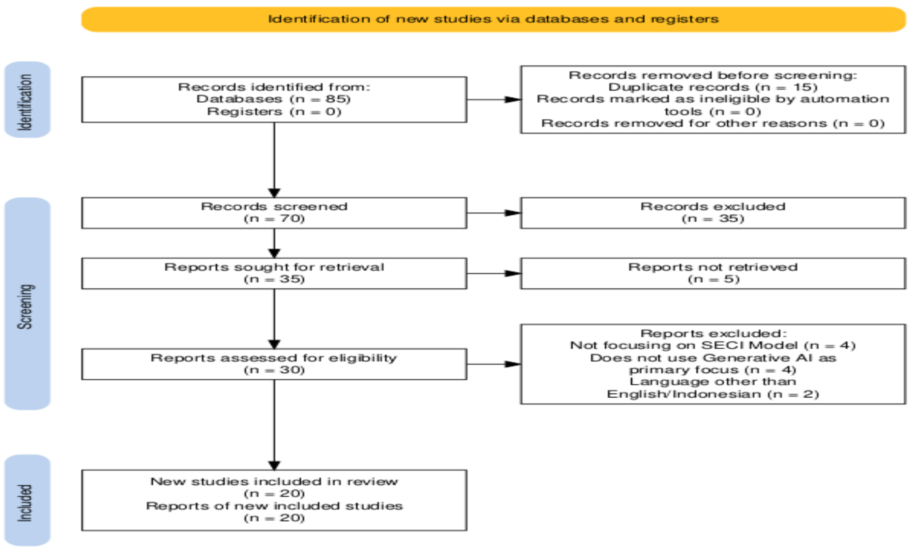

Fig 2. PRISMA Flow Diagram

The literature selection process was conducted following the PRISMA 2020 protocol. The initial search across digital databases yielded 85 records. After removing duplicates (n=15) and screening based on titles and abstracts, 35 reports were assessed for eligibility through a full-text review. Ten articles were excluded as they did not meet specific inclusion criteria regarding the integration of the SECI model and Generative AI infrastructure. Ultimately, 20 selected studies were included in this systematic review for further analysis.

2.3 Analysis Techniques

The analysis techniques used are Content Analysis and Synthesis of Findings. Data were analyzed by comparing AI technology features (such as RAG, LLM, and AI Agents) with activities within each quadrant of the SECI model.

1. The researchers mapped AI capabilities based on the strategic roles (Librarian, Analyst, Coordinator, Scribe, Coach) identified in [6] literature.
2. Subsequently, these findings were synthesized using the GRAI (Generative AI-based Knowledge Framework) proposed by [8] to formulate the concept of "Reinventing the SECI Model," which is the core of this study.

2.4 Methodological Overview of Selected Primary Studies

To facilitate a rigorous comparison of the included literature, a data extraction matrix was developed. This overview systematically categorizes each primary study by its research design, sampling strategy, and analytical methods. By mapping these methodological components, the review identifies the common frameworks used in the field and ensures that the synthesized results are evaluated based on their original research context.

Table 1. Methodological Overview of Selected Primary Studies.

No	Author (Year)	Design	Data Source	Method	Focus
1	Kaczorowska et al. (2024)	Qualitative	Expert survey	Coding (MAXQDA)	Gen-AI in KM
2	Furduescu (2025)	Conceptual	Literature	Conceptual analysis	AI roles (LLM)
3	Saragih & Anggadwita (2026)	Case Study	Organizational data	System analysis (RAG)	Knowledge internalization
4	Böhm & Durst (2025)	Conceptual	Literature	Modeling (GRAI)	SECI extension
5	Barreto & Abarca (2025)	Review	Literature	Synthesis	SECI + ChatGPT
6	Gangemi & Nuzzolese (2025)	Conceptual	Knowledge graph	Semantic modeling	LAG
7	Zuin et al. (2025)	Simulation	Synthetic data	Agent-based model	Tacit knowledge
8	Rezaei (2025)	Mixed	Expert panel	Delphi + CFA	AI challenges

Table 1 shows that most studies are still dominated by conceptual approaches and literature reviews, with limited empirical validation. Although various studies have examined the role of technologies such as LLM, RAG, and LAG

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in knowledge management, the analyses conducted tend to be partial and have not comprehensively integrated all phases of the SECI model. This indicates a need for a more holistic framework to explain the role of Generative AI as a key infrastructure in the transformation of the SECI model.

3. RESULT AND DISCUSSION

3.1 Mapping Gen-AI into the SECI Model

Based on the synthesis of the selected literature, Generative Artificial Intelligence (Gen-AI) can be positioned as a supporting infrastructure that enhances knowledge conversion processes within the SECI model. Its role is not to replace the SECI framework, but to extend its operational capabilities through digital support. Technologies such as Large Language Models (LLMs), Retrieval-Augmented Generation (RAG), and Logic Augmented Generation (LAG) demonstrate different contributions across each phase of the SECI cycle. These contributions are derived from prior studies and should be interpreted as context-dependent rather than universally generalizable.

3.1.1 Socialization (Tacit to Tacit)

In the traditional SECI model, socialization depends heavily on direct human interaction and shared experiences as a way to transfer tacit knowledge. The reviewed studies suggest that AI-based agents may help support this process by simulating conversations and assisting knowledge exchange. For example, one simulation-based study reported a tacit knowledge recall rate of up to 94.9% using LLM-based agents in a controlled experimental environment with structured organizational scenarios [19]. However, this result was obtained under specific simulation conditions and should not be interpreted as representative of all real organizational settings.

Other studies also indicate that AI-supported interaction can improve access to organizational knowledge and support communication in digital environments [18], [19]. Even so, AI systems still have limitations in replicating the contextual understanding, intuition, and experiential aspects that naturally emerge through direct human interaction. Therefore, the findings suggest that Generative AI can support and complement the socialization phase, but it cannot fully replace human-centered knowledge sharing processes.

3.1.2 Externalization (Tacit to Explicit)

Externalization involves translating tacit knowledge into explicit forms. The literature indicates that Gen-AI can support this process by structuring and articulating unstructured inputs. Technologies such as Logic Augmented Generation (LAG) enable the representation of relationships between concepts through the integration of semantic knowledge structures [4]. in addition, AI systems can function as automated documentation tools, transforming informal discussions or fragmented ideas into structured outputs [6]. While these capabilities may improve efficiency, the quality and accuracy of generated knowledge remain dependent on input data and require human validation.

3.1.3 Combination (Explicit to Explicit)

The combination phase aligns closely with AI capabilities in processing large volumes of explicit knowledge. Systems based on Retrieval-Augmented Generation (RAG) can retrieve and synthesize information from multiple sources in real time, enabling more efficient knowledge integration [3].This capability supports cross-domain knowledge connection and may reduce information silos within organizations [7]. However, the effectiveness of this process is influenced by data quality, system configuration, and the potential propagation of biased or incomplete information.

3.1.4 Internalization (Explicit to Tacit)

In the internalization phase, Gen-AI supports learning processes by providing contextualized and adaptive explanations. AI-based systems can facilitate knowledge absorption through interactive and personalized learning experiences [5]. These systems may reduce barriers to accessing information and support faster knowledge acquisition [8]. Nevertheless, effective internalization still depends on user engagement, reflection, and the ability to critically evaluate information.

3.2 Challenges and Risks in Reinventing the Gen-AI-Based SECI Model

Despite the potential benefits, the reviewed studies highlight several important limitations. First, AI hallucination poses a significant risk to knowledge accuracy. AI systems may generate outputs that appear plausible but are factually incorrect, which can compromise the integrity of organizational knowledge if not properly validated [20]. Second, overreliance on AI systems may reduce critical thinking and limit human interaction in knowledge processes. Excessive dependence on automated systems may weaken the social and experiential aspects of

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knowledge sharing [2]. Third, data security and privacy concerns remain critical, particularly in systems that require access to internal organizational data. The use of AI in knowledge management introduces potential risks related to data leakage and intellectual property exposure. Finally, the findings of this study are constrained by the nature of the existing literature. As shown in Table 1, most studies are conceptual or simulation-based, with limited empirical validation in real organizational settings. This limits the generalizability of the conclusions and indicates the need for further empirical research.

3.2.1 Accuracy Risks Leads to Hallucination and Disinformation

The primary technical risk stems from the stochastic nature of large language models, which can threaten the validity of explicit knowledge. AI-generated knowledge risks experiencing “Hallucination,” a condition where the system produces information that is linguistically convincing but factually incorrect. If this incorrect information enters the Combination phase, it will result in widespread contamination of the organization’s knowledge base. Implementation of Self-Critical Loop or Self-Critique Prompting mechanisms. AI agents configured to perform self-evaluation of their responses can align findings with factual data, supported by a Human-in-the-loop system as the final validator.

3.2.2 Organizational Risks are Cognitive Degradation and Loss of the Human Touch

The transformation during the Socialization phase poses a threat to fundamental human elements in knowledge management. Overreliance on AI’s role as an Analyst or Coach can trigger cognitive laziness and the loss of human touch. Ff hybrid interactions completely replace human-to-human dialogue, the emotional nuances and ethical considerations in the transfer of tacit knowledge may be lost. Positioning AI not as a replacement, but as an Augmentation Tool. Organizations need to design digital infrastructure that continues to require collaborative human interaction, where AI serves only as a provider of initial context, while final decisions and intuition remain within the realm of human intellectual authority.

3.2.3 Security Risks Privacy with Vulnerabilities and Intellectual Property Leaks

As a digital infrastructure, AI’s access to an organization’s internal data creates massive security gaps. The risk of sensitive data leakage into public models during massive data processing (RAG). Without strict governance, the Externalization phase involving the conversion of confidential ideas into digital text can be exposed to external parties, threatening the originality and confidentiality of corporate assets. The use of Local/Private Deployment and Data Anonymization protocols. KM infrastructure must be built on a private cloud or local (On-Premise) environment isolated from the public internet, and equipped with AI agents that automatically filter sensitive information before processing. Beyond these technical and organizational risks, Generative Artificial Intelligence also presents broader conceptual limitations in knowledge management. AI-generated outputs are probabilistic and may not reliably distinguish between validated knowledge and plausible synthesis, meaning that risks such as hallucination and misinterpretation cannot be fully eliminated [20]. In addition, increasing reliance on AI may lead to cognitive offloading, potentially reducing critical thinking and weakening the development of tacit knowledge [2]. AI systems also face inherent limitations in representing tacit knowledge, as they lack experiential and contextual understanding central to the SECI model. Furthermore, their effectiveness depends heavily on data quality, where biased or incomplete data can distort knowledge outputs. Governance and accountability remain ongoing challenges, particularly in validating AI-generated knowledge within organizational contexts. Finally, the predominance of conceptual and simulation-based studies limits the generalizability of current findings. Therefore, Generative AI should be viewed as a complementary tool that requires continuous human oversight and further empirical validation.

3.3 Comparative Analysis of Traditional KMS and Gen-AI-Based KMS

Based on a capability analysis of Gen-AI mapping into the SECI Model and risk considerations, the comparative analysis of Traditional KMS and Gen-AI-Based KMS provides a comprehensive comparison to demonstrate how the reinvention of the SECI Model tangibly enhances organizational knowledge management efficiency.

3.3.1 Process Efficiency Comparison

The table below summarizes the operational differences between traditional knowledge management systems and systems integrated with Generative AI.

Table 2. Comparison of KMS Characteristics and Efficiency

Comparison Dimensions	Traditional KMS	Generative AI-Based KMS

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Knowledge Recall (Socialization)	Depends on the availability of time and the memory of human experts.	Very high. The AI agent is capable of simulating expert discussions with a rediscovery accuracy of up to 94.9%.
Speed of Documentation (Externalization)	Manual. It takes days to turn the minutes into a formal document.	Instant. AI as Scribe converts drafts/sounds into structured documents in real-time.
Synthesis of Knowledge (Combination)	Limited to human capacity. It is difficult to connect data between different departments (silos).	Exponential. AI is capable of cross-sectoral data correlation from thousands of documents in seconds.
Access Method (Internalization)	Search-based. Users have to filter documents manually.	Answer-based. AI summarizes solutions contextually through RAG.
Information Validation	It is done manually through peer-review.	Hybrid. It is done through a human-verified AI Self-Critical Loop mechanism.

3.3.2 Analysis of Time Efficiency and Cognitive Capacity

The most significant transformation is seen in the reduction of time barriers in each phase of the SECI spiral.

1. Search Time Reduction
   Referring to the role of a Librarian, AI-based digital infrastructure cuts information search time by over 70% through automatic summarization features. This allows the Internalization phase to occur faster as employees immediately receive work instructions without having to read the entire technical manual.
2. Knowledge Scalability
   In the Combination phase, AI's ability to act as an Analyst enables organizations to conduct periodic knowledge auditsa task impossible to perform manually. This reinvention transforms the KMS from a mere "storage repository" into an "innovation engine" that proactively suggests new connections between data.
3. Socialization Cost Efficiency
   The high level of knowledge recall achieved through simulation agents indicates that organizations can reduce coordination costs and unproductive face-to-face meeting time without losing the essence of tacit knowledge transfer.

These comparative results confirm that the "SECI Model Reinvention" is not merely a change in tools, but a change in the speed of the knowledge spiral. With Gen-AI as the infrastructure, mechanical barriers in knowledge documentation and retrieval are eliminated, allowing organizations to shift from administrative knowledge management to strategic and innovative knowledge management.

4. CONCLUSION

This systematic literature review suggests that Generative AI has the capacity to extend the SECI model by enhancing and accelerating knowledge conversion processes across its four phases. Rather than operating solely as a supportive technological tool, Generative AI demonstrates the potential to perform multiple functional roles within knowledge management, including knowledge retrieval, interpretation, structuring, and decision support. These capabilities indicate a transition toward more digitally mediated and continuous knowledge flows; however, such implications remain conceptual and grounded in prior literature rather than empirical validation. The review further indicates that Generative AI may improve the efficiency of each SECI phase. In the socialization phase, existing studies report increased effectiveness in tacit knowledge capture, including high recall rates observed in simulation-based environments. In the externalization and combination phases, techniques such as Logic Augmented Generation (LAG) and Retrieval-Augmented Generation (RAG) are shown to facilitate the articulation and integration of explicit knowledge. Nevertheless, these findings are predominantly derived from secondary sources and controlled simulations, and thus should be interpreted with appropriate caution regarding their generalizability. Importantly, this study conceptualizes Generative AI as an enabler of human–machine collaboration within knowledge management systems. While AI contributes to increased speed, scalability, and processing capacity, human actors remain essential for critical evaluation, contextual interpretation, and ethical validation. This underscores the continued relevance of human oversight in AI-augmented knowledge ecosystems. It is important to emphasize that the primary contribution of this study is conceptual in nature. The proposed GRAI perspective constitutes a theoretical extension and integrative mapping of the SECI model based on existing literature, rather

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than a novel model that has undergone empirical testing. Consequently, its applicability across diverse organizational contexts and industries remains to be systematically examined. Based on these findings, several implications are proposed. Organizations should consider developing secure and AI-ready knowledge management infrastructures while simultaneously investing in AI literacy to support informed and critical usage. Furthermore, future research should explore mechanisms such as self-critical loops to mitigate the risk of AI-generated inaccuracies. Empirical studies, including case-based and longitudinal approaches, are necessary to validate the effectiveness and robustness of the proposed conceptual extension in real-world settings.

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