VJIKMS
56,2

Received 25 August 2024
Revised 10 February 2025
19 May 2025
11 August 2025
11 September 2025
Accepted 15 September 2025

Transforming organizational knowledge creation through artificial intelligence: a systematic review of the emergent literature

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Abstract

Purpose – This literature review aims to examine the use of artificial intelligence (AI) to facilitate conversions between tacit and explicit knowledge, driving organizational knowledge creation.

Design/methodology/approach – Drawing on Nonaka's socialization, externalization, combination and internalization (SECI) model, the authors applied thematic coding to 82 academic articles to analyze how AI facilitates the four key processes of knowledge creation.

Findings – The authors generated five propositions that highlight the multifaceted role of AI in organizational knowledge creation.

Research limitations/implications – This systematic review serves as a stocktake of current knowledge. Its scope is limited by the time frame, which may exclude insights beyond the emergent phase. Future researchers should examine a broader period to capture the evolution of AI capabilities over time.

Practical implications – Insights from the systematic review can help organizations strengthen their organizational knowledge creation by aligning AI tools with human expertise.

Erratum: It has come to the attention of the publisher that the article Yan J., Husted K., and Fath B. (2025), "Transforming organizational knowledge creation through artificial intelligence: a systematic review of the emergent literature", *VINE Journal of Information and Knowledge Management Systems*, Vol. ahead-of-print No. ahead-of-print. https://doi.10.1108/VJIKMS-08-2024-0296 contains incorrect affiliation details of authors Benjamin Fath and Kenneth Husted.

The affiliations have now been amended to reflect the correct details as follows:

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This error was introduced during the article publication process, for which the publisher apologises.

VINE Journal of Information and Knowledge Management Systems
Vol. 56 No. 2, 2026
pp. 522-540
Emerald Publishing Limited
2059-5891
DOI 10.1108/VJIKMS-08-2024-0296

Originality/value – The findings of this review can be used to refine the SECI model and enhance the limited theoretical understanding of the role of AI in organizational knowledge creation. The study offers a process-based account of how AI facilitates the generation, augmentation and updating of organizational knowledge through micro-level processes.

Keywords Organizational knowledge creation, Artificial intelligence, Knowledge management, Systematic literature review, SECI model of knowledge creation

Paper type Literature review

1. Introduction

Given its self-learning and generative capabilities, artificial intelligence (AI) has the potential to revolutionize organizational knowledge creation, which is constrained by human cognitive limitations (Alavi *et al.*, 2024; Haefner *et al.*, 2021). A firm's capacity to generate new knowledge is tied to its innovative capabilities and competitive edge (Audretsch and Belitski, 2023). For managers, understanding the role of AI in firm value creation is crucial (Bhalerao *et al.*, 2022; Enholm *et al.*, 2022). Therefore, it is essential to develop a theoretical framework to explain the role of AI in organizational knowledge creation, helping firms to integrate AI into their knowledge management strategies, expand their knowledge base and remain competitive (Robertson *et al.*, 2024).

Studies have highlighted the potential of AI in supporting organizational knowledge creation. AI can overcome human cognitive limitations by rapidly identifying patterns and drawing new insights from data, enhancing the quantity and quality of new knowledge (Garbuio and Lin, 2021; Jarrahi *et al.*, 2023). For example, Bag *et al.* (2021) found that AI can enhance rational marketing decision-making. In addition, AI is transforming the creation of tacit knowledge, which is central to human agency (De Bruyn *et al.*, 2020). However, despite the potential of AI for organizational knowledge creation, a comprehensive understanding of how firms can leverage AI for this purpose is lacking (Harfouche *et al.*, 2023), leading to calls for more research on this topic (Chen *et al.*, 2024; Hadjimichael and Tsoukas, 2019).

1.1 The SECI model of knowledge creation

Tacit and explicit knowledge are the fundamental elements of organizational knowledge (Olan *et al.*, 2022). Nonaka's (1994) socialization, externalization, combination and internalization (SECI) model provides a useful framework for examining how AI can generate organizational knowledge by influencing the dynamic interactions between tacit and explicit knowledge across four interdependent processes (Alavi *et al.*, 2024). While it does not specifically address the role of AI in organizational knowledge creation, the SECI model can be applied to AI–human interactions to elucidate how organizational knowledge can be augmented through micro-level processes.

This literature review aims to answer the following research question:

RQ. How does AI contribute to organizational knowledge creation?

It contributes to the existing literature in three important ways. First, while prior research has provided insights into how AI can contribute to firms' knowledge development, few studies have specifically explored how AI influences the conversion between tacit and explicit knowledge. By grounding our analysis in the four micro-processes of the SECI model, we respond to calls for micro-foundational approaches in the knowledge management research (Foss and Pedersen, 2019; Montgomery *et al.*, 2024). Second, while the knowledge management and digital transformation literature is well developed, we examine the specific processes involved in the AI-driven creation of organizational knowledge, responding to calls for a deeper understanding of the connections between knowledge management and Industry 4.0 (De Bem Machado *et al.*, 2022). Third, we extend the SECI model to the AI context, offering a nuanced conceptualization of how AI facilitates organizational knowledge creation. In particular, we articulate AI's impact on the interactions between tacit and explicit knowledge, enriching the scholarly discourse on organizational knowledge creation in the digital transformation era (Chen *et al.*, 2024).

The remainder of this paper is structured as follows. Section 2 reviews the literature on the role of AI in organizational knowledge creation; Sections 3 and 4 present the literature review methodology and findings, respectively; Section 5 discusses the findings; Section 6 presents the limitations and future research directions; and Section 7 concludes the paper.

2. AI as an enabler of organizational knowledge creation

Knowledge is often categorized as explicit and tacit. The interactions between these two types of knowledge generate new organizational knowledge that can drive innovation and strategy (Olan *et al.*, 2022). According to Nonaka *et al.* (2006, p. 1179), "organizational knowledge creation is the process of making available and amplifying knowledge created by individuals as well as crystallizing and connecting it with an organization's knowledge system." Nonaka's (1994) SECI model has been widely adopted in knowledge management research, influencing numerous conceptualizations in the field (Farnese *et al.*, 2019). Nonaka (1994) argued that knowledge is created by the interaction between explicit and tacit knowledge through four distinct processes: *socialization*, where shared experiences of everyday social interactions are converted into new tacit knowledge; *externalization*, where tacit knowledge is made explicit through processes such as dialogue; *combination*, where the knowledge of different individuals is merged; and *internalization*, where explicit knowledge is converted to tacit knowledge through "learning by doing." These four processes comprise the SECI model, explaining how knowledge creation occurs at the individual, group and organizational levels (Nonaka and Toyama, 2003).

Advances in AI have enabled its application to knowledge management, emphasizing the process of identification, capture and utilization of organizational knowledge to enhance a firm's competitiveness (Alavi and Leidner, 2001). AI is defined as "a system's ability to interpret external data correctly, learn from it and use that learning to achieve specific goals and tasks through flexible adaptation" (Haenlein and Kaplan, 2019, p. 5). Machine learning is a subset of AI that can learn patterns from data and experience without being explicitly programmed (Haefner *et al.*, 2021). Through machine learning, AI has the capacity to discover new relationships and patterns in data (Lee and Shin, 2020), thereby creating new organizational knowledge beyond the capabilities of traditional information technology systems. By collecting, processing and analyzing data, AI can enhance organizational knowledge and promote continuous learning (Meyer *et al.*, 2020). Furthermore, AI-generated information and knowledge are stored in a firm's knowledge repository, forming the basis of organizational memory (Okudan *et al.*, 2021).

Despite these advances, the literature on the role of AI in organizational knowledge creation remains fragmented, highlighting the need for a more holistic and comprehensive understanding.

3. Methodology

To systematically explore the literature on the role of AI in organizational knowledge creation, we followed Denyer and Tranfield's (2009) five-step approach. This approach entails:

(1) question formulation;

(2) locating studies;

(3) study selection and evaluation;

(4) analysis and synthesis; and

(5) reporting and using the results.

Following these steps enabled a transparent and replicable methodology (Tranfield *et al.*, 2003). The details of each step are outlined below.

3.1 Literature search

Based on our research question (Step 1), we carried out a literature search (Step 2) using five databases: Web of Science, JSTOR, Scopus, ScienceDirect and EBSCO Business Source Premier, to retrieve articles to be included in the review. These databases have extensive collections and are frequently used in literature reviews on the intersection between AI and business practices (e.g. Loureiro *et al.*, 2021; Toorajipour *et al.*, 2021). We included articles published from 2011 to 2021, a period marked by rapid developments in AI (Ali *et al.*, 2023). Our search phrase was "knowledge management AND (artificial intelligence OR intelligent systems)." By using broad search terms, we aimed to capture the emerging literature and identify relevant publications (Kaushal *et al.*, 2023). We limited our search to peer-reviewed, English-language journal articles and excluded gray literature. The initial search yielded a total of 885 articles.

3.2 Evaluating the sample articles

In Step 3, we screened the articles to identify those for inclusion in the final review. First, we applied content-related criteria to review the titles and abstracts of articles to assess whether they addressed the research question (Hiebl, 2023). This initial screening step yielded 111 articles after merging the results of the five databases and removing duplicates. Next, we read the full text of the 111 articles to assess their relevance. The final sample comprised 82 articles.

3.3 Literature analysis and coding

In Step 4, we used thematic coding to identify information related to the four knowledge creation processes (Gibbs, 2007). Relevant information was recorded in an Excel spreadsheet and organized into multiple categories for detailed analysis. The analytical process involved iterative readings of the articles to ensure that we thoroughly captured their nuances. We then aggregated and coded the data into four themes corresponding to the four SECI model concepts.

3.4 Validity and reliability

By following the prescribed steps, we minimized potential bias and errors and enhanced the replicability, validity and reliability of this literature review (Di Vaio *et al.*, 2020; Tranfield *et al.*, 2003). These steps also helped us to rigorously synthesize and organize the literature (Prikshat *et al.*, 2023). Furthermore, selection bias was mitigated by clearly defining the selection criteria and assessing their relevance (Castañer and Oliveira, 2020). Figure 1 illustrates the literature review process.

4. Multifaceted role of AI in knowledge creation

This section presents the findings (Step 5) on how AI contributes to organizational knowledge creation, organized according to the four knowledge creation processes of the SECI model.

4.1 Socialization

Knowledge creation begins with socialization, whereby tacit knowledge is shared through everyday social interactions (Nonaka and Toyama, 2003). This sharing occurs both within the organization and between the organization and external stakeholders (Adomako *et al.*, 2021). Despite the potential of AI to facilitate this process, given its adaptive, humanlike cognitive abilities (Mele *et al.*, 2021), its role in socialization has been underexplored. This may be because AI is currently limited by its lack of social skills and contextual sensitivity (Hadjimichael and Tsoukas, 2019). Coombs *et al.* (2020) highlight that current AI usage

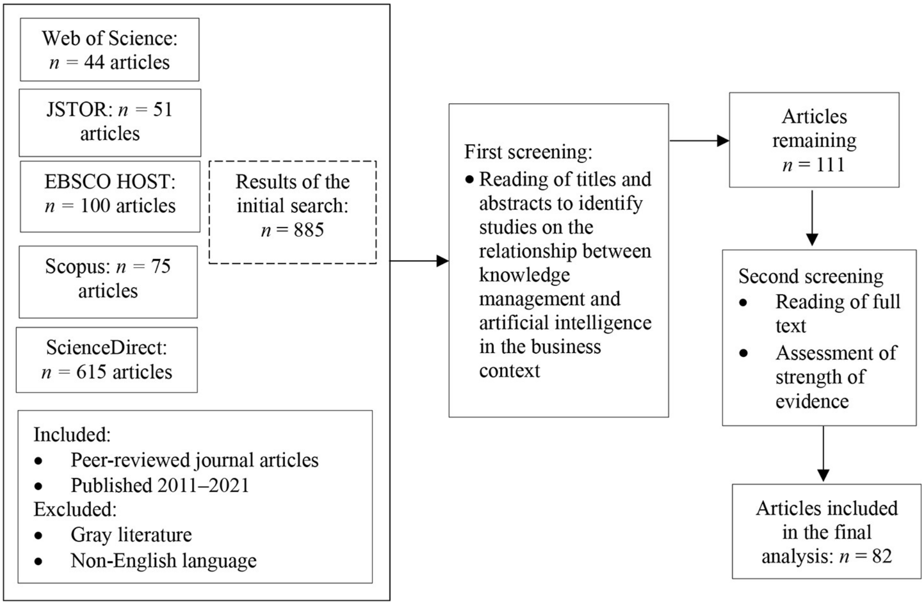

Figure 1. Summary of the sample collection process
Source: Authors' own work

primarily focuses on substituting human employees or optimizing decision-making. They found that organizational performance is enhanced when the technical capabilities of AI are combined with the soft skills of humans.

Nevertheless, AI can act as a catalyst for socialization. Gu *et al.* (2019) found that the use of AI-based knowledge management systems in hospitals improves information dissemination, providing doctors with more time to discuss patient treatments. Intelligent platforms and social robots can also reduce information asymmetry among actors (Mele *et al.*, 2021). Haefner *et al.* (2021) summarized the three key capabilities of AI in promoting innovation. These include:

(1) exploitation: AI can process large volumes of information at an unprecedented pace, alleviating cognitive constraints and supporting human innovation;
(2) expansion: AI promotes innovation by overcoming organizational boundaries, finding distant solutions and introducing new ideas and opportunities; and
(3) exploration: AI discovers new innovation areas, explores and solves problems and generates new ideas.

AI can also reduce barriers to knowledge creation arising from geographical limitations and improve knowledge flow during socialization. By automating repetitive, procedural and data-intensive tasks, AI frees up human workers from physical tasks, enabling them to engage in social activities such as conversing with customers or learning from experts (Gourlay, 2006). AI enhances the frequency of social interactions, providing more opportunities for humans to acquire tacit knowledge through shared experiences. Therefore, we make the following proposition:

P1. AI promotes the acquisition of new tacit knowledge by facilitating social interactions between organizational members.

4.2 Externalization

AI facilitates externalization by helping convert tacit knowledge into explicit knowledge. Chatbots, intelligent agents, machine learning and natural language processing can be used to capture insights from employees, customers and suppliers. These AI methods enhance the scope and depth of organizational tacit knowledge (De Bruyn *et al.*, 2020) and improve organizational functions such as purchasing (Allal-Chérif *et al.*, 2021). Toorajipour *et al.* (2021) note that natural language processing, a critical technique for enhancing human–machine interactions, has received insufficient attention in the supply chain management research.

AI can also optimize managerial decision-making by predicting customer behaviors through pattern recognition (Kozak *et al.*, 2021; Kumar *et al.*, 2021), generating insights for business model innovation (Sjödin *et al.*, 2021) and leveraging knowledge for value cocreation and innovation in business-to-customer firms (Mele *et al.*, 2021). In addition, data mining and automated knowledge acquisition can improve supply chain management (Almuiet and Zawaideh, 2019; Maghrebi *et al.*, 2015; Sundarakani *et al.*, 2021) and industrial platform architecture in business-to-business firms (Jovanovic *et al.*, 2022).

AI also helps convert data into actionable knowledge for developing business strategies. For example, AI can conduct sentiment analyses of text, voice and tone (Paschen *et al.*, 2020b) and proactively scan and process data to reduce information asymmetry (Meyer *et al.*, 2020). In addition, AI enables firms to leverage insights from retail and e-commerce professionals related to consumers, industry trends and competition (Guo *et al.*, 2020; Wang *et al.*, 2021) and identify the causes of poor service quality (Srivastava *et al.*, 2012).

Existing studies have examined the ability of AI to support knowledge externalization by broadening knowledge acquisition. AI can convert structured and unstructured data from everyday communications, such as emails, to detect risks during critical events (Farrokhi *et al.*, 2020; Mercier-Laurent *et al.*, 2018). Using case-based reasoning, Okudan *et al.* (2021) proposed a risk management tool to build corporate risk memory and improve decision-making. AI also enables a comprehensive understanding of crises by transforming data into business intelligence (Wang and Wu, 2021). Rules-based machine learning and data mining models can be used to prevent the deterioration of machinery (Fernandes *et al.*, 2019), detect fraud, monitor business health and support forensic accounting (Amani and Fadlalla, 2017). Text and data mining methods can also help summarize incomplete data and reveal complex relationships to provide qualitative insights (Altuntas *et al.*, 2015; Zhuang *et al.*, 2013).

In addition, AI contributes to explicit knowledge generation by producing textual content and supporting demand forecasting in tourism (Song *et al.*, 2019; Xiang *et al.*, 2020). It can extract knowledge from data for forensic analysis (Quick and Choo, 2014), identify patterns in databases to inform marketing decisions and planning (Lin *et al.*, 2013; Lee *et al.*, 2013) and predict financial statement fraud (Ravisankar *et al.*, 2011). Furthermore, AI enhances decision-making in business and competitive intelligence by converting data into actionable information and relevant knowledge (Bole *et al.*, 2015; Chen and Lin, 2021) and by providing insights from user-generated context (Chau and Xu, 2012). It also helps firms extract knowledge to support complex and unstructured decision-making (Hoffman and Freyn, 2019; Orriols-Puig *et al.*, 2013) and generate knowledge from diverse sources to augment marketing activities (Bag *et al.*, 2021; Paschen *et al.*, 2019).

Nonaka and Toyama (2003) argue that dialogue is an effective way to articulate and transfer tacit knowledge. AI's role in expanding both the breadth and the depth of knowledge can significantly aid in knowledge externalization. From these insights, we propose:

P2. AI can expand the breadth and depth of organizational tacit knowledge acquisition by drawing from internal and external channels. In doing so, AI facilitates the conversion of tacit knowledge to explicit knowledge through algorithmic processing combined with human interpretation and contextualization.

Despite its benefits for externalization, AI also has some limitations, particularly when dealing with relational, somatic and collective tacit knowledge (Sanzogni *et al.*, 2017). De Bruyn *et al.* (2020) argued that the positive influence of AI on business functions may fall short if AI systems fail to incorporate tacit knowledge into their algorithms and transfer their insights back to humans. Trunk *et al.* (2020) observed that AI outcomes significantly depend on the ability and willingness of humans to contribute implicit information. This is supported by the knowledge-sharing hostility theory, which explains organizational members' resistance to knowledge sharing (Husted and Michailova, 2002). According to this theory, the ability of AI to process tacit knowledge is limited if individuals are unwilling to share it. The active participation of individuals in sharing tacit knowledge is essential for its externalization. From these insights, we propose:

P3. AI can facilitate the conversion of tacit organizational knowledge to explicit knowledge, but this capacity is constrained in the presence of knowledge-sharing hostility in organizations.

4.3 Combination

AI plays a critical role in combining different types of explicit knowledge through the efficient integration of internal and external data (Allal-Chérif *et al.*, 2021; de Carvalho Botega and da Silva, 2020). For example, Ladj *et al.* (2021) proposed a machine learning-based system to process large volumes of manufacturing data and create new knowledge related to machining incidents. Lei and Wang (2020) developed a conceptual AI-based knowledge management system that supports various knowledge processes, including knowledge integration between multiple agents. Toorajipour *et al.* (2021) highlighted the use of a multi-agent approach to integrate business and engineering knowledge in product life cycle management. Also, AI can integrate explicit knowledge from diverse domains to make more accurate marketing predictions (AlGhanem *et al.*, 2020; Kumar *et al.*, 2021; Vlačić *et al.*, 2021). For example, Rahman *et al.* (2021) argue that organizations can enhance their marketing performance through AI-enhanced marketing analytics capability. Combining AI insights with the experience of sales practitioners can lead to a deeper understanding of customer needs and the development of better sales strategies (Paschen *et al.*, 2020b).

AI can also enhance explicit knowledge by uncovering hidden relationships. For instance, reinforcement learning, a branch of machine learning, offers new ideas and opportunities by connecting seemingly unrelated knowledge (Haefner *et al.*, 2021). Perez *et al.* (2018) proposed that machine learning can classify new content by learning from existing data. AI can also identify connections in fragmented information by analyzing sources such as webpages or emails, facilitating the development of new knowledge (Maity, 2019). In addition, Parra *et al.* (2017) used text mining to reveal collaboration opportunities, retraining programs and risk mitigation strategies from corporate citizenship reports.

AI and big data contribute to the growth and diversification of customer data, allowing marketers to create new offerings with more compelling value propositions (Fernández-Rovira *et al.*, 2021). Liu *et al.* (2020) empirically examined the effect of AI on organizations' technological innovation, finding that it improves data collection capabilities and offers new ways of examining existing knowledge. Also, they show that AI supports experimentation with new methods of knowledge integration and facilitates further knowledge discovery. From these insights, we propose the following:

P4. AI can enhance organizational knowledge combination by integrating heterogeneous sources of explicit knowledge.

4.4 Internalization

AI fosters knowledge internalization by making explicit knowledge more accessible and distributable, thereby enhancing intraorganizational knowledge sharing. AI-based mechanisms motivate individuals to contribute and share knowledge online (Nguyen and Fry, 2021). Because AI reduces the costs related to information sharing and transfer and improves accessibility, it can facilitate intra- and interorganizational knowledge sharing (Liu *et al.*, 2020; Wu *et al.*, 2020). In addition, AI can aid in knowledge visualization, helping individuals understand and exploit complex data and information (Wu *et al.*, 2020).

AI also helps with knowledge internalization by improving an organization's ability to represent and share expert knowledge (López-Cuadrado *et al.*, 2012). AI can enhance knowledge mapping, which is conducive to organizational knowledge sharing (Hellström and Husted, 2004). It does so by revealing the relationships between knowledge, the location of the knowledge and the knowledge owner (Al Hakim *et al.*, 2021). A shared vision among organizational members is essential for guiding learning and knowledge development (Calantone *et al.*, 2002). AI can support this process by aggregating both internal and external knowledge, facilitating the communication of shared goals, making organizational plans and strategies more explicit and accelerating individual and collective learning.

Furthermore, AI supports knowledge internalization in the context of marketing. Moradi *et al.* (2013) proposed the use of intelligent agents to capture, store, transmit and use employees' tacit knowledge. Data mining enables the extraction of knowledge embedded in a firm's knowledge base, especially in the absence of effective communication mechanisms (Buntak *et al.*, 2020). For example, text mining can be used to extract tacit and explicit data from online customer feedback, revealing customer preferences and enabling product managers to develop strategies (Guo *et al.*, 2020). Gu *et al.* (2019) found that AI adoption enhances knowledge processes and facilitates intradepartmental collaboration and group learning. With a shared vision, individual learning becomes more purposeful.

In summary, AI enhances knowledge acquisition and fosters learning, shared visions and open-mindedness among employees and facilitates knowledge sharing among organizations. Consequently, employees are driven by a strong learning orientation that encourages them to assimilate and internalize AI-enabled explicit knowledge, further creating tacit knowledge through experiments, actions and practices. From these insights, we propose:

P5. Using AI amplifies the learning orientation of employees by extending their access to collective organizational knowledge and improving the desirability and feasibility of applying new knowledge to practical situations.

5. Discussion and implications

Three decades ago, Nonaka (1994) introduced the SECI model to explain how organizations develop knowledge. However, organizational knowledge creation has evolved with the rise of AI, prompting the need to update the model. By applying the SECI framework to analyze our findings, we gained a deeper understanding of AI-driven knowledge creation and identified the conditions that moderate the effects of AI on organizational knowledge creation. The findings confirm that although the SECI model remains crucial for understanding organizational knowledge creation, it no longer fully captures the changes brought about by AI

(Harfouche *et al.*, 2023). Following these insights, we extend the original model to highlight how AI specifically influences the four knowledge conversion processes (see Figure 2).

Much of the literature treats knowledge as a broad concept and rarely emphasizes the distinction between explicit and tacit knowledge, which is central to the SECI model. The literature indicates that AI can enhance the development and sharing of tacit knowledge through socialization, externalization and internalization. For example, it facilitates socialization by reducing the time and cognitive effort required to formalize knowledge. However, we found that AI still lacks the social skills and contextual sensitivity needed to replace humans in socialization activities. Consequently, the socialization aspect of organizational knowledge creation continues to rely on human interactions. Despite this, AI-enabled automation technologies can reduce the cognitive and physical workload of humans, leading to more frequent human interactions and fostering stronger social relationships and the exchange of feelings, perceptions and experiences.

Scholars often highlight the capacity of AI to formalize and articulate unstructured data to generate qualitative insights. However, AI remains limited in its ability to process certain types of tacit knowledge that require human involvement (Sanzogni *et al.*, 2017). Few studies have specifically addressed how AI can contribute to tacit knowledge creation, emphasizing the need for further research in this area (Hadjimichael and Tsoukas, 2019).

AI plays a more prominent role in the combination step of knowledge creation (Alavi *et al.*, 2024). Organizations can use AI technologies, particularly those powered by machine learning, reinforcement learning and multi-agent systems, to obtain explicit knowledge from internal and external sources. We found that AI can integrate and combine data in innovative ways, potentially leading to the creation of new knowledge.

Finally, through multi-agent, data and text mining approaches, AI can enhance knowledge internalization by encouraging a learning orientation in organizational members. A strong learning orientation fosters explorative learning, benefiting both internally and externally sourced knowledge creation (Alerasoul *et al.*, 2022). AI encourages organizational members

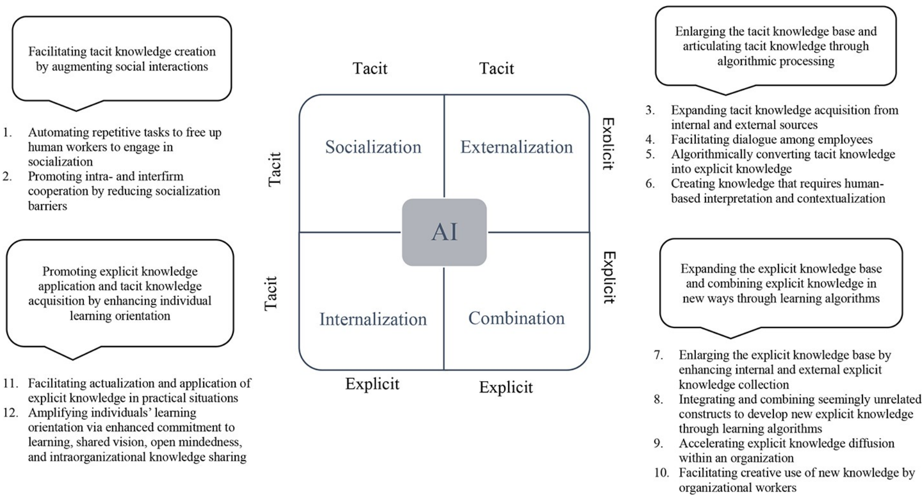

Figure 2. AI-enabled SECI model of knowledge creation
Note(s): AI: artificial intelligence; SECI: socialization, externalization, combination, internalization
Source: Authors' own work; Adapted from Nonaka and Toyama (2003)

to commit to learning, embrace a shared vision, remain open-minded and engage in intraorganizational knowledge sharing, all key dimensions of a learning orientation (Sinkula *et al.*, 1997). Thus, AI helps to convert individual knowledge into collective organizational knowledge, reduce knowledge-sharing barriers and improve knowledge accessibility within the organization.

In the current knowledge economy, knowledge creation is essential for firms to innovate and maintain a competitive edge. Beyond examining the broad effects of digital technologies on organizational knowledge creation (Chen *et al.*, 2024), this study contributes to the literature by applying a nuanced SECI lens to explore how AI can facilitate the conversion between tacit and explicit knowledge. AI's learning and adaptive capabilities enhance organizations' ability to identify, develop and acquire both tacit and explicit knowledge, thereby expanding their knowledge base. AI supports organizational knowledge creation by alleviating human cognitive constraints (Garbuio and Lin, 2021), improving the efficiency of knowledge conversion and facilitating the interaction between tacit and explicit knowledge. However, AI augments the knowledge creation process through different pathways, each requiring varying levels of human involvement to leverage its full potential. Our findings challenge the longstanding belief that organizational knowledge creation – particularly tacit knowledge creation – is a human-centered process that depends on human cognitive capacity, interactions and actions (Sambamurthy and Subramani, 2005).

AI's technological capabilities can be used to complement human social processes to create knowledge, highlighting the value of human–AI interactions in supporting organizational knowledge activities (Harfouche *et al.*, 2023). AI has emerged as a powerful enabler of organizational knowledge creation. We extend the literature by providing insights into when, where and how humans and AI can collaborate to enhance new knowledge development (Robertson *et al.*, 2024). The limitations of AI in organizational knowledge creation underscore the need to keep humans in the loop (Jarrahi *et al.*, 2023) and compel organizations to foster value creation through human–AI collaborations.

Understanding its potential can help organizations integrate AI into their operations and enhance their competitive edge through AI's value-creation mechanisms (Enholm *et al.*, 2022). We provide a practical guide for organizations to map their knowledge management strategies using AI. Although AI can catalyze knowledge creation processes, humans are crucial for providing complementary capabilities to enhance the positive effects of AI. Managers should implement governance mechanisms that foster a knowledge-sharing climate by mitigating knowledge hiding and hoarding, improving tacit knowledge sharing and creation in areas where AI's current capabilities are limited.

6. Limitations and future research avenues

This study has several limitations, generating a range of research opportunities. In line with previous studies, we treat AI as an emerging field (Brem *et al.*, 2021) and use AI as an umbrella term for various technologies and applications (Van Noordt and Misuraca, 2022). This review captured various aspects of AI, including machine learning, reinforcement learning, natural language processing and robotics, that can be used to learn from data, recognize patterns and understand natural language. Because these aspects are a central part of AI functioning (Paschen *et al.*, 2020a), understanding their combined effects offers a more meaningful and comprehensive view of AI's overall knowledge creation effects, especially given that AI is seldom a standalone machine (Camilleri, 2024). While we attempted to be as specific as possible when discussing the knowledge creation effects of different AI techniques and applications, future researchers could offer deeper insights by exploring how each method contributes to organizational knowledge creation based on its distinct architecture and functionalities. For example, rules-based systems, which rely on predetermined rules for problem-solving and decision-making, are beneficial in fields such as law. However, these systems are constrained by their inability to adapt to changing situations (Parycek *et al.*, 2024). This limitation has implications for the argument that knowledge is situated and provisional rather than universal and static (Blackler, 1995). Thus, our study offers avenues for future researchers to explore the subtle differences between various AI methods in terms of knowledge creation. For example, future researchers could investigate generative AI (e.g. ChatGPT), which offers new paths for tacit knowledge representation and processing (Böhm and Durst, 2025) or agentic AI, which has multiple capabilities, enabling greater autonomy and independence in achieving objectives (Murugesan, 2025). Researchers could explore different perspectives of organizational knowledge creation (e.g. practical and possessive perspectives) to understand AI's contribution to organizational knowledge creation (Blackler, 1995).

Although our study focuses on organizational knowledge creation, future research in the knowledge management field could explore other knowledge processes, such as sharing, diffusion, application and rejection, to enhance the literature on the role of AI in organizational knowledge management. Examining the effect of AI on other knowledge processes will clarify how organizational knowledge management strategies should evolve to leverage AI's technological advancements and improve knowledge practices. For example, our study shows that AI can facilitate knowledge socialization and externalization by streamlining tacit knowledge sharing between humans. However, we focused mainly on how knowledge is developed through these mediating mechanisms and did not interrogate the effect of AI on knowledge sharing. This presents an interesting opportunity for future researchers to assess how AI supports knowledge-sharing activities and other knowledge management processes. Example research questions include: How does using AI affect knowledge-sharing processes and outcomes in organizations? How does using AI exacerbate or mitigate knowledge-sharing barriers or hostility in organizations (Husted *et al.*, 2012)? Such research would enrich our understanding of the influence of AI on knowledge processes.

In addition, the period reviewed (2011–2021) may not capture the latest developments in AI. However, this time frame was considered appropriate because it spans a period of rapid AI development, reaching a maturity point at which its implications for organizational knowledge creation could be meaningfully examined. By reviewing papers from this period, we achieved our objective of exploring the role of AI in tacit and explicit knowledge conversion. Given that the knowledge on this topic is still emerging, our findings provide a springboard for future researchers (Edmondson and McManus, 2007). Our subsequent empirical work further supports the findings of this review regarding AI's strengths and limitations. This suggests that despite the recent emergence of new AI systems such as generative AI, the fundamental capabilities of AI remain largely unchanged. However, we encourage researchers to draw on more recent studies to understand how advances in AI capabilities may provide new pathways for organizational knowledge creation and whether AI will entirely replace humans once it overcomes its limitations and reaches the next stage of development (e.g. general or superintelligence) (Kaplan and Haenlein, 2020). Such research could contribute meaningfully to the scholarship.

7. Conclusion

We systematically analyzed the literature to better understand how AI can facilitate the conversion of tacit to explicit knowledge through the four key processes outlined by Nonaka (1994). We analyzed 82 relevant academic articles using the SECI model to assess the specific effects of AI on each knowledge creation step. We integrated our findings into the model to show how organizational knowledge is generated, augmented and updated through these four micro-level processes when AI is applied.

By revisiting the assumption that human cognition limits knowledge acquisition and development, we used insights from existing literature to develop five propositions. These propositions address the shortcomings of previous broad conceptualizations and provide opportunities to deepen our understanding of the specific effect of AI on organizational knowledge creation.

We evaluated the relevance and contemporary applicability of the SECI model and showed how it may be adapted in the context of AI. Using this framework, we organized our findings into structured insights, exposing the conditions under which AI can automate or augment the four micro-processes of organizational knowledge creation. Our conceptualizations align with those of earlier studies, showing that organizations can benefit from collaborative knowledge processing and learning between humans and AI. In this emergent collaboration, humans contribute unique skills such as critical and contextual thinking and emotional intelligence, while AI supports rapid data processing, pattern recognition and efficient knowledge sharing. We also emphasize the "human-in-the-loop" concept, highlighting areas where human social abilities are crucial for complementing AI's technological abilities.

In addition, we outline the specific pathways and mechanisms through which AI facilitates the conversion between tacit and explicit knowledge, extending the original SECI model. By emphasizing the distinction between explicit and tacit knowledge, we provide a micro-foundational understanding of the dynamic interactions between humans and AI in organizational knowledge creation, advancing the literature on AI-enabled knowledge processes.

7.1 Managerial takeaways

Managers and other practitioners involved in developing or updating knowledge management strategies can leverage our propositions to better understand the strengths and limitations of AI in organizational knowledge creation. Two particular takeaways merit managerial attention. First, while AI helps convert some types of tacit knowledge into explicit knowledge, enhancing externalization, managers should invest in social infrastructure and implement formal governance mechanisms to facilitate open, community-based knowledge sharing among employees (Foss *et al.*, 2010). This is because personal experience and wisdom cannot be captured through datafication. Second, innovation managers and practitioners can leverage the knowledge combination capacity of AI to generate novel ideas and solutions by connecting seemingly unrelated knowledge and relationships. In particular, the AI-driven generation of ideas can be used in the early stages of the innovation process before introducing human expertise and experience to develop new products and services. This hybrid approach amplifies AI's positive effects and preserves and strengthens employees' unique knowledge and cognitive capabilities, ultimately maximizing AI's value-creation capacity.

Acknowledging the limitations of this review, we encourage future researchers to investigate how specific AI methods can contribute to the knowledge creation process, offering a more up-to-date understanding of how AI's evolving capabilities may present new opportunities and challenges for organizational knowledge activities. We outline several promising research avenues to further investigate the organizational knowledge management phenomenon in the emergent AI context and advance our understanding and practice.

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