Journal of Information and Organizational Sciences
Volume 50, Number 2 (2026)
Journal homepage: jios.foi.hr

JIOS

DOI: 10.31341/jios.50.2.5
Open Access

UDC 004.8:005.94(049.32)
Review Paper

AI-Driven Knowledge Sharing: A Systematic Literature Review and Future Agenda

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PAPER INFO

Paper history:
Received 30 January 2026
Accepted 29 October 2026

Citation:
El Kaabi, A., Abouliatim, I., & El Maallam, M. (2026). AI-driven knowledge sharing: A systematic literature review and future agenda. In Journal of Information and Organizational Sciences, vol. 50, no. 2, pp. 349-369

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ABSTRACT

The quantity of publications devoted to Artificial Intelligence (AI) has increased significantly in recent decades, reflecting its growing incorporation within knowledge management systems. Although research has examined the value of AI technologies for solving specific problems, the precise mechanisms through which these technologies enhance and transform knowledge sharing (KS) remain underexplored. To address this gap, this study provides a systematic literature review of 35 peer-reviewed articles with the purpose of shedding new light on the connection between AI and KS. By performing a critical review of the literature, it proposes an Integrative AI-KS Framework that maps hypothesized pathways between technologies and organizational outcomes. The review synthesizes current theoretical frameworks, identifies potential outcomes and benefits, and investigates pervasive human implementation barriers. The integration of AI appears to have had three significant effects: (1) it has been associated with greater organizational effectiveness and innovation; (2) it has supported users' learning and adaptation through conversational interfaces that encourage engagement; and (3) it has enabled new knowledge-based competences, especially in the area of privacy-preserving collaboration. However, the analysis also reveals a critical Efficiency-Veracity Paradox, where the risks of algorithmic bias and hallucination offset the speed of sharing. The review contributes two concepts, the Efficiency-Veracity Paradox and a functional account of algorithmic agency, together with a future research agenda. These findings hold implications for managerial practice and provide an opportunity for theory expansion and new management strategies.

Keywords: Artificial Intelligence, knowledge sharing, systematic review, knowledge management

1. Introduction

In the modern knowledge-based economy, knowledge has emerged as an increasingly critical resource for an organization and a basis of competitive advantage (Argote & Fahrenkopf, 2016). Nowadays, organizational landscapes are more characterized by increasing complexity and ambiguity; the acknowledgment of knowledge as a paramount strategic priority has been extensively documented over the last decade. Knowledge, and particularly tacit knowledge, is viewed as a unique, non-substitutable resource capable of providing a competitive advantage (Al-Emran et al., 2024). Nevertheless, the accumulation of knowledge does not inherently result in a strategic edge; it necessitates, however, adept administration via systematic methodologies. Traditionally, it has been argued that Knowledge Management (KM), which addresses the management of both explicit and tacit knowledge in the workplace (Nonaka & Takeuchi, 1996), has emerged

as a mainstream research stream (Ranjan et al., 2024). Previous studies have reported that it is a vital factor in organizational success, specifically directed at the organized management of knowledge creation, organization, storage, dissemination, and exploitation (Zeb et al., 2024).

This critical function leverages organization-wide collective intellectual capacity as a basis for competitive advantage. Such a process covers not only collaboration between employees but also sharing and creation of knowledge. Cheng et al. (2025) reported that knowledge sharing is one of the important components of this framework, considered the main driver of successful KM practices, and understood as the organizational process through which knowledge, experiences, and insights are shared among employees. This creates a culture of collaboration and a sense of ownership, which improves organizational performance and encourages innovative thinking (Khan et al., 2025). In most cases, KS is essential for generating new ideas and improving the learning process, as well as for developing a knowledge-based workforce (Al-Emran et al., 2024; Al-Qaysi et al., 2025; Nguyen & Fry, 2022). A great number of scholars widely regard Knowledge Sharing (KS) as a central topic within the domain of KM. In the literature, KS refers to the institutional processes that enable individuals to exchange information (Lee et al., 2022). In addition, KS is the key process of KM, and its overall performance is largely related to its effectiveness. KS practice is related to the management of organizational knowledge and intangible assets, including know-what, know-how, know-when and know-why (Olan et al., 2022). KM is a key activity related to organizational knowledge (Olan et al., 2022). It is a fundamental ingredient that underpins successful and intuitively informed decision-making within such organizations (Rezaei et al., 2024). Therefore, prioritizing KS allows organizations to function with more agility, robustness and adaptability. As the operating context becomes increasingly turbulent, such adaptability is fundamental for gaining competitive advantage and ensuring sustainable success (Rezaei et al., 2024).

In this landscape, numerous firms are searching for newer tools and innovations to improve efficiency and gain an edge. Consequently, the focus has expanded on the idea of Artificial Intelligence (AI) in previous years. AI presents various applications for institutions to effectively handle and disseminate information (Jarrahi et al., 2023; Olan et al., 2024). Recently, a new generation of disruptive technologies, particularly AI, has the ability to improve society's work and has had a tremendous impact on how organizations function. AI is generally understood to refer to a system's capability to accurately analyze data, derive conclusions from it, and utilize that knowledge to accomplish specific organizational and societal goals (Haenlein & Kaplan, 2019; Mikalef & Gupta, 2021). It is also defined as "computational systems that involve algorithms, machine learning methods, natural language processing, and other techniques that operate on behalf of an individual" (Haenlein & Kaplan, 2019). AI presents opportunities to enhance employees' performance. Organizations are leveraging these opportunities to mitigate uncertainties and reduce supervision time, thereby offering powerful new ways to augment knowledge-related processes (Olan et al., 2022). It can deal with real-world situations, spot real-time errors for executives and allow them to solve problems in real time (Mikalef & Gupta, 2021). AI is deployed in many different ways, built to perform specific tasks using data gathered through learning to achieve specific goals (Huang & Rust, 2018). The rise of AI has significantly transformed technological innovation, leading to a paradigm shift in business operations. In fact, having such implementation enhances operational effectiveness, reduces costs and improves performance (Huang & Rust, 2018). Nonetheless, AI technologies such as text mining, natural language processing (NLP), data mining, as well as machine learning (ML), can help firms assess enormous quantities of data, detect trends and beneficial insights, and, as a result, make better decisions (Khan et al., 2025). In recent years, AI has attracted significant critical attention as a major tool to support this initiative. AI tools help search information, translate languages (Cheng et al., 2025), summarize complex subjects, and produce new, valuable content (Al-Qaysi et al., 2025). The application of these AI tools in sharing knowledge enhances users' individual performance (Khan et al., 2025).

However, successful adoption of this strategic technology largely depends on effective management of knowledge and resources, driven by the accessibility of massive data and cutting-edge infrastructural developments (Mikalef & Gupta, 2021). As a result, it is observed that AI technologies help to greatly advance the modern Knowledge Management (KM) (Al Halbusi et al., 2025). KM procedures are vital in helping to facilitate the success of certain technologies. The effective utilization of AI is largely determined by the successful implementation of these knowledge management processes (Mikalef & Gupta, 2021). Several AI-driven processes have been investigated in this context, which promote the efficient utilization of organizational knowledge. Pai et al. (2022) found that the advancement of KM cannot occur without the incorporation of AI, which is a key infrastructural factor. The increasing focus on AI has led to a synergistic connection with KS. However, existing literature argues that integrating AI technologies alone is insufficient to improve corporate outcomes (Pai et al., 2022). In contrast, models integrating both AI and KS have been shown to yield superior long-term organizational performance. Therefore, the successful implementation and impact of AI increasingly depend on its integration with efficient KS practices (Olan et al., 2022). Recent

evidence suggests that AI-driven tools are of paramount importance for knowledge sharing practices (Olan et al., 2024).

Several researchers have addressed related topics within review studies. Charband and Jafari Navimipour (2016) conducted a systematic review to analyze key KS methods employed within online contexts. In the same vein, the objective of the study by Asrar-ul-Haq and Anwar (2016) was to highlight the elements that impede or enable KM within organizational settings. More recently, reviews have begun to touch upon the role of modern technology, with some exploring the impact of digital disruption on KM and others focusing on the workplace ethics involved in AI. Several attempts have also been made to examine AI in educational context (Al-Emran et al., 2024) and the marketing landscape (De Bruyn et al., 2020), as well as in manufacturing (Kernan Freire et al., 2024). Although these studies provide valuable research synthesis, few writers have been able to draw on any systematic research into the influence of AI technologies, specifically on KS practices. Since such studies are dispersed across educational, industrial, and manufacturing contexts, a systematic literature review (SLR) is warranted: this approach provides an extensive assessment of current research and identifies potential directions for further exploration, setting it apart from traditional or narrative reviews (Do & Mai, 2020).

However, to date, no synthesis exists on the relationship between AI and KS as conjoint factors contributing to organizational performance. While various studies provide substantial information regarding either the technical capabilities of AI or the socio-behavioral influence of KS, no effort has been made to synthesize the empirical evidence on their combined impact. Given that, this study aims to systematically review literature related to AI and KS to determine the extent to which the application of AI tools affects the KS process. To achieve this objective, an integrative conceptual framework is developed that maps the hypothesized relationships between AI technologies, KS mechanisms, and subsequent organizational consequences.

Based on this objective, the study addresses the following research questions:

RQ1. What are the main theoretical frameworks that are currently applied to elucidate the influence of AI in KS context?

RQ2. What are the specific artificial intelligence technologies, tools, and techniques that are mostly used for the enhancement of various knowledge sharing processes?

RQ3. How does the implementation of AI impact knowledge sharing outcomes and organizational efficacy?

RQ4. What are the key success drivers and barriers linked with the implementation of integrated AI-KS systems across different organizational and industrial contexts?

RQ5. What existing knowledge gaps should the literature address concerning the connection between AI technologies and KS, enabling further research to explore more of these areas?

2. Materials and Methods

To examine the effects of AI on Knowledge Sharing (KS), this study conducted a Systematic Literature Review (SLR) following a structured and transparent protocol. Rather than relying on traditional or narrative reviews, an SLR provides a fair, rigorous, and replicable assessment of the extant literature while identifying potential avenues for further exploration (Do & Mai, 2020). To reduce selection bias and ensure methodological rigor, the search strategy was designed a priori in accordance with the guidelines of Kitchenham and Charters (2007) and adheres to the PRISMA 2020 reporting statement. Specifically, this procedure entails four sequential phases:

1. The establishment of the criteria for inclusion and exclusion.
2. The development of data sourcing and search strategy.
3. The quality assessment and study selection.
4. Data coding and analysis.

As the following sub-sections demonstrate, these phases have specific details.

2.1. Inclusion/exclusion criteria

Inclusion criteria	Exclusion criteria
● Peer-reviewed journal articles. ● Published in the English language.	● Papers addressing AI in contexts unrelated to knowledge sharing. ● Book chapters, conference papers, editorials and lecture notes.

• Studies published between January 2014 and June 2025. • Included studies could be empirical (quantitative, qualitative, or mixed methods). • Articles must primarily focus on the intersection of AI (or its sub-fields) and KS (or its core processes). Both concepts must be central to the paper's main arguments or empirical investigation.	• Studies focusing exclusively on traditional knowledge management systems without a significant and identifiable AI component. • Articles where AI or KS were only peripherally mentioned or not substantively integrated.

Table 1. Inclusion/exclusion criteria.

This review study will critically analyze papers that adhere to the inclusion and exclusion selection conditions outlined within Table 1.

2.2. Data sourcing and search strategy

To address the aforementioned research questions, we followed a two-step process to identify the relevant studies. The first step was to determine an appropriate database to retrieve documents for the study. Two main academic databases, namely Scopus and Web of Science, were selected in order to identify the major portion of the reviewed literature. The two journal repositories were selected due to their extensive coverage of high-quality publications, and articles published until the end of June 2025 were included in this review.

The second step consisted of selecting appropriate keywords to extract relevant documents. Search terms for searching related works were carefully defined to cover our two topics of interest: one related to “knowledge sharing” and the other to “artificial intelligence." The knowledge-related category included the terms “knowledge management,” “knowledge transfer,” “knowledge exchange,” and “information sharing,” in addition to “knowledge sharing.” Although these constructs are recognized in the literature as related yet distinct processes, their boundaries are inconsistently defined across research streams. Consequently, all were incorporated as search terms to maximize the sensitivity of the search. However, the synthesis includes only studies in which knowledge sharing, or a directly equivalent construct, is central to the analysis.

Scopus: TITLE-ABS-KEY ("knowledge management" OR "knowledge sharing" OR "knowledge transfer" OR "knowledge exchange" OR "information sharing") AND ("artificial intelligence" OR "AI" OR "machine learning" OR "natural language processing" OR "deep learning" OR "generative AI" OR "recommender system*" OR "chatbot*" OR "knowledge graph*" OR "cognitive technology*" OR "intelligent system*").

Web of Science: (TS= ("knowledge management" OR "knowledge sharing" OR "knowledge transfer" OR "knowledge exchange" OR "information sharing")) AND TS= ("artificial intelligence" OR "AI" OR "machine learning" OR "natural language processing" OR "deep learning" OR "generative AI" OR "recommender system*" OR "chatbot*" OR "knowledge graph*" OR "cognitive technology*" OR "intelligent system*").

The initial searches returned 4,903 records, of which 1,675 duplicates were identified and removed, leaving 3,228 records for screening.

To minimize the risk of selection bias and of inadvertent exclusion of eligible primary studies, title-and-abstract screening was performed through a dual-review process, an approach supported by empirical evidence indicating that screening by a single reviewer can miss relevant studies (Stoll et al., 2019). Two researchers independently screened all records at the title-and-abstract stage against the inclusion and exclusion criteria specified in Table 1, using the Rayyan application to manage the process and to blind the reviewers to one another's decisions. Disagreements were rare and were resolved through joint re-examination and discussion until a final consensus was reached between the two reviewers. This stage resulted in the exclusion of 3,166 records, the overwhelming majority of which addressed AI in contexts unrelated to knowledge sharing or treated one of the two focal constructs only peripherally. The remaining 62 records were sought for retrieval, of which 10 could not be obtained in full text. Only records in which the relationship between AI and knowledge sharing was assessed as a central theme were carried forward from this point. The full texts of the remaining 52 records were then independently assessed for eligibility by the same two reviewers, resulting in 17 further exclusions: 5 because no substantive relationship between AI and knowledge sharing could be established, 3 because AI or knowledge sharing was addressed only peripherally, 5 because "knowledge transfer" was used in a technical, machine-learning sense, or because the AI tool itself, rather than

the sharing process, was the object of study, 3 because AI was employed only as a theoretical lens and its impact on knowledge sharing was not empirically investigated, and 1 because the article had been retracted. The final sample comprised 35 articles. The complete selection process adheres to the PRISMA 2020 statement and is documented in Figure 1.

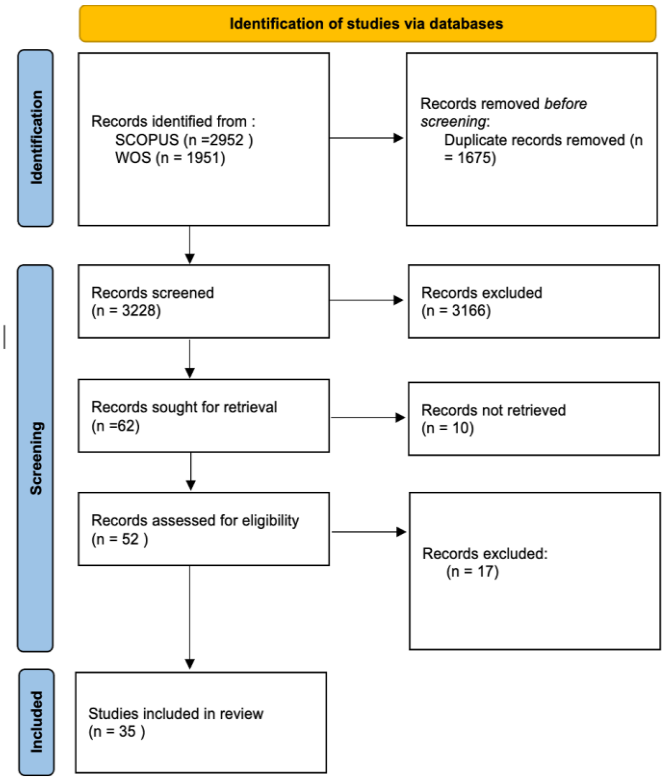


Figure 1. Prisma flowchart

2.3. Quality assessment

One of the critical elements that requires assessment in relation to the exclusion and inclusion criteria is the quality assessment. It is a paramount component of systematic literature reviews, enabling researchers to evaluate methodological rigor and mitigate potential study bias (Al-Emran et al., 2018).

To facilitate this assessment, a quality analysis checklist with five criteria, adapted from the guidelines proposed by Kitchenham and Charters (2007), was prepared to examine the methodological rigor of the 35 research articles selected for in-depth analysis (Table 2). The criteria address whether the research aims are clearly stated, whether the context or setting is adequately described, whether the data collection methods are clearly documented and justified, whether the data analysis process is clearly described and systematically applied, and whether the results are explicitly presented and supported by the data.

The application of this checklist was purely evaluative and was not intended to critique the scholarly merit of any included study (Kitchenham & Charters, 2007). As a result, each qualifying study could attain a total quality score ranging from 0 to 5, with a higher cumulative score indicating greater alignment with the defined research questions. All 35 articles were scored independently by two researchers, and any differences in scoring were resolved through discussion. The scores were used to characterize the strength of the evidence base and are reflected in the synthesis, rather than serving as an additional exclusion mechanism.

Topics of questions
Have the research aims been clearly stated?
Is the context or setting in which the research was performed adequately described?
Are the data collection methods clearly documented and justified (e.g., interview protocol, survey instrument)?
Is the data analysis process clearly described and systematically applied to the collected data?
Are the results and findings of the study explicitly and clearly presented, and are they supported by the data?

Table 2. Quality assessment questions

2.4. Data coding and analysis

During this phase, a Microsoft Excel spreadsheet was created in order to capture the essential data that addresses the critical questions of the current study. In light of the research questions of the study, data were organized in terms of descriptive, methodological, and thematic categories. The descriptive and methodological analysis was deductive in nature and focused on categorizing the identified studies by bibliographic details, organizational context, study type, the AI technology investigated, and the knowledge-sharing process addressed.

A more inductive approach was taken for the thematic analysis, which analyzed and mapped the findings of the selected studies on the relationship between AI and knowledge sharing. The goal of this analysis was to identify the themes reported in Section 3, organized around the five research questions, including the theoretical frameworks applied, the AI technologies investigated, the reported impacts, benefits, and drawbacks, the key barriers and success factors, and the future research directions proposed by the authors of the included studies, as well as to identify gaps in the literature.

Two researchers coded the data independently; the coding framework was maintained as a shared Excel spreadsheet and was refined inductively as codes emerged from the studies, and issues of disagreement were discussed between the researchers until resolved (Miles and Huberman, 1994). The coded data were then synthesized thematically into the descriptive themes reported in Section 3 and the analytical themes developed in Sections 4 and 5.

3. Results

In this section and with respect to the 35 included studies, the outcomes, which were derived from the examination of the literature, were explored based on the five research questions.

3.1. Which main theoretical frameworks are currently applied to elucidate the influence of AI in KS context?

Table 3 summarizes the most frequently used theories. The extant literature relies mainly on conventional theoretical frameworks as summarized in Table 3. The data analysis reveals, however, that these theoretical lenses rarely operate in isolation; rather, they form an interconnected lattice of strategic, behavioral, and contextual perspectives.

3.1.1. The strategic lens

According to our review, the Knowledge-Based View (KBV) serves as the foundational theory in this cluster, positing that knowledge is the organization's most valuable strategic resource (Ranjan et al., 2024). However, in the context of AI, KBV is often insufficient on its own because it treats knowledge as a static asset. Consequently, recent studies have complemented KBV with the Dynamic Capabilities framework.

As Al Halbusi et al. (2025) posit, businesses must amalgamate internal and external knowledge to navigate dynamic environments; dynamic capabilities therefore appear better suited than KBV to AI-intensive contexts, as they explain the process of sensing and seizing data to reconfigure the organization's knowledge base (Al Halbusi et al., 2025). In the same vein, technological determinism features in this cluster as a competing lens, according to which AI systems themselves constitute the primary drivers of societal change and innovation, particularly in driving sustainable performance (Al Halbusi et al., 2025).

Theories	Sample articles
Knowledge-Based View (KBV)	(Ranjan et al., 2024)
Social Exchange Theory (SET)	(Khan et al., 2025)
Technological Determinism	(Al Halbusi et al., 2025)
Dynamic Capabilities	(Al Halbusi et al., 2025)
Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT)	(Khan et al., 2025)
Situational Learning Theory	(Hussain et al., 2024)
Expectation Confirmation Model	(Al-Sharafi et al., 2023)
Information-seeking behavior theories	(Subaveerapandiyan et al., 2024)
Social Cognitive Theory (SCT)	(Hu et al., 2025)

Table 3. Most frequently used theories.

3.1.2. The behavioral and motivational lens

The review reveals a significant theoretical dichotomy between initial system adoption and active knowledge contribution. On the one hand, the Technology Acceptance Model (TAM) and UTAUT reliably account for technology adoption via perceived usefulness and ease of use; on the other hand, they offer limited explanatory power with respect to why individuals choose to contribute knowledge. In this sense, recent studies have synthesized Social Exchange Theory (SET) with traditional acceptance models, advancing the premise that employees weigh implicit personal costs against expected social and organizational benefits prior to engaging in knowledge exchange. In line with this premise, AI functions as a mechanism that reduces the costs of sharing (time and effort), thereby increasing the likelihood of engagement (Khan et al., 2025). Of particular importance, this stream of research indicates that perceived risk, such as job insecurity, acts as a boundary condition. It, therefore, challenges the direct application of TAM: even if an AI tool is useful, employees may reject it should the SET cost-benefit analysis reveal high personal risk.

With respect to social-cognitive mechanisms, SCT, emphasizing observational learning, advances that emulating role models lead to the acquisition of behaviors (Hu et al., 2025). According to Hu et al. (2025), this theory is particularly suitable for explaining how transformational leadership fosters a culture of innovation in AI-KS contexts, insofar as AI assistants reinforce these positive behaviors by providing timely feedback and connecting team members to resources, while leaders act as exemplary models.

3.1.3. The contextual and learning lens

Turning to the theoretical landscape, the examination of the selected studies indicates that only certain theories directly address the process of information retrieval. With respect to training and simulation contexts, Situational Learning Theory appears particularly effective. In this respect, Hussain et al. (2024) applied this theory to design immersive VR scenarios for migrant workers, thereby ensuring that knowledge acquisition was both authentic and contextually relevant.

On the other hand, information-seeking behavior theories, though grounded in a different tradition, are better suited to designing the architecture of information systems so as to match human search patterns (Subaveerapandiyan et al., 2024). Taken across these contexts, therefore, the choice of theory appears to follow the context of use rather than the technology itself.

3.1.4. Theoretical Gaps

The analysis revealed that the most utilized theories, such as the Knowledge-Based View and the Technology Acceptance Model, are human-centric and were developed before the advent of generative AI. The synthesis further indicates a paucity of research employing interactionist theories that account for algorithmic agency, where AI is understood not merely as a tool to be accepted (TAM) or exchanged with (SET), but as a system performing epistemic functions that shape the creation of knowledge itself.

The reviewed studies indicate that AI systems now generate unfounded outputs and perform epistemic functions once exclusive to humans. Current frameworks such as TAM or KBV appear to lack the ontological complexity to account for a non- human actor in the knowledge-sharing network that generates, obscures, or

biases knowledge independently of human intent in the moment. Accordingly, this gap represents an opportunity for future theoretical development, and it motivates the two conceptual contributions developed in Section 5.1, the Efficiency- Veracity Paradox and the functional account of algorithmic agency.

3.2. What specific artificial intelligence technologies, tools, and techniques are most frequently investigated and utilized for the enhancement of various knowledge sharing processes?

To answer the second research question, this section investigates the specific AI technologies that enhance KS; researchers identified a wide spectrum of tools. However, the analysis of the findings revealed a distinct evolutionary pattern: the field is shifting from backend analytic models (focused on the combination of explicit knowledge) toward user-facing generative agents (focused on socialization and externalization).

Within this landscape, a distinction is drawn between conversational agents, which primarily support interactive, retrieval-oriented dialogue, and generative AI or LLM-based systems, which produce new content from learned patterns; a further distinction separates user-facing applications from system-level analytic and privacy-preserving architectures. The classification in Table 4 follows these distinctions, and each study is assigned to the single category corresponding to its primary technology focus.

The analysis indicates that conversational AI applications, such as chatbots and virtual assistants, attract the most attention in this stream of research (N = 10). Specifically, these studies primarily concentrate on the individual level of analysis, examining how interactive interfaces enhance the socialization component of knowledge sharing. In this regard, AI-based chatbots are frequently examined as platforms for interactive, two-way KS and learning (Al-Emran et al., 2024; Al-Sharafi et al., 2023; Malik et al., 2021; Soleimani et al., 2022; Subaveerapandiyan et al., 2024), whereas various virtual assistants have been investigated in specialized environments (Hui et al., 2024; Khan et al., 2025; Macchia et al., 2021; Radhakrishna et al., 2024; Rezaei et al., 2024).

The emergence of generative AI and LLMs represents the second major focus (N = 4), with studies investigating ChatGPT, Bard, and comparable systems (Al-Qaysi et al., 2025; Arbulú Ballesteros et al., 2024; Sumbal et al., 2024; Kernan Freire et al., 2024). This suggests a technological shift in which AI is no longer limited to retrieving information but also generates content, highlighting its role in transcribing unstructured, tacit inputs into codified, explicit outputs.

A further group of studies (N = 4) focuses on classical ML and NLP pipelines operating at the system level (De Bruyn et al., 2020; Nguyen and Fry, 2022; Wang et al., 2022; Xia et al., 2022), typically addressing the efficiency of data aggregation (combination). Several of the conversational studies additionally detail the NLP and machine learning components that power their systems; because these studies are classified by their primary technology focus, they are listed in the first category, and this overlap is reflected in the description of that category rather than in a separate assignment.

Finally, the literature proposes novel AI-driven techniques (N = 8) that highlight a tension between sharing and security. Specifically, these methodologies encompass privacy-centric techniques such as federated learning (Zheng et al., 2025; Zhou et al., 2024) in conjunction with knowledge distillation (Shi et al., 2020), together with knowledge-graph construction, incentive mechanisms, and cognitive assistant architectures (EL ASRI et al., 2024; Freire et al., 2023; Du et al., 2023; Bilogrevic et al., 2016; Grum and Gronau, 2024).

In total, Table 4 covers the 26 included studies in which a specific AI technology, tool, or system was the object of investigation. The remaining nine included studies examine AI at the level of strategic capability, adoption, or organizational context rather than a specific tool, and they are therefore discussed in the narrative rather than assigned to a technology class; these include studies of AI capability and organizational creativity (Li et al., 2022), AI-driven knowledge sharing and employee performance (Olan et al., 2024), the decline of tacit knowledge sharing among practitioners (Toscani, 2022), knowledge management in investment banking (Ranjan et al., 2024), AI adoption and sustainable learning (Hu et al., 2025; Al Halbusi et al., 2025), conversational AI-based VR training (Hussain et al., 2024), AI-enhanced design software (Qi Dongkai et al., 2023), and knowledge sharing in AI service markets (Mohammed et al., 2023).

Artificial intelligence technologies, tools, and techniques	Description	References
Traditional Conversational Agents (non-generative): chatbots and virtual assistants	User-facing dialogue interfaces supporting information retrieval, questioning, and two-way knowledge exchange, without generative content synthesis	(Al-Emran et al., 2024; Al-Sharafi et al., 2023; Malik et al., 2021; Soleimani et al., 2022; Subaveerapandiyan et al., 2024; Hui et al., 2024; Khan et al., 2025; Macchia et al., 2021; Radhakrishna et al., 2024; Rezaei et al., 2024)
Generative AI and Large Language Models (LLMs)	Content-generating foundation models used as cognitive assistants or tutoring cores	(Al-Qaysi et al., 2025; Arbulú Ballesteros et al., 2024; Sumbal et al., 2024; Kernan Freire et al., 2024)
ML/NLP models	Machine learning and natural language processing pipelines operating at the system level	De Bruyn et al. (2020); Nguyen and Fry (2022); Wang et al. (2022); Xia et al. (2022)
Novel AI-driven sharing techniques	Privacy-centric and incentive mechanisms (federated learning, knowledge distillation, knowledge graphs, incentive design)	(Zheng et al., 2025; Zhou et al., 2024; Shi et al., 2020; EL ASRI et al., 2024; Freire et al., 2023; Du et al., 2023; Bilogrevic et al., 2016; Grum and Gronau 2024)

Table 4. Artificial intelligence technologies, tools, and techniques

3.3. How does the implementation of AI impact knowledge sharing outcomes and organizational efficacy?

To address RQ3, the findings of each article were classified according to the reported results. The analyzed literature yielded 24 findings related to the impacts, benefits, or drawbacks of using AI in a KS context. Because several studies reported multifaceted outcomes, some papers appear in more than one category, and percentages are therefore computed against the 24 reported findings.

The analysis of these findings was grouped into five main categories: four substantive impact categories and one additional group of null or negative findings. The most common theme, enhanced organizational performance and innovation, accounted for 29.2% (N = 7) of the reported findings.

Additionally, a critical category, identified risks and drawbacks (e.g., inaccuracy, bias), represented 29.2% (N = 7) of the findings. This was followed by improved user experience, adoption, and learning, which comprised 25.0% (N = 6) of the findings. Finally, enabled new knowledge-centric capabilities (e.g., tacit capture) were the focus of 8.3% (N = 2) of the findings, and null or negative empirical findings accounted for an equal proportion (8.3%, N = 2). Table 5 summarizes these categories, the counts, the proportions of reported findings, and the corresponding study references. Table 5 presents the references organized by group, which will be analyzed in the following subsections.

Impacts and Benefits	Count (N)	Proportion of reported findings (%)	References
Enhanced organizational performance and innovation	7	29.2%	(**Olan et al**., 2024; Hu et al., 2025; Li et al., 2022; Hui et al., 2024; Macchia et al., 2021; Shi et al., 2020; Zheng et al., 2025)
Identified risks and drawbacks	7	29.2%	(Hussain et al., 2024; Freire et al., 2023; Al-Emran et al., 2024; De Bruyn

			et al., 2020; Soleimani et al., 2022; Rezaei et al., 2024; Khan et al., 2025)
Improved user experience, adoption, and learning	6	25.0%	(Khan et al., 2025; Malik et al., 2021; Al-Sharafi et al., 2023; Arbulú Ballesteros et al., 2024; Sumbal et al., 2024; Hussain et al., 2024)
Enabled new knowledge-centric capabilities	2	8.3%	(Du et al., 2023; Freire et al., 2023)
Null or negative findings	2	8.3%	(Ranjan et al., 2024; Al-Qaysi et al., 2025)

Table 5. Impacts and Benefits of AI in KS

The analysis of RQ3 reveals significant tensions across different levels of analysis. Although 29.2% of the reported findings indicate improved performance, the distribution of these benefits is not uniform, exposing what we term an efficiency-veracity paradox (developed in Section 5).

3.3.1. Enhanced organizational performance and innovation

At the macro-level, several studies reported a direct, positive link between AI-based KS and key performance metrics, such as employee performance (Olan et al., 2024) and organizational creativity (Hu et al., 2025; Li et al., 2022). This impact on innovation was a recurring finding. For instance, AI-based virtual assistants were found to foster team innovation by enhancing the team's underlying knowledge sharing behaviors (Hui et al., 2024). Similarly, AI was shown to improve teamwork and decision-making quality in complex medical (Macchia et al., 2021) and public sector environments (Macchia et al., 2021).

At the strategic level this performance effect was seen too. A well-functioning Knowledge Management System (KMS) can strengthen the link between a company's AI skills and its green innovation results (Macchia et al., 2021). Moreover, data indicated that certain publications on advanced AI technologies (e.g., federated learning, knowledge distillation) positively influenced model accuracy and performance by facilitating knowledge sharing among models while maintaining data privacy (Shi et al., 2020; Zheng et al., 2025). This suggests that AI successfully scales combination processes to drive strategic agility.

3.3.2. Improved user experience, adoption, and learning

On the other hand, at the micro-level, AI tools consistently enhance self-efficacy and learning trajectories, functioning as a scaffold for internalization by allowing users to absorb new knowledge rapidly through personalized feedback (Khan et al., 2025; Malik et al., 2021).

Another major theme in the literature is how AI systems benefit end users. Specifically, these tools improve the daily experience of employees by providing accurate and current information (Khan et al., 2025). Furthermore, AI supports personalized career growth. This often leads to higher job satisfaction and stronger commitment to the organization (Malik et al., 2021).

Naturally, a positive user experience directly encourages people to keep using the technology. For instance, a chatbot's ability to share knowledge is a strong predictor of whether students intend to use it (Al-Sharafi et al., 2023). Similarly, the way ChatGPT shares knowledge has a significant effect on its actual adoption by users (Arbulú Ballesteros et al., 2024).

Besides improving the experience, AI also helps people learn more effectively. AI-based conversational interfaces were found to lower the perceived social cost of seeking help, which was associated with greater user confidence and greater disclosure of tacit knowledge (Sumbal et al., 2024). Finally, quantitative research shows the power of these tools in training. For example, a VR system using AI increased the knowledge scores of migrant workers by 23% (Hussain et al., 2024).

3.3.3. Enabled new knowledge-centric capabilities

Further beyond general performance, AI was found to support completely new abilities. A study explained that a cognitive assistant could aggregate and transfer expert tacit knowledge into a dynamic, shareable knowledge base (Freire et al., 2023). Another paper showcased how generative AI was employed to derive

AI-generated incentive mechanisms, thereby successfully incentivizing users to disclose their data (Du et al., 2023).

3.3.4. Identified risks, drawbacks

The synthesized literature also indicates several significant risks and drawbacks. A critical inconsistency emerges between the speed of sharing and the reliability of knowledge. The most significant limitation cited is that of producing false information through AI, known as hallucinations (Freire et al., 2023), which was found to create a perceived threat for the user (Al-Emran et al., 2024). This is strongly associated with the black box characteristics of AI which may inhibit trust and organizational learning (De Bruyn et al., 2020; Rezaei et al., 2024).

Another major risk is the amplification of human biases by AI systems (De Bruyn et al., 2020; Soleimani et al., 2022). In addition, one empirical study showed that employee perceived risk related to job security and privacy negatively moderated the relationship between AI and KS (Khan et al., 2025), indicating that benefits are not automatic if users feel threatened. This suggests that while AI solves the quantity problem of sharing, it introduces a quality problem regarding bias and truthfulness (Soleimani et al., 2022; Khan et al., 2025).

3.3.5. Cross-cutting synthesis and theoretical tensions

Our analysis of the selected studies revealed three cross-cutting patterns beyond the preceding category-by-category examination. Of particular note, positive performance effects were predominantly observed in studies involving structured, verifiable knowledge within well-resourced environments, such as inter-organizational supply chains and enterprise IT systems, whereas risks and null effects were mostly found in contexts where the knowledge shared is tacit, context-dependent, or safety-critical. In this sense, the benefits reported in the literature seem to be conditional on the verifiability of the knowledge being shared, although this observation remains tentative; it is discussed further as the Efficiency-Veracity Paradox in section 5. Second, the methodological tradition of a study appears to shape its findings: survey-based acceptance studies consistently report positive user-perception outcomes, whereas technical benchmarking studies and qualitative workplace studies surface accuracy, integration, and trust problems that perception surveys do not capture. In this respect, the pattern suggests that part of the apparent contradiction in the literature would seem to reflect differences in what is measured rather than genuine disagreement about the underlying phenomena.

Third, the field remains conceptually fragmented at the level of theory: deterministic readings, in which AI capability is modeled as a direct driver of outcomes, coexist with social-cognitive and exchange-based accounts in which outcomes depend on human interpretation and organizational context, without any study in the corpus explicitly adjudicating between these assumptions. We return to this fragmentation and to its implications for the ontology of knowledge sharing in Section 5.

A further distinction concerns technological maturity: studies of established NLP/ML pipelines, focused on the combination of explicit knowledge, differ in their reported findings and risks from studies of emergent generative AI agents, focused on socialization and externalization, yet the corpus rarely compares the two directly.

This unresolved contrast is also examined in Section 5, where it informs the two theoretical contributions developed there.

3.4. What are the key success drivers and barriers linked with the implementation of integrated AI-KS systems across different organizational and industrial contexts?

To address RQ4, findings across the 30 papers that specifically investigated challenges, obstacles, and critical success factors were systematically synthesized. The analysis suggests that these barriers are not isolated; rather, technical failures at the system level appear to precipitate psychological resistance at the individual level.

These findings were organized into four primary thematic clusters. Technical, data, and ethical concerns represented the most prevalent theme, forming the focal point of 46.7% (N = 14) of the analyzed papers. Human and organizational barriers followed, examined by 40.0% (N = 12) of the studies. Conversely, on the success side, organizational and strategic enablers were reported in 13.3% (N = 4) of the literature, with

technical and human success factors identified in an equal proportion of studies (13.3%, N = 4). Table 6 lists the references in each of these categories, which are reviewed in the subsections below.

Barrier Factors for AI - KS Systems	References	Critical success factors for AI-KS systems	References
Technical, data, and ethical issues	(Bilogrevic et al., 2016; De Bruyn et al., 2020; Kernan Freire et al., 2024; Macchia et al., 2021; Qi Dongkai et al., 2023; Radhakrishna et al., 2024; Rezaei et al., 2024; Shi et al., 2020; Soleimani et al., 2022; Sumbal et al., 2024; Toscani, 2022; Zhou et al., 2024; Zheng et al., 2025)	Organizational and strategic success (top management support and transformational leadership, supportive and collaborative culture)	(Hui et al., 2024; Li et al., 2022; Malik et al., 2021; Ranjan et al., 2024)
Human and organizational factors	(Al-Emran et al., 2024; Al-Qaysi et al., 2025; Du et al., 2023; Hu et al., 2025; Kernan Freire et al., 2024; Khan et al., 2025; Mohammed et al., 2023; Rezaei et al., 2024; Subaveerapandiyan et al., 2024; Zheng et al., 2025 ; Freire et al., 2023)	Technical and human aspects (quality of the AI system, social influence, self-efficacy)	(Al-Qaysi et al., 2025; Al-Sharafi et al., 2023; Arbulú Ballesteros et al., 2024; Qi Dongkai et al., 2023)

Table 6. Key success drivers and barriers

3.4.1. Barrier factors for AI-KS systems

Technical, Data, and Ethical Issues

Within this category, data privacy and security emerge as the primary concern across the reviewed studies. In this respect, multiple studies, particularly those examining advanced techniques such as federated learning, identify data leakage, privacy risks, and security as central obstacles that may hinder organizations from engaging in KS (Bilogrevic et al., 2016; Qi Dongkai et al., 2023; Shi et al., 2020; Zheng et al., 2025; Zhou et al., 2024). These concerns, moreover, are closely intertwined with broader ethical considerations, notably algorithmic bias: researchers highlight that AI systems can amplify existing human biases, and their black box nature may make it difficult for users to trust or validate their results (De Bruyn et al., 2020; Rezaei et al., 2024; Soleimani et al., 2022; Sumbal et al., 2024). Beyond these concerns, several studies note significant data and model quality issues, ranging from the risk of AI hallucinations or inaccuracy and the high cost of LLMs (Kernan Freire et al., 2024) to the lack of a gold standard for data (Macchia et al., 2021) and the challenge of integrating with existing systems and data silos (Radhakrishna et al., 2024). Finally, the inability of current AI to capture tacit knowledge or account for context was noted as a major technical limitation (De Bruyn et al., 2020; Toscani, 2022), in this way delimiting the scope of what AI-mediated KS can currently achieve.

Human and organizational factors

The second key barrier category relates to human and organizational resistance. First, a frequent theme is users' lack of trust, which discourages adoption (Kernan Freire et al., 2024; Hu et al., 2025; Mohammed et al., 2023; Zheng et al., 2025). In this respect, such distrust can often be traced back to perceived risk or threat from AI, and is characterized by employee concern over job security or data privacy (Al-Emran et al., 2024; Hu et al., 2025; Khan et al., 2025). Second, a further human barrier concerns limitations in skills, digital

literacy, or training, which restrict employees from using the new tools effectively (Rezaei et al., 2024; Subaveerapandiyan et al., 2024). Finally, at the organizational level, the barriers include resistance to change (Al-Qaysi et al., 2025), a lack of time or incentives for employee knowledge sharing (Freire et al., 2023), and knowledge-hoarding behavior on the part of users (Du et al., 2023), which was associated with reduced willingness to share. Taken across these strands, therefore, the resistance documented in the literature appears to be not merely a general reluctance to change but, in significant part, a specific form of algorithm aversion, triggered by a lack of explanation.

3.4.2. Critical success factors for AI-KS systems

The literature identifies several conditions associated with successful implementation, which, taken together, suggest that organizations should treat AI implementation as a change management project, not just a software installation. At the organizational and strategic levels, the most prominent condition is management commitment and transformational leadership (Hui et al., 2024; Li et al., 2022); in this respect, such leadership is key to a supportive and collaborative culture characterized by innovation and knowledge sharing (Li et al., 2022; Malik et al., 2021), as well as to the provision of a supportive infrastructure (Ranjan et al., 2024).

With respect to the technical and human dimensions, success is closely related to the quality of the AI system itself, namely its information quality, service quality, and perceived usefulness (Al-Qaysi et al., 2025; Al-Sharafi et al., 2023; Qi Dongkai et al., 2023), and these system-related factors are further augmented by human factors, including social influence (Al-Sharafi et al., 2023; Arbulú Ballesteros et al., 2024) and individual user self-efficacy (Al-Sharafi et al., 2023).

3.5. What existing knowledge gaps should the literature address concerning the connection between AI technologies and KS, enabling further research to explore more of these areas?

Despite confirming that the literature review reveals an increasing number of studies examining the connection between AI and KS, the outcomes consistently suggest that this area remains in its infancy and is characterized by numerous unresolved questions and challenges. This section outlines the results from the investigation related to RQ5.

According to the analyzed literature, 22 papers provided specific directions for future research. These gaps were grouped into three main categories. The most frequently cited limitation was methodological and contextual scope, which was mentioned by 54.5% (N = 12) of the articles. This was followed by technical AI and integration challenges, a theme in 22.7% (N = 5) of the papers. Finally, the need to investigate the human-AI interaction and the dark side of AI was noted in 22.7% (N = 5) of the papers.

Table 7 displays the references associated with each of these categories. The subsequent subsections elaborate on these challenges and suggestions.

Knowledge gaps and future research directions	References
Methodological and contextual limitations	(Al Halbusi et al., 2025; Al-Qaysi et al., 2025; Al-Sharafi et al., 2023; Hu et al., 2025; Hui et al., 2024; Khan et al., 2025; Malik et al., 2021; Nguyen & Fry, 2022; Qi Dongkai et al., 2023; Ranjan et al., 2024; Rezaei et al., 2024; Toscani, 2022)
Human-AI interaction and the dark side	(Freire et al., 2023; Hui et al., 2024; Kernan Freire et al., 2024; Khan et al., 2025; Malik et al., 2021)
Technical AI and integration gaps	(De Bruyn et al., 2020; EL ASRI et al., 2024; Hussain et al., 2024; Kernan Freire et al., 2024; Sumbal et al., 2024)

Table 7. Knowledge gaps and future research directions

3.5.1. Methodological and contextual limitations

According to the literature review results, the connection between AI and KS was addressed by studies with significant methodological weaknesses. The most common gap identified was the reliance on cross-sectional, one-time surveys (Al Halbusi et al., 2025; Ranjan et al., 2024). This is important because the reviewed findings suggest that user trust may decline over time in the presence of hallucinations or limited explainability. The

researchers repeatedly called for longitudinal studies to explore the evolution of these AI-driven relationships over time (Hu et al., 2025; Hui et al., 2024; Khan et al., 2025; Qi Dongkai et al., 2023).

Moreover, quantitative data were often not sufficient, and qualitative methods similar to in-depth interviews are suggested to provide a depth of knowledge about the reasons behind the findings (Al Halbusi et al., 2025; Al-Qaysi et al., 2025; Al-Sharafi et al., 2023; Rezaei et al., 2024). This methodological weakness is accompanied by a contextual one.

Several authors also emphasized the limitations that these findings were made in one single country or industry (China, Malaysia, construction, education, etc.) and they may not be generalizable. Additionally, they emphasized the necessity to conduct comparative research across both cultures and geography (Malik et al., 2021; Nguyen & Fry, 2022; Toscani, 2022) and across sectors (Hu et al., 2025; Khan et al., 2025; Malik et al., 2021). This background provided the context for the development of Proposition 1.

Proposition 1: Future investigations could employ longitudinal mixed-methods designs to track the evolution of user trust over time, investigating how initial enthusiasm for generative AI tools evolves into skepticism or more sophisticated usage strategies, and how this trajectory moderates knowledge sharing behaviors.

3.5.2. Human-AI interaction and the dark side

Literature review findings indicate the negative consequences and ethical considerations of AI-driven KS remain underexplored. Even though some papers acknowledged obstacles such as fear and distrust (Freire et al., 2023), the authors argue that there is a need for more exploration on the dark side or negative employee consequences of these systems (Hui et al., 2024; Malik et al., 2021).

This requires, for example, a call for a further exploratory study on human-AI interaction design (Kernan Freire et al., 2024) and the significance of trust in AI (Khan et al., 2025), as well as the long-term safety and ethical considerations in deploying such tools in high-stakes settings (Kernan Freire et al., 2024). The review further suggests that fear of surveillance and deskilling may actively inhibit sharing, and that current theories such as TAM do not account for AI as a consequential actor in the knowledge-sharing network that may compete with employees for tasks (Khan et al., 2025).

Based on this, the following proposition is advanced:

Proposition 2. Further work is needed to develop algorithmic agency frameworks that explain potential negative feedback loops between AI deployment and employee silence. More broadly, research is also needed to test whether the introduction of high-agency AI tools (e.g., autonomous coding assistants) is associated with knowledge-hiding behaviors among experts seeking to protect their professional status.

3.5.3. Technical AI and integration gaps

As the reviewed studies indicate, several major technical challenges remain unsolved. The most significant, identified in the selected papers, is the difficulty of transferring tacit knowledge. Future work should explore how humans can effectively convey tacit, common-sense knowledge to AI systems, and how knowledge generated by AI systems can be transferred back to humans in an explainable way (De Bruyn et al., 2020). In terms of Nonaka's knowledge conversion processes, AI appears to excel at combination (explicit-to-explicit) yet struggles with internalization without significant human intervention.

More practical and urgent gaps were also identified, including the need to develop methods to reduce AI hallucinations and to create on-premise (local) LLMs to solve the security risks of using third-party tools (Kernan Freire et al., 2024).

Finally, a major theme was the gap between generic AI tools (like ChatGPT) and organizational knowledge.

Future investigation is required to assess the practical feasibility of incorporating LLMs in internal Knowledge Management Systems (Sumbal et al., 2024) in order to build domain-specific models (EL ASRI et al., 2024; Hussain et al., 2024). Proposition 3 reflects this difficulty.

Proposition 3. Technical research should move from generic model application toward domain-specific knowledge distillation. Future work should investigate how Human-in-the-Loop (HITL) fine-tuning processes can effectively capture local organizational context, thereby reducing the hallucination rates that currently undermine Knowledge Management Systems.

4. Proposed framework for integrating AI technologies into KS practice

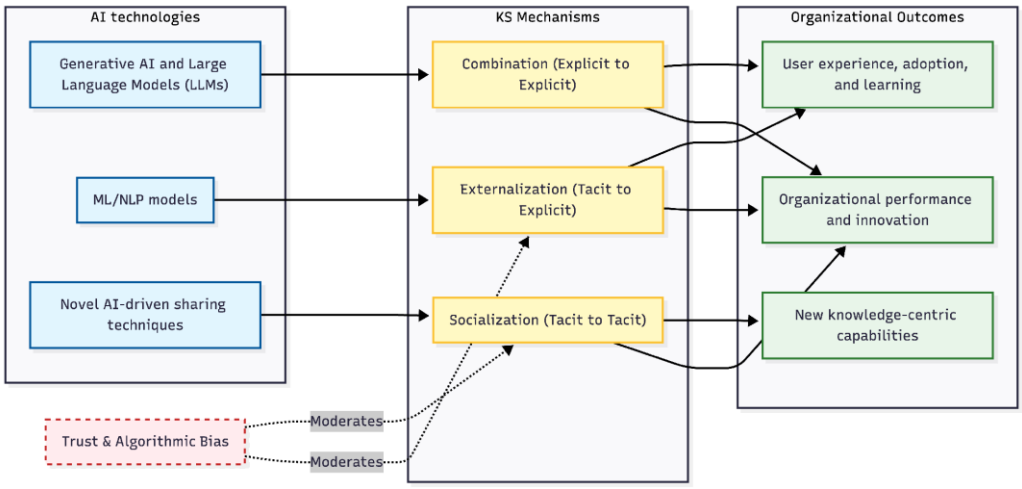


Figure 2. The proposed framework

Our study has sought to present a conceptualization of the influence of artificial intelligence technologies in optimizing knowledge-sharing practices and thus organizational efficacy. Based on previous studies and on the systematic review in this paper, a conceptual framework has been proposed for AI-enabled knowledge sharing. It highlights the hypothesized pathways between specific AI technologies and Knowledge Sharing (KS) mechanisms (see Figure 2).

The proposed model positions AI systems as active components of the knowledge-sharing process that are proposed to support the transformation of knowledge forms by virtue of the epistemic functions they perform rather than any intent of their own, in contrast with traditional views of technology as a passive repository.

Therefore, this framework makes a major contribution to this research by illustrating how specific AI capabilities may facilitate the access to tacit knowledge. Cognitive assistants are no longer limited to explicit data retrieval; they have been reported to aggregate expert tacit knowledge and transfer it into dynamic, shareable knowledge bases (Freire et al., 2023). By transcribing and categorizing unstructured dialogue, these tools lower the barrier to articulating subjective insights, facilitating the externalization process (Olan et al., 2022). Such automated expert location reduces the search cost of knowledge, fostering a culture of collaboration even in geographically dispersed teams. Furthermore, ML and NLP algorithms significantly augment cognition by identifying patterns and insights in large data volumes (Olan et al., 2022), thereby supporting both the externalization of tacit knowledge and the combination of explicit knowledge. In line with this, AI tools are well suited to summarizing complex subjects and producing new value from existing data (Khan et al., 2025). Beyond these cognitive functions, the framework identifies novel AI-driven sharing techniques that enable privacy-centric knowledge merging, such as federated learning and knowledge distillation (Zheng et al., 2025; Shi et al., 2020). However, the framework highlights that these pathways are moderated by trust and algorithmic bias: the black box nature of AI, read through the lens of Social Cognitive Theory, may explain why users hesitate to engage fully with these systems, as an employee who perceives the system as opaque may experience a lack of trust or fear regarding job security and data privacy. Notwithstanding these frictions, conversational AI interfaces can lower the perceived social cost of seeking help, thereby supporting the disclosure of tacit knowledge that employees might otherwise withhold (Sumbal et al., 2024).

Extending these mechanisms to the team level, studies have further reported that AI-driven virtual assistants foster knowledge-sharing behaviors among group members, thereby supporting team innovation (Hui et al., 2024). In this sense, the model proposes that the alignment of AI tools with specific knowledge-sharing (KS) processes mediates organizational outcomes: where AI is effectively deployed to augment these processes, it is associated with measurable improvements in employee performance (Olan et al., 2024). Such synergy, it follows, may translate into enhanced organizational agility and sustainable competitive advantage, as the organization is able to leverage its collective intellectual capital more efficiently than would be possible

through manual KS practices alone. Drawing these strands together, therefore, the conceptual framework posits that AI technologies (generative AI, NLP, and ML), user adoption factors (trust and skills), and organizational context (leadership and culture) are proposed as antecedents of effective knowledge-sharing processes, which are in turn associated with organizational performance and innovation.

5. Discussion and Implications

Our systematic literature review synthesizes fragmented findings into a cohesive understanding of how AI reconfigures knowledge sharing. Transcending a mere descriptive categorization of tools, our analysis identifies a fundamental ontological shift in Knowledge Sharing (KS): a transition from purely human-mediated systems to complex, AI-mediated ecosystems.

5.2. Theoretical contributions

This study makes two main theoretical contributions to the growing literature on knowledge sharing and artificial intelligence.

The first contribution is the Efficiency-Veracity Paradox. Across the corpus, the mechanisms through which AI technologies enhance knowledge sharing, namely large-scale pattern extraction from unstructured data, generative synthesis, and rapid retrieval and recommendation, are precisely the mechanisms through which the veracity of shared knowledge can be degraded. The same statistical character of these systems that makes tacit and distributed knowledge shareable at unprecedented speed and volume also makes them prone to plausible but unfounded outputs (Freire et al., 2023), to the amplification of biases present in their training data (De Bruyn et al., 2020; Soleimani et al., 2022), and to outputs that users cannot readily validate, a concern the literature associates with the opacity of these systems (De Bruyn et al., 2020; Rezaei et al., 2024). Therefore, the paradox appears to be structural rather than incidental: efficiency gains in knowledge sharing are strongest exactly where veracity is most difficult to establish. The outcomes further offer a better understanding of how this concept differs from three adjacent literatures: research on hallucinations treats unfounded outputs as a technical reliability defect to be mitigated through model improvements (Kernan Freire et al., 2024); research on misinformation concerns the accuracy of content irrespective of its provenance; and research on algorithmic bias frames the problem as one of fairness toward individuals and groups (Soleimani et al., 2022). Each addresses a necessary component of the phenomenon, but each localizes it, respectively, in the model, in the content, or in the distribution of outcomes. This study indicates that the Efficiency-Veracity Paradox relocates the problem at the level of the knowledge-sharing process itself: organizations face a continuous trade-off between the volume and speed of knowledge flows, on the one hand, and their trustworthiness, on the other, such that governance mechanisms (verification practices, provenance labeling, human-in-the-loop review) do not eliminate the trade-off but reposition it. The evidence synthesized in Section 3 is consistent with this reading, in that the studies reporting the largest efficiency gains operate on structured, verifiable knowledge, whereas those flagging veracity concerns operate on tacit or context-dependent knowledge. Nevertheless, this study still has some limitations: because the corpus is predominantly cross-sectional and heterogeneous, this proposition should be read as a theorized conjecture for future longitudinal research rather than as an established empirical regularity. The second contribution concerns the ontological status of AI systems within knowledge-sharing processes. The reviewed literature suggests a shift from a process in which knowledge moves only between human knowers to one in which epistemic functions previously exclusive to humans, such as summarizing, translating, combining, and recommending, are partially delegated to computational systems (Jarrahi et al., 2023). This shift is characterized here as one of algorithmic agency, understood in strictly functional terms: AI systems exercise agency in the knowledge-sharing network by performing epistemic functions, not by possessing intent, understanding, or volition. As a result, this functional definition disciplines the theoretical claims the concept can support.

What the literature documents is a redistribution of epistemic labor, and an associated shift in where organizations must locate responsibility for knowledge quality: from the individual sharer to a socio-technical configuration of humans, models, data, and governance.

What the literature does not yet establish, and what this deliberately non-anthropomorphic framing avoids implying, is that AI systems participate in knowledge sharing as social actors with motives of their own. This reading also clarifies why human-AI partnership, rather than substitution, recurs across the reviewed studies (Jarrahi et al., 2023; Olan et al., 2024): the delegation of epistemic functions complements, but does not replicate, the interpretive and relational capacities that human knowers bring to sharing processes. In the same vein, the present study confirms previous findings suggesting that traditional KS theories (e.g., KBV) treat systems as static storage. On the other hand, one of the issues that emerges from our

findings is that generative AI and cognitive assistants now perform epistemic functions, including socialization and externalization support, that were previously exclusive to human actors.

In fact, these challenges existing organizational behavior models, requiring new frameworks that account for the distribution of machine agency in team dynamics. We identify a critical tension where AI enhances capability but erodes trust. Organizational research must now focus more on algorithmic trust as a distinct construct from interpersonal trust. If, however, employees perceive AI as a surveillance tool rather than a support tool, knowledge-hiding behaviors may increase.

5.3. Implications for research and practice

For the IS community, the synthesis suggests that technical architecture must now prioritize explainability and privacy over raw performance. The review identifies a rising trend in privacy-preserving techniques such as federated learning. In this sense, future Knowledge Management Systems (KMS) should be designed with privacy-by-design principles so as to encourage the sharing of sensitive tacit knowledge. Notably, the most successful implementations reported in the literature are not fully automated but human-in-the-loop systems.

Accordingly, IS designers should focus on creating interfaces that augment, rather than replace, human judgment, specifically by using NLP to capture contextual knowledge that structured databases fail to capture. Finally, the cross-cutting synthesis in Section 3.3.5 indicates that future studies should treat the verifiability of the shared knowledge as an explicit design variable, since the present evidence suggests that this factor conditions whether efficiency gains materialize without veracity costs.

6. Conclusion

Previous reviews of knowledge management processes have afforded valuable insight into the role of technology as a tool for organizational efficiency. Nevertheless, these review studies neglected the specific analysis of Artificial Intelligence (AI) as a transformative infrastructural capability for automating and augmenting Knowledge Sharing (KS) processes. Some of this excitement stems from AI's ability to address challenging business problems; however, effective KS remains the critical bottleneck for competitive advantage. Accordingly, the focus of research has shifted from simple digitization to investigating how AI may augment these essential KS processes.

For this, the present study has performed a systematic literature review to illuminate the intersection of AI and KS and to propose an integrative AI-KS framework. More specifically, the framework organizes the literature into three analytical perspectives. First, user-facing applications (e.g., chatbots and generative AI) facilitate socialization and adoption. Second, data-private strategies (e.g., federated learning) enable performance-oriented combination across organizational boundaries. Third, analytic technologies (e.g., NLP and ML) process unstructured data to facilitate externalization and decision-making. These findings hold important implications for advancing theoretical models and management practices within the information systems and organizational sciences domain. At the theoretical level, our results suggest that AI is shifting the ontology of KS from human-mediated to AI-mediated exchange. This shift leads to the next critical contribution of this review: the identification of the Efficiency-Veracity Paradox (RQ3), whereby AI is associated not only with faster sharing but also with new risks regarding bias and hallucinations.

This highlights that current theories (such as TAM or KBV) appear methodologically underdeveloped for AI contexts, in that they do not account for algorithmic agency or for the trust dynamics observed in longer-term use. With respect to organizational success, the results suggest that the alignment between technical readiness (privacy infrastructure) and cultural readiness (psychological safety) may serve as the primary driver of performance. In addition, most of the analyzed studies focused on the benefits of AI, whereas comparatively few addressed the long-term impact of 'black box' opacity and trust dynamics on users. As well as contributing to the advancement of AI-integrated KM knowledge, these findings may have implications for practitioners: from a managerial standpoint, human-in-the-loop strategies were found to be the most effective approach for mitigating user resistance and data privacy concerns. Overall, these findings give rise to three priorities for future research. First, future studies should explore the long-term evolution of trust between humans and AI systems, given the significant impact of AI on the speed and scale of KS. Second, further research can go deeper into the ethical implications of algorithmic agency, which remain underexplored in relation to traditional KM theories. Lastly, a study on how 'black box' opacity affects the quality of shared knowledge can be a fruitful venue, as research often overlooks the impact of hallucinations on organizational decision-making, in line with recent scholarship. Considerably more work will therefore be needed to address these gaps and to examine AI-mediated sharing across more diverse industrial contexts. This study still has some limitations. The systematic review was restricted to two databases, Web of Science and Scopus, which

may not provide a comprehensive representation of all specialist technical articles or important grey literature. Moreover, the review was further restricted to English-language, peer-reviewed articles published between January 2014 and June 2025, which may exclude relevant earlier or non-English work; as such, future studies should consider broadening the search string and extending the present research by including studies from additional databases, such as IEEE Xplore, the ACM Digital Library, or the AIS eLibrary.

Additionally, further research could concentrate on determining the specific type of benefit and degree of impact that different AI systems have on the KM processes with which they correlate.

In conclusion, this study offers insights into the current trend of AI-integrated KM and serves as a resource for further research on AI-mediated knowledge sharing.

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