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The Impact of Artificial Intelligence on Knowledge Management Practices and Organizational Effectiveness

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Abstract

This study examines how artificial intelligence (AI) is reshaping knowledge management (KM) practices and influencing organizational effectiveness. Using a PRISMA-guided systematic review, 42 studies published between 2019 and 2026 were analyzed. The findings show that AI enhances knowledge capture, retrieval, and tacit knowledge conversion, leading to improvements in decision-making, innovation, and knowledge transfer. However, these outcomes are not automatic. They depend on enabling conditions such as leadership support, digital infrastructure, and organizational culture. Key barriers include data privacy concerns, skill gaps, and resistance to change. The study argues that AI becomes valuable only when embedded within organizational capabilities and routines. It contributes a unified framework that integrates the Knowledge-Based View, Dynamic Capabilities, and Socio-Technical Systems theory to explain how AI-driven KM translates into organizational effectiveness.

Keywords: artificial intelligence, knowledge management, organizational effectiveness, generative AI, dynamic capabilities, systematic literature review

1 INTRODUCTION

Organizational knowledge is not simply a resource; it is the substrate from which sustained competitive advantage grows. The knowledge-based view of the firm, as elaborated by Mercier-Laurent and Boulanger (2019) and developed further through the strategic management literature, holds that heterogeneous and difficult-to-imitate knowledge assets are the primary determinants of superior long-term performance. Knowledge management, therefore, is a strategic function. When the tools available for that function change radically, theory and practice must both be reconsidered.

Three structural gaps motivate this review. First, conceptual fragmentation: prior reviews address discrete slices of the AI-KM intersection, focusing on storage efficiency (Gadde, 2025), adoption barriers (Rezaei, 2025), or the specific effects of generative AI on knowledge creation (He et al., 2026), but none synthesize the full AI-KM-effectiveness chain. Second, empirical inconsistency: quantitative studies report divergent effect sizes for AI-KM outcomes, a pattern that reflects methodological variation and sector-specific conditions not yet systematically catalogued. Third, shallow theoretical anchoring: most existing syntheses invoke the Knowledge-Based View descriptively without integrating Dynamic Capabilities theory or Socio-Technical Systems perspectives, both of which are needed to explain how AI transforms organizational KM routines over time.

This review addresses all three gaps through a PRISMA-guided synthesis of 42 peer-reviewed studies published between 2019 and 2026. The theoretical scaffolding rests on three complementary frameworks: the Knowledge-Based View explains why knowledge assets matter; Dynamic Capabilities theory explains how AI enables organizations to reconfigure those assets; and Socio-Technical Systems theory explains why human-AI co-evolution shapes adoption outcomes. Three research questions structure the analysis: (RQ1) How does AI integration alter established KM practices across organizational contexts? (RQ2) What barriers and enablers shape AI adoption in KM, and through which mechanisms do they operate? (RQ3) What is the empirically documented relationship between AI-enabled KM and organizational effectiveness?

In this review, organizational effectiveness is understood as the ability of an organization to achieve desired outcomes through improved knowledge processes. Across the analyzed studies, this construct is reflected in three recurring dimensions: innovation performance, decision-making quality, and knowledge transfer efficiency. These dimensions provide a consistent basis for interpreting how AI-enabled KM contributes to organizational outcomes.

2 METHODS

2.1 Search Strategy and Database Selection

Three databases with strong management-science indexing formed the search base: Web of Science, Scopus, and EBSCO. Google Scholar was excluded from primary search to preserve replicability, a standard requirement for systematic reviews in management research. Search strings were constructed across three concept blocks using Boolean operators: ("artificial intelligence" OR "machine learning" OR "generative AI" OR "large language model") AND ("knowledge management" OR "knowledge sharing" OR "knowledge capture" OR "tacit knowledge") AND ("organizational effectiveness" OR "organizational performance" OR "innovation" OR "decision support"). Searches were executed in January 2026 with no geographic restriction. Reference lists of high-citation included articles were hand-searched to reduce publication bias.

2.2 Inclusion and Exclusion Criteria

The review primarily focuses on peer-reviewed journal articles indexed in major scientific databases. However, a limited number of high-quality book chapters and working papers were also included where they provided significant theoretical or empirical insights into the AI–KM relationship. This approach ensures both methodological rigor and conceptual completeness.

Table 1: Inclusion and Exclusion Criteria for the Systematic Literature Review

Criterion	Inclusion	Exclusion
Publication period	2019 to 2026	Before 2019

Criterion	Inclusion	Exclusion
Language	English only	Non-English publications
Document type	Peer-reviewed journal articles indexed in Web of Science, Scopus, or EBSCO, high-quality book chapters and working papers	Majorly Book chapters, preprints, working papers, editorials, conference proceedings
Topic relevance	AI and KM addressed jointly with organizational outcomes reported or theorized	Pure engineering, hardware, or management topics without AI-KM intersection
Methodological quality	Clear and replicable methodology; quality appraised via Mixed Methods Appraisal Tool	No stated methodology or study failed MMAT quality appraisal threshold

Note. All included studies are peer-reviewed journal articles indexed in Web of Science, Scopus, or EBSCO, and some book chapters. Quality appraisal was conducted via the Mixed Methods Appraisal Tool (MMAT).

2.3 Screening, Quality Appraisal, and Data Synthesis

From 387 identified records, 86 duplicates were removed. Of the 301 records screened at title and abstract level, 207 were excluded as irrelevant. Of 94 full-text articles assessed, 52 were excluded: 19 for failing the peer-review indexing criterion, 18 for absent AI-KM linkage, and 15 for insufficient methodological quality following MMAT appraisal. The final corpus comprised 42 studies (see Figure 1). Two coders independently extracted data using a structured template covering study objectives, theoretical frameworks, design type, AI technologies examined, KM processes addressed, organizational outcomes, and reported barriers and enablers. Cohen's kappa of kappa = 0.83 confirmed strong intercoder reliability. Thematic synthesis followed the Thomas and Harden three-stage protocol: line-by-line coding, development of descriptive themes, and generation of analytical themes. Empirical and conceptual studies were coded and reported separately throughout to prevent conflation of evidence types.

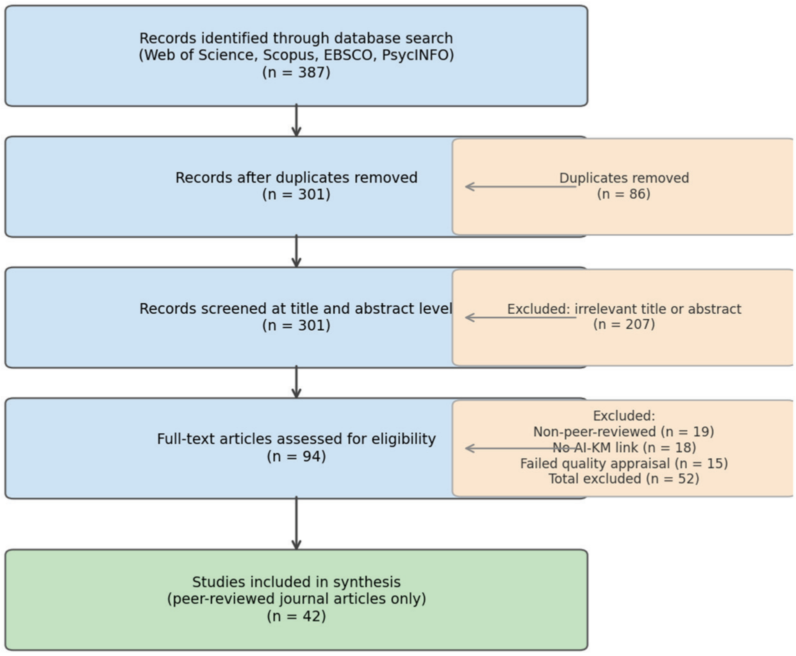

Figure 1. PRISMA flow diagram of the systematic literature review process.

3 RESULTS

3.1 Characteristics of Included Studies

All 42 included studies are peer-reviewed journal articles from indexed databases and limited high-quality book chapters and working papers. Table 2 reports the full methodological breakdown. Empirical studies total 18 (quantitative n = 8, qualitative n = 5, mixed n = 5); review and conceptual studies total 24 (systematic or bibliometric n = 12, conceptual n = 12). Seventy-four percent of all studies were published from 2024 onwards. Sectoral coverage spans manufacturing and engineering (n = 9), higher education (n = 8), software and IT (n = 7), healthcare (n = 6), multi-sector or general management (n = 7), and financial services (n = 5). Figure 3 presents the full profile.

Table 2: Methodological Classification and Characteristics of Included Studies (N = 42)

Study type	n	%	Design or approach	Illustrative studies
Empirical quantitative	8	19	Survey, regression, structural equation modelling	Zhang et al. (2025); Heinrich et al. (2025); Zhong and Wang (2025)
Empirical qualitative	5	12	Case study, interview-based thematic analysis	Kirchner et al. (2025); Santoro et al. (2026)
Mixed methods	5	12	Sequential or concurrent mixed designs	Rodriguez Benito et al. (2026); Boamah et al. (2025)
Systematic or bibliometric review	12	29	PRISMA-guided SLR; bibliometric mapping	Chatti and Argoubi (2025); Stan et al. (2026); Panda and Puri (2025)

Study type	n	%	Design or approach	Illustrative studies
Conceptual or theoretical	12	29	Framework development; theoretical proposition	Böhm and Durst (2026); Khalili and Jahanbakht (2026); He et al. (2026)

Note. E = empirical studies; C = conceptual or review studies. Percentages are rounded to the nearest whole number.

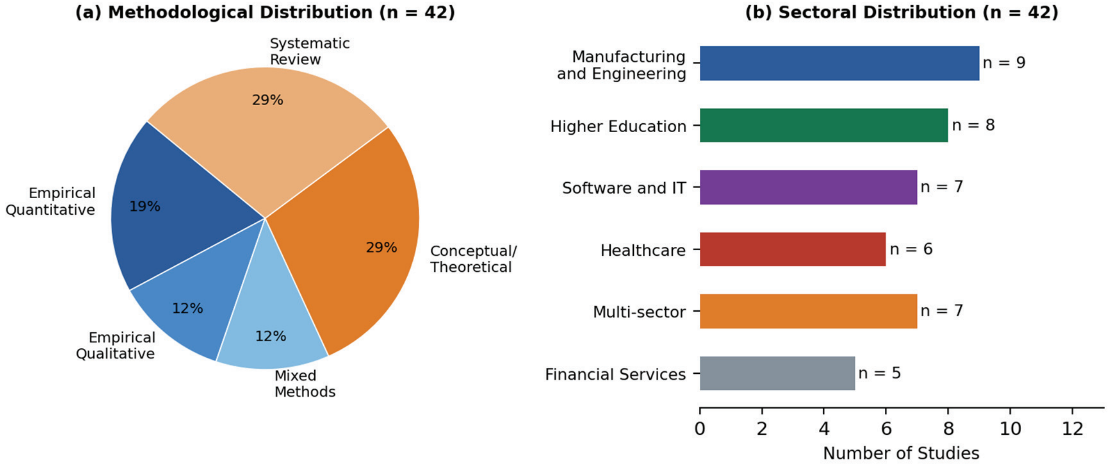

Figure 3. Methodological and sectoral distribution of included studies.

3.2 Thematic Synthesis

Five thematic clusters emerged from systematic coding. Throughout, findings from empirical studies are distinguished from conceptual or theoretical contributions. Table 3 reports each theme with the split of empirical (E) and conceptual (C) studies contributing to it. The integrative theoretical framework is presented in Figure 2.

Table 3: Thematic Synthesis of AI-KM Integration Findings (E = Empirical; C = Conceptual or Review)

Theme	E / C	Key finding (empirical evidence weighted)	Representative studies
Knowledge capture and storage	E: 8; C: 6	RAG and transformer-based NLP improve retrieval precision and reduce knowledge redundancy in enterprise settings.	Boamah et al. (2025); Pondel et al. (2024); Gadde (2025); Salem et al. (2024)
Tacit knowledge externalization	E: 5; C: 7	GenAI and NLP support conversion of expert tacit knowledge into sharable assets via conversational agents.	Khalili and Jahanbakht (2026); Zaoui Seghroucheni et al. (2025); He et al. (2026)
Organizational performance and innovation	E: 8; C: 4	AI-KM integration predicts innovation output and decision quality; tacit knowledge conversion mediates the effect.	Zhang et al. (2025); He and Yang (2025); Santoro et al. (2026); Heinrich et al. (2025)
Adoption barriers	E: 7; C: 5	Privacy concerns, skill deficits, cost, and change resistance are the most frequently documented empirical inhibitors.	Rezaei (2025); Madanchian and Taherdoost (2025); Jarrahi et al. (2023)

Theme	E / C	Key finding (empirical evidence weighted)	Representative studies
Human-AI collaboration	E: 4; C: 8	Effective KM requires sociotechnical co-evolution; competitive AI perceptions suppress voluntary knowledge sharing.	Gerlich (2025); Zhong and Wang (2025); Böhm and Durst (2026); Alavi et al. (2024)

Note. E/C counts indicate the number of empirical versus conceptual studies contributing to each theme. Findings are weighted toward empirical evidence throughout the text.

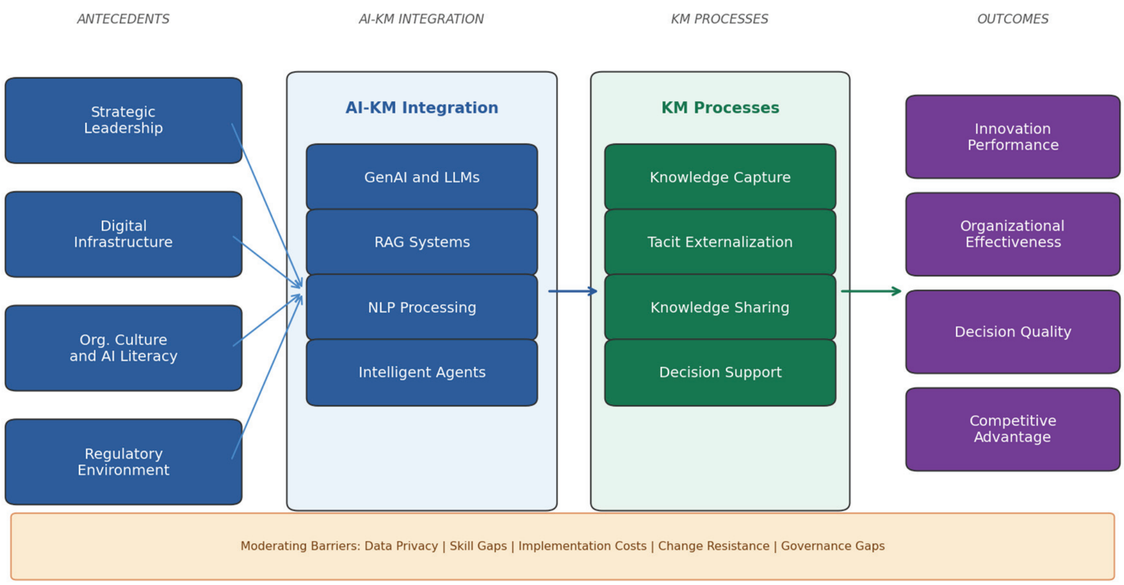

Figure 2. Theoretical framework: antecedents, AI-KM integration, and organizational effectiveness outcomes, grounded in the Knowledge-Based View, Dynamic Capabilities theory, and Socio-Technical Systems theory.

3.3 Theme 1: AI-Enabled Knowledge Capture and Storage

Across 14 studies contributing to this theme (E: 8; C: 6), retrieval-augmented generation architectures and transformer-based natural language processing consistently improved both knowledge accessibility and retrieval precision. Boamah et al. (2025), working with a mixed-method design in infrastructure project settings, documented measurable reductions in knowledge search latency following RAG implementation. Pondel et al. (2024) demonstrated, under controlled comparison conditions, that LLM-powered knowledge bases produced semantically superior results relative to conventional keyword-based systems. Gadde (2025) extended findings to enterprise contexts, reporting that AI-enhanced KM contributed to faster onboarding cycles and reduced knowledge redundancy across organizational units. Salem et al. (2024) identified natural language processing as the mechanism through which unstructured organizational data, including emails, meeting transcripts, and project reports, could be systematically converted into formal knowledge assets. These gains align with the Knowledge-Based View proposition that knowledge accessibility is a precondition for capability development (Taherdoost & Madanchian, 2023).

3.4 Theme 2: Tacit Knowledge Externalization

Twelve studies addressed tacit-to-explicit knowledge conversion (E: 5; C: 7), a problem that has occupied KM researchers since Nonaka's original formulation. Khalili and Jahanbakht (2026) proposed a framework for AI-enabled tacit knowledge co-evolution, in which conversational agents iteratively elicit expert knowledge through structured dialogue and progressively encode it into organizational memory. The empirical basis came from Zaoui Seghroucheni et al. (2025), who compared NLP methods directly: transformer-based models outperformed rule-based and traditional machine learning approaches on both coherence and completeness metrics. He et al. (2026) took a different angle, revisiting Nonaka's ba concept to argue that generative AI creates virtual knowledge-sharing spaces that accelerate socialization and externalization processes in geographically distributed organizations. Viewed through a Dynamic Capabilities lens, this theme reveals AI's potential to renew tacit knowledge stocks, a function previously dependent entirely on face-to-face interaction and mentorship.

3.5 Theme 3: Adoption Barriers

Figure 4 presents barrier frequencies separated by study type to avoid conflating conceptual claims with empirical observations. Twelve studies focused directly on adoption barriers (E: 7; C: 5). Data privacy and security concerns were reported in 78% of empirical studies, consistent across sectors and organizational sizes (Rezaei, 2025; Madanchian & Taherdoost, 2025). Lack of AI literacy was documented in 72% of empirical studies; high implementation costs in 61%; and resistance to organizational change in 56%. All four are structurally modifiable through deliberate organizational interventions, which distinguishes them from purely technical constraints and makes them tractable within a Dynamic Capabilities framework. Legacy system integration (50%) and ethical governance gaps (44%) rounded out the barrier profile across empirical studies.

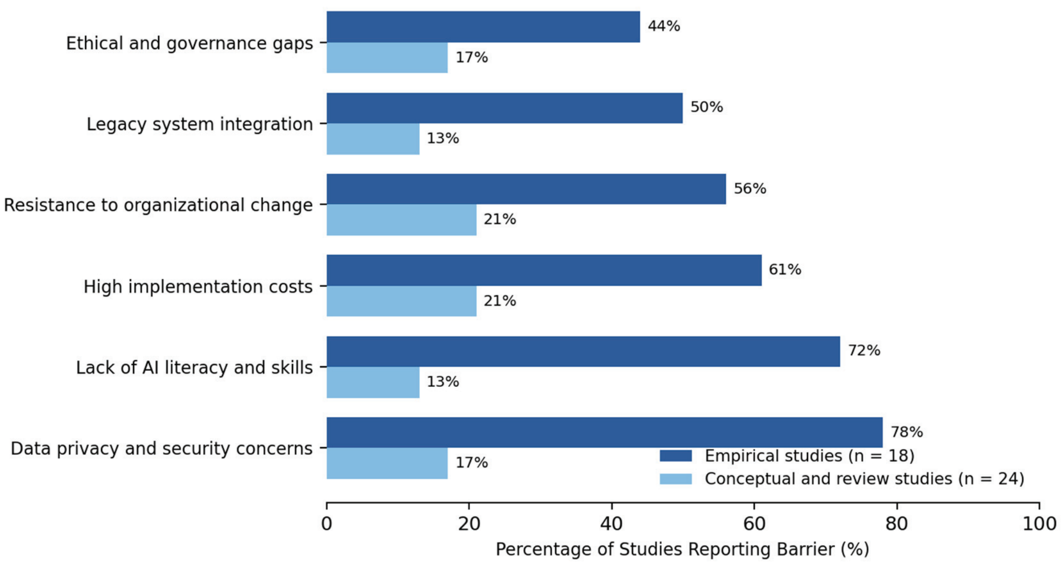

Figure 4. Frequency of AI adoption barriers by study type, differentiating empirical from conceptual or review studies.

3.6 Theme 4: Adoption Enablers

Table 4 presents five enabler categories mapped to the theoretical frameworks anchoring this review. Strategic leadership commitment was identified as the most consistent organizational enabler, appearing across both empirical studies (Kirchner et al., 2025; Santoro et al., 2026) and conceptual work (Dawarka et al., 2026; Rai et al., 2026). Digital infrastructure, covering cloud platforms, API-accessible repositories, and RAG-enabled knowledge bases, constitutes a necessary technical precondition, consistent with Socio-Technical Systems theory's insistence that technology and social systems must be co-designed (Khan et al., 2025). At the macro level, Bloom and Makridis (2026) showed that national regulatory environments moderate organizational adoption trajectories in ways that no firm-level intervention can fully offset.

Table 4: Key Enablers of AI Adoption in KM Contexts, Mapped to Theoretical Frameworks

Enabler	Theoretical lens	Mechanism	Key studies
Strategic leadership	Knowledge-based view	Executive commitment drives resource allocation and signals organizational AI readiness.	Dawarka et al. (2026); Rai et al. (2026)
Digital infrastructure	Socio-technical systems theory	Cloud platforms, APIs, and RAG-enabled repositories are necessary technical preconditions.	Pondel et al. (2024); Khan et al. (2025)
Organizational culture	Socio-technical systems theory	Knowledge-sharing cultures and psychological safety reduce resistance to AI tools.	Zhong and Wang (2025); Kirchner et al. (2025)
AI literacy programs	Dynamic capabilities	Upskilling closes the competence gap and improves the quality of human-AI knowledge work.	Gerlich (2025); Madanchian and Taherdoost (2025)
Regulatory frameworks	Institutional theory	Data-ethics governance reduces compliance risk and builds organizational confidence in AI adoption.	Rezaei (2025); Bloom and Makridis (2026)

Note. KBV = Knowledge-Based View; STS = Socio-Technical Systems theory.

3.7 Theme 5: AI-Enabled KM and Organizational Effectiveness

Organizational effectiveness outcomes were most reliably documented in empirical quantitative and mixed-method studies (n = 13). Zhang et al. (2025), using structural equation modelling on a manufacturing firm sample (n = 312), found that GenAI-enabled KM systems significantly predicted innovation performance (beta = 0.47, $p < .001$), with tacit knowledge conversion operating as a full mediator. The effect held after controlling for firm size, industry, and prior IT investment. Heinrich et al. (2025) reported that AI-augmented decision support improved task-delegation accuracy by 31% relative to unaided human judgment in a prognostics setting. Santoro et al. (2026) documented a 43% reduction in knowledge search time and significant increases in cross-departmental knowledge transfer following deployment of an AI assistant in an Italian enterprise. One study introduced a complicating finding: Zhong and Wang (2025) showed that competitive AI perceptions among employees significantly suppressed voluntary knowledge sharing, attenuating effectiveness gains. That result is not an outlier; it reflects a structural tension that Socio-Technical Systems theory predicts when technology deployment precedes cultural alignment.

4 DISCUSSION

The central finding is conditional, not unconditional. AI-enabled KM produces documented gains in knowledge accessibility, decision quality, and innovation performance when antecedent conditions, namely leadership commitment, digital infrastructure, and knowledge-sharing culture, are present. When those conditions are absent, the relationship weakens or reverses. Dynamic Capabilities theory provides the clearest explanation: AI tools do not become organizational capabilities automatically; they require embedding in complementary routines, learning processes, and governance structures (Jarrahi et al., 2023). The technology is necessary but not sufficient.

Three theoretical contributions differentiate this review from prior syntheses. First, the proposed framework (Figure 2) advances existing models (Taherdoost & Madanchian, 2023; Alavi et al., 2024) by positioning adoption barriers as moderating conditions between antecedent enablers and KM transformation outcomes, rather than treating them as independent variables. The design implication is direct: organizations cannot sequence technology installation ahead of barrier remediation and expect positive results. Second, the integration of Socio-Technical Systems theory explains why findings like those of Zhong and Wang (2025), where competitive AI perceptions suppress knowledge sharing, arise systematically and not as idiosyncratic exceptions. Third, the tacit knowledge externalization theme extends the SECI model (Böhm & Durst, 2026) by specifying the AI mechanisms, including conversational agents, transformer-based NLP, and virtual ba creation, through which each phase of the socialization-externalization-combination-internalization cycle is affected.

Three underexplored risks deserve explicit attention. Algorithmic bias in AI-generated knowledge artifacts appears in the publishing and library science literature (Gao et al., 2025) but remains largely absent from management-focused studies, a methodological blind spot that warrants correction. Knowledge deskilling, the erosion of expert judgment through AI dependence, is raised theoretically by Gerlich (2025) but lacks empirical treatment in organizational contexts. Epistemic dependency, where organizational decision-making becomes contingent on AI outputs whose provenance is opaque to decision-makers, raises governance concerns that no current management SLR has addressed directly. Each of these risks is worsened, not ameliorated, by rapid adoption without parallel investment in governance.

While the overall direction of findings is positive, the strength of evidence is uneven. Empirical studies, particularly those using quantitative designs, provide more robust support for the AI–KM–performance relationship. In contrast, many conceptual contributions remain speculative and require validation. Sectoral differences are also evident. Technology-intensive industries tend to report clearer gains, whereas service and public-sector contexts show more variable outcomes, often shaped by cultural and institutional constraints. These variations suggest that the impact of AI on KM is not universal but contingent on context, maturity, and implementation approach.

4.1 Limitation

This review is subject to several limitations. First, the included studies vary considerably in terms of methodology, sector, and analytical depth, which limits direct comparability. Second, although emphasis was placed on peer-reviewed literature, the inclusion of a small number of conceptual and non-journal sources introduces variation in evidence strength. Third, the balance between empirical and conceptual studies means that some themes, particularly tacit knowledge externalization, remain under-validated. Finally, most studies adopt cross-sectional designs, making it difficult to assess long-term organizational effects of AI-enabled KM. These limitations point to the need for more longitudinal and sector-specific research.

5 CONCLUSION

Forty-two peer-reviewed studies, synthesized using PRISMA protocols and dual-coder thematic analysis, yield three main conclusions. AI integration advances KM across knowledge capture, retrieval, and tacit knowledge conversion, with effect sizes documented across manufacturing, healthcare, and service contexts. Adoption is conditional: privacy concerns, skill deficits, cost barriers, and change resistance must be addressed through structured enablement before technology deployment scales. Where antecedent conditions are favorable, AI-enabled KM produces measurable gains in innovation performance, decision accuracy, and cross-unit knowledge transfer rates, with tacit knowledge conversion as the consistent mediating mechanism.

Practitioners should sequence adoption deliberately: map the barrier profile first, build infrastructure and AI literacy in parallel, establish data governance before scaling, and monitor for knowledge deskilling effects once deployment is underway. Researchers face three priority gaps. Longitudinal studies tracking AI-KM effectiveness over time are absent. Sector-specific analyses of tacit knowledge conversion via generative AI, particularly in creative, professional service, and public sector contexts, are needed before existing findings can be generalized. Cross-national comparisons of regulatory effects on adoption trajectories have yet to appear. As agentic AI systems and autonomous knowledge generation move toward operational deployment, the precision with which researchers and practitioners understand this relationship will determine whether the organizational gains already documented in controlled settings can be replicated at scale.

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