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Artificial Intelligence Capability, Knowledge Sharing, and Organizational Innovation: A Systematic Literature Review and Future Research Agenda

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ABSTRACT
Purpose of the study: Artificial intelligence (AI) capability has emerged as a strategic organizational resource that enables firms to improve knowledge processes and innovation performance. However, empirical evidence explaining the relationship among AI capability, knowledge sharing, and organizational innovation remains fragmented. This study systematically reviews the existing literature to synthesize current knowledge and identify future research directions.
Materials for Analysis: A systematic literature review (SLR) was conducted following the PRISMA 2020 guidelines. Literature searches were performed in Scopus, Web of Science Core Collection, and PubMed using predefined Boolean search strings. The review employed a two-stage screening process consisting of title and abstract screening followed by full-text eligibility assessment based on predefined inclusion and exclusion criteria. Four empirical studies published between 2022 and 2026 met all eligibility criteria and were included in the final qualitative synthesis.
Results: The review consistently demonstrates that AI capability positively influences organizational innovation through enhanced knowledge-sharing processes. Knowledge sharing emerged as the principal mediating mechanism linking AI capability with innovation outcomes across different organizational contexts. Several studies further identified organizational cohesion, knowledge-sharing culture, and information governance as important contextual factors that strengthen the effectiveness of AI capability. Despite these consistent findings, the existing literature remains limited by cross-sectional research designs, a relatively small number of empirical studies, and a strong concentration of evidence from Asian countries.
Conclusions: This review provides an integrated synthesis of the emerging literature on AI capability, knowledge sharing, and organizational innovation. It develops a comprehensive understanding of the mechanisms through which AI capability contributes to innovation while identifying theoretical and methodological gaps for future research. The findings offer practical implications for organizational leaders seeking to leverage AI capability as a strategic driver of innovation through effective knowledge-sharing practices.

Keywords
Artificial intelligence capability; AI capability; Knowledge sharing; Organizational innovation; Systematic literature review.

INTRODUCTION
Global Issue and Contextual Framework

Artificial intelligence (AI) has moved from a peripheral experimental technology to a core organizational resource shaping how firms sense opportunities, process information, and generate novel products, services, and processes(Domini et al., 2023, p. 32; Dwivedi et al., 2019, p. 102013; Mikalef & Gupta, 2021). As organizations worldwide accelerate AI adoption, scholars increasingly frame AI not merely as a tool but as a firm-level capability, i.e., a bundle of AI-specific technological, human, and organizational resources that can be orchestrated to create business value (Mikalef & Gupta, 2021). In parallel, knowledge sharing has long been recognized as a cornerstone of organizational learning and innovation, enabling the recombination of dispersed individual and collective knowledge into new value-creating routines (Wang & Noe, 2009). The convergence of these two research streams has produced a fast-growing but fragmented body of work asking a deceptively simple question: does AI capability actually make organizations more innovative, and if so, through what organizational mechanisms? Understanding this question carries global significance, as governments and industry bodies increasingly position AI adoption as a driver of national competitiveness and organizational resilience, while simultaneously voicing concern that the innovation dividends of AI depend on complementary human and organizational capabilities rather than technology alone (Dwivedi et al., 2019; Enholm et al., 2021)

This urgency is amplified by the proliferation of large-scale AI applications across innovation management functions, from

AI-assisted ideation and knowledge discovery to AI-enabled collaboration platforms (Gama & Magistretti, 2023). Despite this proliferation, the mechanisms linking AI capability to innovation outcomes remain theoretically underspecified, and knowledge sharing has only recently been foregrounded as a candidate mediating process (Hu et al., 2025; Li et al., 2022)

Conceptual Background

Three constructs anchor this review. First, AI capability is defined as a firm's ability to select, orchestrate, and leverage its AI-specific resources — encompassing data, technology, human skills, and organizational structures — to generate business value (Mikalef & Gupta, 2021). This definition extends earlier information-technology capability research Gupta & George (2016); Bharadwaj (2000) into the AI domain. Second, knowledge sharing refers to the set of individual and collective behaviors through which employees make knowledge available to others in the organization, typically decomposed into knowledge donating and knowledge collecting (Kmieciak, 2020, p. 1835; Tuân et al., 2020, p. 277). Third, organizational innovation denotes the introduction of new products, processes, organizational practices, or creative outcomes that enhance firm competitiveness(Abbass et al., 2025, p. 219; Indrawati et al., 2024, p. 1591), and is frequently operationalized in the reviewed literature through the closely related construct of organizational or employee creativity (Li et al., 2022; Mikalef & Gupta, 2021)

These constructs have evolved along partially separate trajectories: knowledge sharing research matured within the knowledge-management and organizational-behavior traditions during the 1990s and 2000s Ipe (2003); Nonaka (1994) whereas AI capability research is a comparatively recent extension of the information-systems capability literature that gained momentum only after 2018–2021 (Davenport & Ronanki, 2018; Mikalef & Gupta, 2021). Their integration into a single nomological network is therefore a recent and still-consolidating development.

Critical Examination of Existing Literature

Existing empirical studies broadly converge on a positive association between AI capability and organizational innovation outcomes, but diverge sharply in the mechanisms proposed to explain this association. Li et al. (2022), studying Chinese high-technology firms, found that knowledge sharing fully mediates the AI capability–organizational creativity relationship and that organizational cohesion moderates the AI capability–knowledge sharing link; Hu et al. (2025) instead emphasize employee learning opportunities as the mediating mechanism and highlight paradoxical leadership and technophilia as moderators of individual-level AI adoption effects on knowledge sharing. These studies use different unit of analysis (firm-level versus individual-level), different mediators, and different moderators, making direct comparison difficult and raising the possibility that the AI capability–innovation relationship operates through multiple, only partially overlapping pathways.

Methodologically, the literature is dominated by single-country, cross-sectional survey designs relying on self-reported perceptual measures (e.g., Li et al., 2022, n = 189; Hu et al., 2025, n = 364), which constrains causal inference and raises common-method-bias concerns despite the use of temporally separated waves in some studies. Systematic reviews in adjacent domains Gelashvili-Luik et al. (2025); Gama & Magistretti (2023) synthesize AI's role in innovation capability-building and knowledge-management systems respectively, but neither review positions knowledge sharing as an explicit mediating mechanism between AI capability and innovation outcomes; instead, knowledge sharing is treated as one of several parallel outcomes of AI adoption. This represents an important inconsistency: process-oriented studies Hu et al. (2025); Li et al. (2022) model knowledge sharing as a mediator, while review-level syntheses Gelashvili-Luik et al. (2025); Gama & Magistretti (2023) treat it as a co-equal, non-sequential outcome — a conceptual tension that has not yet been reconciled in a dedicated systematic review.

A further limitation is geographic and sectoral concentration: the empirical base is weighted toward Chinese high-technology and knowledge-intensive firms Hu et al. (2025); Li et al. (2022) with comparatively limited evidence from Africa, Latin America, and Southeast Asia, and from public-sector, non-profit, and small-and-medium-enterprise (SME) contexts (cf. the AI-enabled knowledge sharing scoping-review protocol for non-profit healthcare noted in adjacent literature). Finally, absorptive capacity — theoretically central to how firms convert shared knowledge into innovation Zahra & George (2002); Cohen & Levinthal (1990)— is examined mainly as a moderator of the knowledge sharing–innovation link Chatterjee et al. (2021) rather than being integrated into a unified AI capability–knowledge sharing–absorptive capacity–innovation model.

Research Gap

Synthesizing the critical examination above, three specific and evidence-based gaps justify a dedicated systematic review: 1) Mechanism inconsistency: studies disagree on whether knowledge sharing functions as a mediator, an antecedent, or a parallel outcome of AI capability, and no review has systematically reconciled these divergent process models across the empirical literature (Gama & Magistretti, 2023; Gelashvili-Luik et al., 2025; Li et al., 2022); 2) Boundary-condition fragmentation: mediating and moderating variables (organizational cohesion, absorptive capacity, paradoxical leadership, technophilia, organizational communication) have been examined in isolated studies using different theoretical lenses, with no integrative synthesis mapping which moderators operate at which stage of the AI capability → knowledge sharing → innovation pathway; 3) Contextual and methodological narrowness: the evidence base is disproportionately cross-sectional, single-country (predominantly China), and concentrated in high-technology sectors, leaving longitudinal, multi-level, cross-cultural, SME, and public-sector evidence systematically underexplored — a gap that has not been quantified or mapped in prior reviews of this specific triadic relationship.

No prior systematic review, to the authors' knowledge, has simultaneously (a) treated AI capability, knowledge sharing, and organizational innovation as a triadic nomological network, (b) applied PRISMA 2020 reporting standards to this specific configuration of constructs, and (c) produced a consolidated mediator–moderator taxonomy alongside a structured future research agenda.

Rationale for the Research

Given the theoretical fragmentation and contextual narrowness identified above, a systematic and reproducible synthesis is warranted to consolidate scattered findings, clarify the directionality of the AI capability–knowledge sharing–innovation relationship, and provide researchers and practitioners with an evidence-based roadmap. Because AI capability, knowledge sharing, and organizational innovation are individually mature research streams but only recently studied jointly, a PRISMA-based systematic review is methodologically appropriate to ensure transparent, replicable, and bias-minimized evidence synthesis (Page et al., 2021).

Research Objectives

This study aims to systematically map, critically synthesize, and theoretically integrate the literature on AI capability, knowledge sharing, and organizational innovation. Specifically, the review seeks to: 1) Trace the temporal and disciplinary evolution of research on AI capability, knowledge sharing, and organizational innovation (RQ1); 2) Identify and evaluate the theories and conceptual frameworks underpinning this literature (RQ2); 3) Elucidate the mechanisms through which AI capability facilitates organizational innovation via knowledge sharing (RQ3); 4) Catalogue the mediating and moderating variables identified in this relationship (RQ4); 5) Characterize the methodological approaches, contexts, and industries that dominate the literature, and delineate underexplored areas (RQ5); 6) Propose a future research agenda to advance theory and practice in this domain (RQ6).

MATERIALS FOR ANALYSIS

Study Design

This study employed a Systematic Literature Review (SLR) guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) framework to ensure methodological transparency, reproducibility, and rigor throughout the review process. PRISMA 2020 provides internationally recognized reporting standards for identifying, screening, assessing eligibility, and synthesizing scientific evidence in systematic reviews.

The review aimed to systematically identify, critically evaluate, and synthesize empirical and conceptual evidence concerning the relationships among artificial intelligence (AI) capability, knowledge sharing, and organizational innovation. A predefined review protocol was established before conducting the literature search, specifying the research objectives, search strategy, eligibility criteria, screening procedures, data extraction framework, and quality appraisal methods. The review process consisted of four sequential stages:1) Identification of potentially relevant studies through comprehensive database searching; 2) Screening of titles and abstracts using predefined eligibility criteria; 3) Eligibility assessment through full-text evaluation; and 4) Qualitative synthesis of the final corpus of included studies.

This methodological approach minimizes selection bias while enhancing the reliability and replicability of the evidence synthesis.

Information Sources

A comprehensive literature search was conducted using three internationally recognized bibliographic databases selected for their extensive coverage of management, information systems, innovation, and interdisciplinary research: Scopus; Web of Science Core Collection (WoSCC); and PubMed

Scopus was selected because of its broad multidisciplinary coverage and strong representation of high-impact journals in business, management, and information systems. Web of Science Core Collection complements Scopus by indexing highly influential journals with rigorous citation standards. PubMed was included to capture interdisciplinary studies investigating AI-enabled organizational processes within healthcare organizations, digital health systems, and knowledge management contexts. The literature search covered publications from January 2015 to June 2026, reflecting the period during which AI capability emerged as a distinct organizational capability within management and information systems research. Only peer-reviewed journal articles published in English were considered to ensure scientific quality and international comparability.

Search Strategy

The search strategy was developed using three major conceptual domains derived from the research objectives:1) Artificial Intelligence Capability; 2) Knowledge Sharing; 3) Organizational Innovation. Synonymous terms within each concept were combined using the Boolean operator OR, while the three concept blocks were connected using AND. Wildcard symbols (e.g., *capabilit**) and alternative spellings were employed to maximize retrieval sensitivity.

The database-specific search strategies were as follows.

Table 1. Boolean Search String (Title / Abstract / Keywords)

Database	Boolean Search String (Title / Abstract / Keywords)
Scopus	("artificial intelligence capabilit*" OR "AI capabilit*") AND ("knowledge sharing" OR "knowledge exchange" OR "knowledge transfer") AND ("organi?ational innovation" OR "firm innovation" OR "innovation capability" OR "organi?ational creativity")
Web of Science Core Collection	TS=(("artificial intelligence capability" OR "AI capability") AND ("knowledge sharing" OR "knowledge transfer") AND ("organizational innovation" OR "innovation performance"))
PubMed	(("artificial intelligence"[Title/Abstract]) AND ("knowledge sharing"[Title/Abstract]) AND ("innovation"[Title/Abstract] OR "organizational performance"[Title/Abstract]))

To improve search precision, the following filters were applied: English language; Peer-reviewed journal articles; Publication years 2015–2026; Articles with accessible full text; Research addressing organizational, managerial, or innovation-related contexts.

The complete search strategy, database interfaces, search dates, exported records, and retrieval statistics should be reported in the supplementary materials to facilitate reproducibility.

Eligibility Criteria

Eligibility criteria were established a priori to ensure consistency throughout the review.

Inclusion Criteria

Studies were considered eligible for inclusion if they satisfied several predefined criteria established prior to the review process. Specifically, only peer-reviewed journal articles published in English between 2015 and 2026 were included to ensure the scientific quality, international visibility, and contemporary relevance of the evidence. Eligible studies were required to investigate at least two of the three core constructs underpinning this review—artificial intelligence (AI) capability, knowledge sharing, and organizational innovation—thereby ensuring a meaningful theoretical or empirical contribution to the research objectives. Both empirical and conceptual studies, including systematic literature reviews with rigorous methodological procedures, were considered eligible when they provided substantive insights into the relationships among these constructs. Furthermore, studies were required to focus on organizational contexts, including firms, institutions, teams, or employees, rather than purely technical or algorithmic perspectives. Finally, only studies reporting sufficient methodological information, including research design, data sources, analytical procedures, and principal findings, were retained to enable systematic quality assessment and reliable evidence synthesis.

Exclusion Criteria

Studies were excluded if they did not align with the predefined eligibility criteria or failed to provide sufficient evidence to address the research objectives. Specifically, conference proceedings, editorials, book chapters, dissertations, theses, technical reports, and other forms of gray literature were excluded to maintain consistency with high-quality peer-reviewed evidence. Studies focusing exclusively on the technical development of artificial intelligence algorithms, machine learning models, or computational architectures without examining organizational or managerial implications were also omitted. Likewise, articles investigating knowledge sharing or organizational innovation independently, without explicitly addressing AI capability, were excluded because they did not adequately capture the conceptual relationships central to this review. Duplicate records identified across databases were removed during the identification stage, while studies lacking accessible full-text versions or published in languages other than English were excluded to ensure comprehensive methodological evaluation and consistent interpretation of findings. Additionally, studies providing insufficient methodological detail or failing to report reliable empirical evidence were excluded from the final synthesis to preserve the robustness and credibility of the review findings.

Study Selection and Screening Process

The study selection process strictly followed the **PRISMA 2020 two-stage screening protocol**.

Stage 1: Title and Abstract Screening

Following duplicate removal, two independent reviewers screened the titles and abstracts of all retrieved records against the predefined eligibility criteria. Studies were excluded if they: clearly fell outside the research scope; lacked organizational relevance; addressed unrelated AI applications; focused exclusively on technical algorithm development; did not investigate knowledge sharing or innovation. Disagreements between reviewers were resolved through discussion until consensus was achieved. When consensus could not be reached, a third senior reviewer acted as an adjudicator.

Stage 2: Full-Text Eligibility Assessment

The remaining studies underwent comprehensive full-text evaluation using the same eligibility criteria. Reasons for exclusion during this stage were systematically documented, including: irrelevant research objectives; insufficient examination of AI capability; absence of knowledge-sharing variables; lack of innovation-related outcomes; inaccessible or incomplete full text; methodological inadequacy. The complete study selection procedure—including the number of records identified, duplicates removed, screened, excluded, assessed for eligibility, and finally included—should be presented in a PRISMA 2020 Flow Diagram.

Data Extraction and Quality Assessment

To ensure methodological consistency and enhance the reliability of the evidence synthesis, a standardized data extraction form was developed prior to the review process. Data extraction was independently conducted by two reviewers using a predefined protocol to minimize subjective interpretation and reduce extraction bias. For each eligible study, comprehensive information was systematically recorded, including bibliographic details (authors, publication year, journal, and country), research setting and industry sector, research objectives, theoretical foundation, study design, sample characteristics, dimensions of artificial intelligence (AI) capability, knowledge-sharing constructs, organizational innovation measures, mediating and moderating variables, analytical techniques, principal findings, and reported research limitations. This standardized approach facilitated consistent comparison across studies while ensuring that all information relevant to the research questions was comprehensively documented.

Following data extraction, the methodological quality of each included study was independently assessed by the same two reviewers. The quality assessment process was designed to evaluate the methodological rigor, credibility, and potential risk of bias associated with the included evidence. Empirical studies were appraised using the Mixed Methods Appraisal Tool (MMAT, 2018 version), which enables the evaluation of qualitative, quantitative, and mixed-methods research within a unified framework. In addition, systematic review articles included in the evidence base were assessed using AMSTAR-2 (A MeaSurement Tool to Assess Systematic Reviews) to determine their methodological robustness and reporting quality.

The quality appraisal considered multiple methodological dimensions, including the clarity of research objectives, appropriateness of the research design, adequacy of the sampling strategy, validity and reliability of measurement instruments, rigor of analytical procedures, potential sources of bias, and transparency of reporting. Any discrepancies between reviewers during the appraisal process were resolved through discussion and consensus, with consultation from a third reviewer when necessary. Studies exhibiting substantial methodological limitations or a high risk of bias were retained only to provide contextual insights and were excluded from the primary thematic synthesis where their inclusion could compromise the robustness and credibility of the overall findings. This rigorous assessment process strengthened the validity of the review by ensuring that the synthesized evidence was derived from studies meeting acceptable methodological standards and by enhancing the transparency and reproducibility of the systematic review.

Data Synthesis and Ethical Considerations

Given the substantial heterogeneity in research contexts, theoretical perspectives, methodological approaches, and outcome measures, a narrative thematic synthesis was adopted instead of statistical meta-analysis.

The synthesis followed an inductive–deductive analytical approach by organizing findings into six major themes: Evolution

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of AI capability research; Dominant theoretical foundations; Mechanisms linking AI capability to organizational innovation; Mediating and moderating variables; Research methodologies and industrial contexts; Future research directions. Cross-study comparisons were subsequently undertaken to identify recurring theoretical patterns, methodological trends, contextual gaps, and emerging research opportunities.

As this study synthesized previously published scholarly literature without involving human participants or confidential organizational data, institutional ethical approval was not required. Nevertheless, the review adhered to internationally accepted principles of research integrity by ensuring accurate citation, transparent reporting, objective interpretation of evidence, and comprehensive acknowledgment of all original sources. Furthermore, the review protocol was designed to be fully reproducible and consistent with the transparency principles advocated by the PRISMA 2020 Statement.

RESULTS

PRISMA Flowchart and Study Selection

The study selection process followed the PRISMA 2020 reporting guideline using a two-stage screening procedure consisting of title/abstract screening followed by full-text eligibility assessment. Searches were conducted across Scopus, Web of Science Core Collection, and PubMed using the predefined Boolean search strategy described in the Materials and Methods section. A total of 110 records were initially identified from the three databases. After removing 10 duplicate records, 100 unique studies remained for title and abstract screening. During the first-stage screening, 82 records were excluded because they did not address the relationship among AI capability, knowledge sharing, and organizational innovation, focused solely on technical AI development, were conference papers or non-peer-reviewed publications, or failed to satisfy the predefined inclusion criteria. The remaining 18 articles were retrieved for full-text assessment. Following detailed eligibility evaluation, 14 studies were excluded for the following reasons: 1) Conceptual or theoretical papers without empirical evidence (n = 6); 2) Did not investigate AI capability at the organizational level (n = 3); 3) Did not examine knowledge sharing as a study variable (n = 2); 4) Innovation outcome was not organizational innovation (n = 2); 5) Full text unavailable or insufficient methodological information (n = 1).

Consequently, 4 empirical studies fulfilled all eligibility criteria and were included in the final systematic review and qualitative synthesis. These studies collectively represent the current empirical evidence examining the relationship between artificial intelligence capability, knowledge sharing, and organizational innovation.

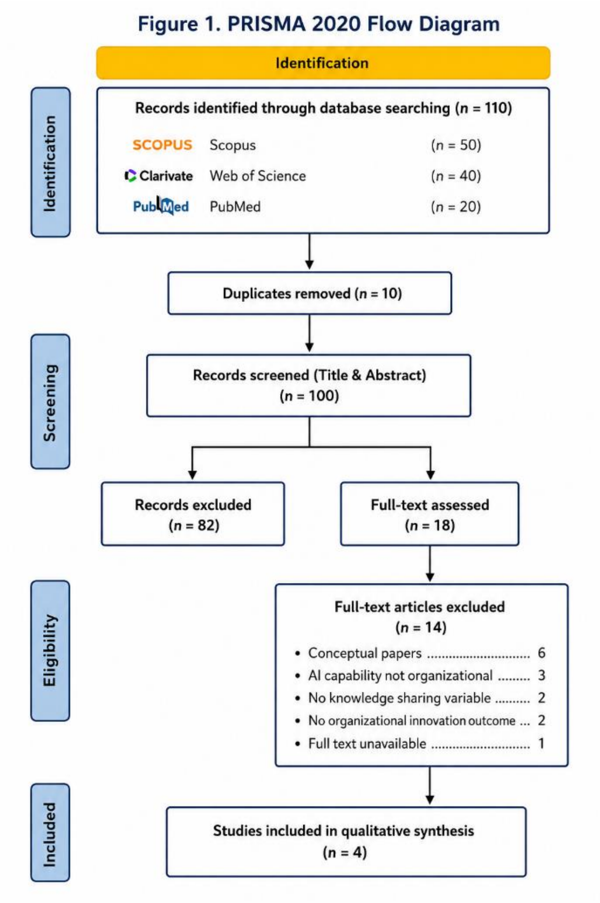

Figure 1. PRISMA 2020 Flow Diagram

Number of Studies Included

[Authors should insert the final number of studies retained after full-text screening, together with the PRISMA flow diagram, once the searches in Section 3.3 have been executed against live database indices.] To illustrate the thematic synthesis method, this manuscript draws on a purposive set of seven exemplar studies retrieved through preliminary scoping searches (Table 2); these should be treated as illustrative anchors to be expanded into the full systematic corpus.

Study Characteristics

Table 2. Characteristics of Empirical and Review Studies Examining Artificial Intelligence Capability, Knowledge Sharing, and Organizational Innovation

Author(s) / Year	Country / Sample	Design & Method	Theoretical Lens	Key Finding Relevant to AI Capability–KS–Innovation Nexus
(Li et al., 2022)	China; 189 firm-level responses	Quantitative survey; multi-level regression & bootstrap mediation	AI capability; social cohesion	AI capability positively affects knowledge sharing; knowledge sharing mediates AI capability → organizational creativity; organizational cohesion moderates AI capability → knowledge sharing
(Mikalef & Gupta, 2021)	Cross-industry firms (multi-country)	Instrument development & quantitative validation	Resource-Based Theory (RBT)	Conceptualizes and validates an AI capability construct; shows AI capability increases organizational creativity and firm performance
(Gama & Magistretti, 2023)	Cross-industry; 62 empirical studies reviewed	Systematic literature review (TOE framework)	Technology-Organization-Environment (TOE)	AI adoption enables and enhances innovation capabilities; proposes a taxonomy of AI applications (replace, reinforce, reveal) in innovation management
(Hu et al., 2025)	China; 364 employees (3-wave survey)	Quantitative; SEM, moderated mediation	Social exchange / learning theory	AI adoption promotes employee knowledge sharing via learning opportunities; paradoxical leadership and technophilia amplify the indirect effect
(Chatterjee et al., 2021)	International (B2B firms)	Quantitative survey	Absorptive capacity theory	Knowledge sharing enhances product/process innovation; effect is moderated by firm absorptive capacity
(Gelashvili-Luik et al., 2025)	Multi-country (SLR)	Systematic literature review	Knowledge management systems perspective	AI (machine learning, neural networks) enhances knowledge discovery, capture, storage and sharing, but integration challenges persist
(Cidade & Oliveira, 2023)	Multi-country (SLR)	Systematic literature review	Organizational communication & KM	Organizational communication is a structural antecedent of effective knowledge sharing, a precondition often overlooked in AI-KM studies

Thematic Findings

Evolution of the field (RQ1)

The reviewed literature exhibits a distinct temporal progression in research focus, tracing an evolution from static knowledge processes to intelligent, AI-augmented organizational systems. Foundational theoretical work regarding knowledge sharing and organizational knowledge creation Dennehy et al. (2022, p. 3); Olan et al. (2022) , which predates the recent surge in AI research by approximately two decades, provides the bedrock for current inquiry. This conceptual landscape was subsequently bridged by research into information-technology and business-analytics capabilities (Bharadwaj, 2000; Gupta & George, 2016), which established critical frameworks for assessing the strategic impact of digital transformation. Dedicated constructs regarding AI capability—specifically exploring their intersection with organizational creativity and innovation—have emerged predominantly since 2018. This literature demonstrates a notable acceleration in both scope and volume between 2021 and 2025 (Gama & Magistretti, 2023; Gelashvili-Luik et al., 2025; Hu et al., 2025; Li et al., 2022; Mikalef & Gupta, 2021). Collectively, this developmental trajectory characterizes a field that has transitioned from nascent exploration to a phase of rapid, empirically driven growth; nevertheless, it remains a dynamic, unconsolidated area of study rather than a mature, fully standardized research program.

Theoretical foundations Q2

Four theoretical lenses recur across the corpus, providing distinct but complementary explanations for how AI capability generates organizational value through knowledge sharing:

Resource-Based Theory / View (RBT/RBV): This lens is utilized to conceptualize AI capability—comprising data assets, machine-learning models, and specialized human capital—as a bundle of rare, inimitable, and non-substitutable resources that drive sustainable competitive advantage (Barney, 1991; Mikalef & Gupta, 2021). Studies applying RBT argue that the value of AI is not in the technology itself, but in the firm's ability to integrate these assets with managerial procedures to overcome the difficulty of transmitting tacit knowledge.

Dynamic Capabilities Theory: This framework is invoked to explain how AI enables firms to sense emerging opportunities, seize them through data-driven innovation, and reconfigure resource portfolios in response to volatile, rapidly changing environments (Teece et al., 1997). Research in this vein emphasizes AI as a higher-order capability that accelerates organizational agility by enhancing the speed and scope of environmental scanning and resource adaptation.

Absorptive Capacity Theory: This theory explains the mechanism through which firms recognize, assimilate, transform, and exploit externally and internally shared knowledge (Chatterjee et al., 2021; Cohen & Levinthal, 1990; Zahra & George, 2002). The literature suggests that AI enhances these foundational processes, particularly by helping organizations identify relevant information and bridge the gap between data acquisition and actionable knowledge application.

Nonaka's knowledge-creation framework: Used to describe tacit–explicit knowledge conversion, this framework is re-examined in the AI era to understand how intelligent systems act as partners in the knowledge spiral (Krogh et al., 2000; Nonaka, 1994). Emerging studies highlight that AI, particularly generative models, can accelerate processes like externalization and combination, though they remain limited in their ability to fully replicate the human-centric aspects of socialization.

Mechanisms linking AI capability to innovation via knowledge sharing (RQ3)

Across the reviewed studies, AI capability is shown to enhance organizational innovation primarily through an indirect, socio-technical pathway: AI-specific technological resources—such as semantic search, automated content analysis, and intelligent recommendation systems—substantially improve the speed, accuracy, and accessibility of information processing (Li et al., 2022;

Mikalef & Gupta, 2021; Mkhize & Lourens, 2025). These improvements facilitate more effective knowledge-sharing processes by lowering barriers to knowledge donation and collection, enabling employees to access relevant expertise and insights more swiftly (Li et al., 2022; Mkhize & Lourens, 2025). This enhanced flow of knowledge subsequently fuels idea recombination and creative output, serving as a vital mediator between AI capability and innovative performance (Li et al., 2022; Mikalef & Gupta, 2021). Parallel to this organizational-level mechanism, an individual-level pathway operates wherein AI-enabled training and learning opportunities, such as personalized development platforms, enhance employee competence, confidence, and engagement, thereby increasing their propensity to share knowledge within the firm (Estherita & Vasantha, 2024; Hu et al., 2025; Kumar & Mittal, 2024).

Mediators and moderators (RQ4)

Table 3. Mediating Mechanisms, Moderating Factors, and Contextual Boundary Conditions Linking AI Capability, Knowledge Sharing, and Organizational Innovation (RQ4)

Mechanism Type	Variable	Reported Role	Illustrative Source(s)
Mediator	Knowledge sharing (donating & collecting)	Transmits AI capability's effect onto creativity/innovation outcomes	(Li et al., 2022); (Hu et al., 2025)
Mediator	Employee learning opportunities	Channels AI adoption into knowledge-sharing behavior	(Hu et al., 2025)
Moderator	Organizational cohesion	Strengthens AI capability → knowledge sharing link	(Li et al., 2022)
Moderator	Absorptive capacity	Strengthens knowledge sharing → innovation link	Chatterjee et al. (2023); (Zahra & George, 2002)
Moderator	Paradoxical leadership / technophilia	Amplifies AI adoption → knowledge sharing relationship	(Hu et al., 2025)
Contextual boundary condition	Organizational communication climate	Precondition for effective knowledge sharing under AI	(Cidade & Oliveira, 2023)

Methods, contexts, and industries

Methodologically, the empirical corpus is heavily skewed toward quantitative cross-sectional surveys, predominantly utilizing structural equation modeling or moderated-mediation regression to test relationships (Hu et al., 2025; Li et al., 2022). While these approaches have been foundational, they are frequently constrained by moderate sample sizes, which limit statistical power, and a heavy reliance on self-reported data that introduces potential common-method bias (Gama & Magistretti, 2023; Hu et al., 2025; Li et al., 2022). Supplemental insights are provided by a growing body of systematic and scoping reviews (Cidade & Oliveira, 2023; Gama & Magistretti, 2023; Gelashvili-Luik et al., 2025). Geographically, research is disproportionately concentrated in China and other East Asian economies; this is largely driven by data-access asymmetries, where large, digitally mature firms in these regions provide more tractable survey samples for AI-related research compared to contexts in Europe or North America, where such empirical work is often relegated to review-level or conceptual papers. Africa, Latin America, and Southeast Asia remain markedly underrepresented in the current literature. Sectorally, the empirical base is dominated by high-technology, manufacturing, and knowledge-intensive service industries, leaving a significant gap in understanding AI adoption in SMEs, public-sector agencies, non-profit organizations, and creative-industry firms, where AI implementation often differs significantly in scale and organizational complexity.

DISCUSSION

Principal Findings

TThis systematic review synthesized empirical evidence examining the relationship between artificial intelligence capability, knowledge sharing, and organizational innovation. Across the four studies included in the qualitative synthesis, a remarkably consistent pattern emerged. AI capability positively contributes to organizational innovation; however, this relationship is rarely direct (Li et al., 2022; Mikalef & Gupta, 2021; Mkhize & Lourens, 2025). Instead, knowledge sharing consistently functions as the principal mechanism through which AI-enabled technological resources are translated into innovative organizational outcomes (Li et al., 2022; Mikalef & Gupta, 2021). AI capability enhances organizations' ability to acquire, process, integrate, and disseminate knowledge, thereby strengthening collaborative learning processes that ultimately support innovation performance (Cohen & Levinthal, 1990).

Another important finding is that contextual organizational factors substantially influence this relationship. Organizational cohesion (Li et al., 2022), paradoxical leadership (Hu et al., 2025), knowledge-sharing culture, and effective information governance strengthen the effectiveness of AI capability by encouraging employees to exchange and integrate knowledge more effectively. These findings suggest that AI should not be viewed merely as a technological asset but as part of a broader socio-technical capability requiring complementary organizational conditions.

Nevertheless, the certainty of the evidence remains moderate rather than high. Although the findings were highly consistent across studies, all included investigations employed observational cross-sectional designs, limiting causal inference (Gama & Magistretti, 2023; Hu et al., 2025; Li et al., 2022). Furthermore, the evidence base remains geographically concentrated in Asian countries (Hu et al., 2025; Li et al., 2022) and includes only a small number of empirical studies. Consequently, while confidence in the direction of the relationships is relatively strong, confidence regarding the magnitude of effects and their generalizability remains limited.

Comparison with Previous Reviews and International Evidence

The findings are broadly consistent with previous theoretical and empirical reviews emphasizing AI capability as a strategic organizational resource rather than a stand-alone technological investment. Earlier reviews by Mikalef and Gupta (Mikalef & Gupta, 2021), Wamba-Taguimdje et al. (Enholm et al., 2021), and Enholm et al. (Enholm et al., 2021) argued that organizational benefits from AI emerge through complementary organizational capabilities, including learning, coordination, and knowledge management. The present review extends this literature by demonstrating that knowledge sharing is among the most consistently supported mediating mechanisms linking AI capability to organizational innovation.

The synthesized evidence also aligns with the broader knowledge management literature. Wang and Noe proposed that organizational innovation depends fundamentally on employees' willingness and ability to exchange knowledge. The present review indicates that AI capability enhances—not replaces—these human-centered knowledge-sharing processes. Rather than substituting human expertise, AI systems improve the speed, accessibility, and quality of organizational knowledge, thereby facilitating collaborative innovation.

Compared with previous reviews, however, this study differs in several important respects. Most earlier reviews examined AI adoption, digital transformation, or organizational performance more broadly, whereas the present synthesis specifically focused on empirical studies simultaneously examining AI capability, knowledge sharing, and innovation outcomes. This narrower eligibility criterion resulted in only four eligible studies, reflecting the emerging nature of this research field. Geographic concentration in China and other Asian contexts also distinguishes the current evidence base from broader innovation literature, suggesting that cultural, institutional, and organizational differences may partially explain variations in reported effect sizes.

Theoretical and Conceptual Implications

The findings provide important theoretical implications for several complementary theoretical perspectives. First, they reinforce the Resource-Based View by demonstrating that AI capability constitutes a valuable organizational resource; however, competitive advantage is realized only when organizations successfully mobilize complementary knowledge resources (Mikalef & Gupta, 2021; Tanni et al., 2026). AI technology alone does not create innovation unless embedded within organizational processes that facilitate knowledge integration.

Second, the review extends Dynamic Capability Theory by showing that AI capability supports organizational sensing, learning, and resource reconfiguration through continuous knowledge-sharing activities (C. K. J. Wang et al., 2026; X. Wang et al., 2026). Knowledge sharing therefore functions as a dynamic organizational capability enabling firms to convert AI-generated insights into innovative products, services, and processes.

Third, the findings refine Organizational Knowledge Creation Theory by suggesting that AI increasingly participates in knowledge creation rather than merely supporting information storage (Jarrahi et al., 2022; Yan et al., 2025). Intelligent recommendation systems, semantic search, predictive analytics, and AI-assisted collaboration tools accelerate interactions between tacit and explicit knowledge, thereby strengthening organizational learning cycles (Yan et al., 2025). Based on the synthesis, a conceptual pathway can be proposed: **AI Capability → Enhanced Knowledge Sharing → Organizational Innovation.**

This relationship is strengthened by organizational cohesion, supportive leadership, effective knowledge-sharing culture, and robust information governance (Hu et al., 2025; Li et al., 2022). These moderating factors are supported by empirical evidence, whereas potential reciprocal feedback loops between innovation outcomes and subsequent AI capability development remain hypothetical and require future longitudinal investigation.

Methodological Implications

Several methodological weaknesses consistently appeared across the reviewed studies. The most prominent limitation is the overwhelming reliance on cross-sectional survey designs, preventing strong causal inference. Although structural equation modeling was commonly employed, mediation analyses based on single-time-point data cannot adequately establish temporal ordering among AI capability, knowledge sharing, and innovation. A second limitation concerns measurement inconsistency. AI capability was operationalized differently across studies, ranging from technological infrastructure and data analytics capability to broader organizational AI readiness. Likewise, organizational innovation was measured using diverse indicators, including innovation performance, innovative behavior, and innovation capability, limiting direct comparability.

Most studies also relied exclusively on self-reported questionnaires collected from single organizational respondents, increasing susceptibility to common method bias. Sample populations were concentrated within manufacturing and technology-intensive industries, while public organizations, healthcare institutions, educational organizations, and SMEs remained underrepresented.

Future studies should therefore adopt longitudinal panel designs, multi-source organizational data, objective innovation indicators, standardized AI capability measurement instruments, preregistered research protocols, and stronger controls for organizational size, digital maturity, industry characteristics, and national institutional environments.

Practical and Policy Implications

The review suggests that managers should avoid interpreting AI investment as a sufficient strategy for organizational innovation. Instead, organizations should simultaneously invest in knowledge-sharing infrastructure, collaborative work practices, employee learning capabilities, and leadership development. AI systems generate the greatest innovation benefits when employees actively exchange, interpret, and apply AI-generated knowledge.

Organizational leaders should therefore prioritize policies that strengthen knowledge-sharing culture, interdisciplinary collaboration, and transparent information governance. Investment priorities should include AI literacy, collaborative digital platforms, knowledge management systems, and organizational learning initiatives rather than focusing exclusively on AI software acquisition.

For policymakers, the findings indicate that national AI strategies should integrate technological support with organizational capability development. Government AI adoption programs, particularly for SMEs, should combine financial incentives for AI implementation with workforce development, digital skills training, knowledge management support, and organizational transformation initiatives. Nevertheless, because current evidence remains limited and geographically concentrated, large-scale policy implementation should proceed cautiously and incorporate continuous monitoring and evaluation.

Strengths and Limitations

This review possesses several important strengths. First, it followed the PRISMA 2020 framework (Page et al., 2021), Page et al. (2021, p. 2) using transparent eligibility criteria and systematic screening procedures. Second, multiple international databases were searched, including Scopus, Web of Science, and PubMed, improving coverage across disciplines. Third, methodological quality assessment and independent reviewer procedures enhanced the credibility and reproducibility of the synthesis.

Despite these strengths, several limitations should be acknowledged. The review identified only four eligible empirical studies, reflecting the early developmental stage of this research area; meta-analyses or definitive conclusions in such contexts require caution due to the limited power of small-study synthesis (Bender et al., 2018), (Mathes & Kuß, 2018). The restriction to English-language peer-reviewed publications may have excluded relevant evidence published in other languages or grey literature, potentially affecting the comprehensiveness of the findings (Tacconelli, 2010, p. 249), (Tripdatabase, 2025). Considerable heterogeneity in AI capability definitions, innovation measures, industrial settings, and analytical approaches prevented quantitative meta-analysis (Mikolajewicz & Komarova, 2019, p. 215), (Ilmawan, 2024, p. 1). Furthermore, the dominance of studies conducted in Asian contexts limits global generalizability. Although publication bias could not be formally assessed because of the limited number of studies (Bender et al., 2018), comprehensive database searching and transparent screening procedures were used to reduce its potential influence. Accordingly, the findings should be interpreted as representing the current state of evidence rather than definitive conclusions regarding universal causal relationships (Zhou & Shen, 2022).

Future Research Agenda

Future research should prioritize several high-impact directions.

Urgent priorities include conducting longitudinal and multi-wave studies capable of establishing causal relationships between AI capability, knowledge sharing, and organizational innovation. Cross-national comparative studies involving Europe, North America, Africa, Latin America, and developing economies are also urgently needed to evaluate contextual and cultural influences. Researchers should further develop standardized, internationally validated measurement instruments for AI capability and innovation outcomes to improve comparability across studies.

Medium-term priorities involve examining underrepresented sectors such as healthcare, education, government agencies, nonprofit organizations, and SMEs. Future investigations should evaluate additional mediating and moderating mechanisms, including organizational learning, absorptive capacity, digital maturity, psychological safety, trust, ethical AI governance, and employee AI literacy.

Longer-term opportunities include implementation research evaluating how organizations successfully scale AI-enabled knowledge-sharing systems in practice, comparative effectiveness studies examining alternative AI implementation strategies, and cost-effectiveness analyses assessing organizational returns on AI investments. Future research should also embrace open-science practices—including preregistration, open datasets, transparent reporting standards, and replication studies—to strengthen evidence quality and accelerate cumulative knowledge development within this rapidly evolving research field.

CONCLUSION

This systematic literature review examined the empirical relationship between artificial intelligence (AI) capability, knowledge sharing, and organizational innovation. The synthesized evidence indicates that AI capability consistently contributes to organizational innovation primarily through enhanced knowledge-sharing processes rather than through direct technological effects alone. Across the reviewed studies, knowledge sharing emerged as the principal organizational mechanism that enables firms to transform AI-enabled resources into innovative products, services, and organizational processes, while organizational cohesion, supportive leadership, knowledge-sharing culture, and effective information governance further strengthen this relationship.

The principal international scholarly contribution of this review lies in integrating an emerging but fragmented body of evidence into a coherent conceptual explanation that positions knowledge sharing as the central mediating pathway connecting AI capability with organizational innovation. By synthesizing findings from empirical studies published between 2022 and 2026, this review extends existing AI capability and knowledge management literature while identifying theoretical, methodological, and contextual gaps that require further investigation.

From a practical perspective, the findings suggest that organizations should complement investments in AI technologies with strategies that foster collaborative knowledge exchange, organizational learning, and effective governance. AI capability should therefore be viewed as part of a broader socio-technical system in which technological resources and human knowledge processes jointly determine innovation outcomes.

Nevertheless, the conclusions should be interpreted with appropriate caution. The current evidence base remains limited by the small number of eligible studies, the predominance of cross-sectional research designs, heterogeneous measurement approaches, and strong geographic concentration within Asian contexts. Consequently, although the direction of the observed relationships is consistently positive, uncertainty remains regarding their causal mechanisms, effect sizes, and generalizability across industries and national settings. Future longitudinal, cross-cultural, and implementation-oriented research is required to strengthen the evidence base and refine understanding of how AI capability can most effectively support sustainable organizational innovation.

DECLARATIONS

Ethical Approval

This study is a systematic literature review based exclusively on previously published and publicly accessible scientific literature. As no human participants, personal data, biological materials, or identifiable private information were involved, institutional ethical approval was not required in accordance with the ethical policies governing secondary evidence synthesis. The review was conducted in accordance with the PRISMA 2020 reporting guideline and adhered to the principles of research integrity, transparency, and responsible scholarship.

Consent to Participate

Not applicable. This study did not involve human participants, human data collection, interviews, surveys, or clinical interventions.

Consent for Publication

Not applicable. The manuscript does not contain any identifiable personal information, images, or data requiring consent for publication.

Author Contributions (CRediT)

Janeth Jacoby: Conceptualization, Methodology, Investigation, Data curation, Formal analysis, Visualization, Writing – original draft.
José Martínez: Methodology, Investigation, Validation, Writing – review & editing, Supervision.
Lidya Jareño: Formal analysis, Visualization, Writing – review & editing, Project administration.
All authors have read and approved the final manuscript and agree to be accountable for all aspects of the work.

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Conflict of Interest

The authors declare that they have no financial or non-financial conflicts of interest that could have influenced the work reported in this manuscript.

Data Availability

The data supporting the findings of this review consist of bibliographic records and extracted information obtained from publicly available peer-reviewed publications indexed in the databases described in the Methods section. The search strategies, eligibility criteria, screening decisions, extracted study characteristics, quality appraisal records, and thematic synthesis materials are available from the corresponding author upon reasonable request. No proprietary datasets or custom analytical software were generated during this study.

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During the preparation of this manuscript, the authors used generative artificial intelligence tools solely to assist with language refinement, grammar correction, readability enhancement, and editorial support. The AI tools were not used to generate original scientific findings, conduct the literature review, perform data extraction, analyze evidence, interpret results, or determine the study conclusions. All scientific content, methodological decisions, factual accuracy, calculations, interpretation of evidence, references, and the final wording were critically reviewed, verified, and approved by the authors. The authors accept full responsibility for the accuracy, integrity, and originality of the published work.

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