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Artificial Intelligence in Knowledge Management: Mapping a Decade of Research and Emerging Directions

Kecerdasan Buatan dalam Manajemen Pengetahuan: Pemetaan Satu Dekade Riset dan Arah Perkembangan Baru

Gunawan[1*], Siska Ayudia Adiyanti[2], Adi Dadan Ramdana[3], Granit Agustina[4], Dadar Supriatna[5]

[1,2,4,5]Fakultas Ekonomi dan Bisnis, Universitas Kebangsaan Republik Indonesia, Bandung, Indonesia
[3]Fakultas Ekonomi dan Bisnis, Universitas Mayasari Bakti, Tasikmalaya, Indonesia

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ABSTRACT

This study maps the intellectual landscape of research at the intersection of artificial intelligence (AI) and knowledge management (KM) to explain the field's evolution, key contributors, and dominant and emerging themes. A science-mapping analysis was conducted on 209 English-language journal articles indexed in Scopus from 2015 to 2025, using Biblioshiny to generate performance indicators, collaboration patterns, and thematic structures based on keyword co-occurrence and factorial clustering. The findings reveal a sharp increase in KM–AI publications after 2020, indicating a transition from early exploratory studies to a rapidly expanding research domain. Social-structure analysis shows that knowledge production is globally distributed but concentrated among a core group of countries, institutions, and author networks, with collaboration influencing topic diffusion. Conceptually, the field is organized around three interconnected streams: AI-enabled decision support and analytics, people- and leadership-driven adoption dynamics, and governance and sustainability issues related to responsible knowledge processes. This study integrates fragmented KM–AI research and proposes a focused agenda for future organizational studies.

Corresponding Author:
Gunawan,
Fakultas Ekonomi dan Bisnis, Universitas Kebangsaan Republik Indonesia, Bandung, Indonesia.
Email: gunawan.lect@gmail.com

INTRODUCTION

Knowledge management (KM) refers to systematic organisational practices for creating, storing, sharing, and applying knowledge to improve decision quality and organisational performance. In knowledge-intensive and digitally transforming firms, KM is no longer limited to codifying best practices; it increasingly includes governing knowledge flows across teams, digital platforms, and inter-organisational ecosystems. This makes KM central to competitiveness because knowledge functions as a strategic asset—one that can be leveraged, protected, and recombined for innovation and value creation (Bloodgood & K. Chen, 2021; L. Hu et al., 2024; Mauro et al., 2020). However, the same digital transformation that amplifies KM's importance also introduces new organisational tensions, including technostress and sustainability-related pressures, which require more adaptive and technology-enabled KM capabilities (Martínez-Navalón et al., 2023; Pellegrini et al., 2020).

A major challenge in KM implementation is that knowledge processes depend on social and behavioural conditions—trust, leadership, and shared norms—rather than on repositories alone. Empirical work highlights how top management support and trust-based affiliations shape knowledge sharing and the effectiveness of KM initiatives (Zia, 2020). In parallel, leadership styles that reinforce knowledge-oriented behaviours strengthen innovation outcomes, especially in project-based and resource-constrained contexts (Zia, 2020). Yet, knowledge governance problems remain persistent: organisations face risks of knowledge leakage, uneven participation in sharing, and vulnerabilities that may undermine sustainability performance if KM processes are poorly designed or weakly enforced (Bloodgood & K. Chen, 2021; Shahzad et al., 2020; Zieba et al., 2022). These challenges motivate a growing interest in how advanced digital technologies can enhance KM execution while managing associated risks.

In this context, artificial intelligence (AI) increasingly functions as an enabler of KM by automating and augmenting knowledge discovery, interpretation, and dissemination. AI-supported analytics can accelerate knowledge generation from large and heterogeneous data sources and improve the accuracy and timeliness of managerial insights (Moretto et al., 2022). AI applications such as chatbots and recommender systems can also personalise knowledge access and facilitate context-aware sharing across organisational units (Marvi et al., 2024; Reyhan Ghazaldi & Wijaya, 2025). Furthermore, predictive analytics can support proactive decision-making, enabling firms to respond to emerging risks and opportunities with greater agility (Fait et al., 2022). As organisations experiment with AI adoption, scholars have begun to examine its consequences for knowledge workers—often conceptualised as a "double-edged sword" in which AI can simultaneously enable productivity and generate new tensions around autonomy, learning, and innovation (Dong et al., 2024; Rahmawati & Riani, 2025). These developments position AI not only as an IT tool but also as a socio-technical mechanism reshaping KM practices.

The accelerating diffusion of AI technologies has coincided with a sharp increase in scholarly attention to the KM–AI nexus, particularly after 2020. The COVID-19 pandemic acted as a catalyst for digital transformation, intensifying the need for AI-enabled collaboration and decision support in distributed work arrangements (Abdulkareem & Petersen, 2021; Naudé, 2020). At the same time, rapid advances in machine learning and natural language processing expanded AI's applicability for analysing organisational data and supporting data-driven decision-making (Zeng et al., 2022). Adoption dynamics are also shaped by managerial and institutional factors: senior management support affects the likelihood of successful implementation and operational gains (Ghani et al., 2022; Weinert et al., 2022), while training and skills development influence how effectively employees use AI to share and mobilise knowledge (Giffari et al., 2024; X. Hu et al., 2025; Rahmawati & Riani, 2025). Additionally, leadership that promotes AI integration can foster collaboration and organisational learning, strengthening the KM outcomes of digital initiatives (Dong et al., 2024; Q. Hu et al., 2019). Collectively, these forces help explain the rapid growth of publications and the widening scope of research topics at the intersection of KM and AI.

As the KM–AI literature expands, the research domain becomes harder to interpret: contributions emerge across multiple disciplines, journals, and methodological traditions. In fast-growing and multidisciplinary fields, bibliometric analysis is well-suited to provide a consolidated map of the intellectual landscape because it quantifies publication dynamics, identifies influential sources and contributors, and reveals thematic structures through keyword and network relationships (Donthu et al., 2021; Greener, 2022; Mulet-Forteza et al., 2022; Reyhan Ghazaldi & Wijaya, 2025). Bibliometric workflows also allow researchers to examine collaboration patterns among authors, institutions, and countries, supporting more evidence-based assessments of how knowledge production is organised globally (Ghosh et al., 2024; Saputro et al., 2023). Tools such as Biblioshiny/Bibliometrix facilitate science mapping and network visualisations, enabling transparent and replicable analysis of large bibliographic datasets (Aria & Cuccurullo, 2017). Moreover, bibliometric rigor includes attention to sampling and database design choices, which can influence the interpretability and generalisability of derived trends (Rogers et al., 2020). However, the rapid expansion of KM–AI publications has also increased conceptual dispersion, making it difficult to identify a coherent intellectual structure and priority research directions.

Despite growing interest, three gaps remain evident and motivate the present study. First, the literature lacks a consolidated, time-sensitive mapping of KM–AI development that distinguishes early exploratory work from the post-2020 acceleration. Without a periodised understanding of growth, it is difficult to interpret whether observed topic shifts reflect genuine intellectual evolution or short-term publication surges driven by external shocks and diffusion effects (Abdulkareem & Petersen, 2021; Naudé, 2020). Second, social-structural evidence remains fragmented: while many studies discuss AI adoption and KM outcomes, fewer studies integrate collaboration patterns (countries, institutions, and author networks) into a single narrative that explains how dominant actors and cross-national cooperation shape the research agenda (Ghosh et al., 2024). Third, the conceptual structure of the field is still insufficiently synthesised in terms of how core KM–AI themes relate to peripheral or emerging streams. In particular, it is not yet clear how managerial topics (e.g., decision-making, innovation, sustainability, and governance) interconnect with technology-anchored themes (e.g., machine learning and decision support systems) and human-centric concerns (e.g., knowledge sharing, leadership, and adoption behaviours) (Dong et al., 2024; Shahzad et al., 2020; Zieba et al., 2022).

To address these gaps, we provide a consolidated bibliometric mapping that combines performance indicators, collaboration patterns, and thematic clustering within a single analytical narrative. Using Scopus-indexed journal articles (2015–2025) analysed via Biblioshiny/Bibliometrix (Aria & Cuccurullo, 2017), this study pursues three research objectives: **RO1**—to identify publication trends, leading sources, and highly cited contributions; **RO2**—to map prolific authors, key institutions, and prominent contributing countries; and **RO3**—to reveal the dominant and emerging thematic structure of KM–AI through keyword co-occurrence and clustering techniques (Donthu et al., 2021; Rogers et al., 2020). Beyond offering a descriptive overview, the study contributes by translating bibliometric patterns into a research agenda relevant to business and management scholarship, especially regarding AI-enabled KM for decision quality, innovation, and sustainability performance.

METHOD

This study applies a bibliometric science-mapping design to synthesise research at the intersection of knowledge management (KM) and artificial intelligence (AI). Bibliometric mapping is appropriate for rapidly growing and multidisciplinary domains because it quantifies publication dynamics and impact while revealing the field's social structure (authors, affiliations, countries) and conceptual structure (themes and their relationships) (Donthu et al., 2021; Ghosh et al., 2024). The workflow followed established bibliometric procedures—dataset construction, pre-processing, analysis, visualisation, and interpretation—to support transparent trend and gap identification (Agbo et al., 2021; Priyanka et al., 2024; Zanko, 2025). Data source, sampling, and search strategy: Bibliographic records were retrieved from Scopus. The population comprised Scopus-indexed publications relevant to KM and AI, and the analytical sample consisted of 209 English-language journal articles published during 2015–2025 (Rogers et al., 2020; Zanko, 2025).

A title–abstract–keyword search anchored by TITLE-ABS-KEY (knowledge AND management AND ai) was combined with filters for subject areas (BUSI, SOCI, PSYC, DECI), document type (article), source type (journal), and language (English); open-access availability was not restricted (OA: all). To strengthen topical precision and reduce irrelevant retrieval, Scopus EXACTKEYWORD constraints were applied to retain records aligned with KM–AI constructs and applications (e.g., Knowledge Management, Artificial Intelligence, Machine Learning, Knowledge Sharing, Decision Support Systems, Knowledge Management System, Organizational Performance, Digital Transformation, Human Resource Management) (Polat et al., 2023).

Data pre-processing and analyses: Records were exported with standard bibliographic fields (authors, affiliations, titles, abstracts, keywords, sources, references, and citation counts) and analysed using Biblioshiny (Bibliometrix, R) (Aria & Cuccurullo, 2017; Reyhan Ghazaldi & Wijaya, 2025). Prior to mapping, duplicate records (where present) were removed using DOI/title matching, and a brief relevance screening was conducted to ensure alignment with the KM–AI scope. Keyword pre-processing included basic normalisation to reduce fragmentation in the conceptual maps, including merging obvious variants (spelling, hyphenation), consolidating singular/plural forms where appropriate, and removing non-informative terms.

Analyses were organised to address RO1–RO3. Performance analysis profiled annual publication trends and influential sources/documents (RO1). Social-structure mapping examined leading authors, affiliations, and countries and their linkages (RO2). Conceptual-structure mapping used author keyword co-occurrence and Biblioshiny's factorial clustering (Multiple Correspondence Analysis on the keyword–document matrix followed by clustering on the reduced space) to identify dominant and emerging themes (RO3). To improve interpretability, the co-occurrence network was constructed using a minimum-occurrence threshold and a retained set of the most frequent keywords; the selected parameter settings are reported with the outputs (and can be documented in an appendix if required) (Donthu et al., 2021; Rogers et al., 2020).

RESULT AND DISCUSSION

RO1: Publication dynamics and field maturity

Figure 1 traces the evolution of KM–AI publications over 2015–2025 and shows a clear two-stage trajectory. Output is modest and relatively steady through 2015–2020, then rises sharply after 2020. This inflection aligns with the wider acceleration of digital transformation and the growing reliance on AI-enabled tools to support distributed work, collaboration, and decision-making during and after the pandemic period (Abdulkareem & Petersen, 2021; Naudé, 2020; Reyhan Ghazaldi & Wijaya, 2025). At the same time, progress in machine learning and language-related methods has expanded what AI can realistically contribute to KM, particularly in automated knowledge extraction, analytics-driven discovery, and decision-support functionalities (Zeng et al., 2022).

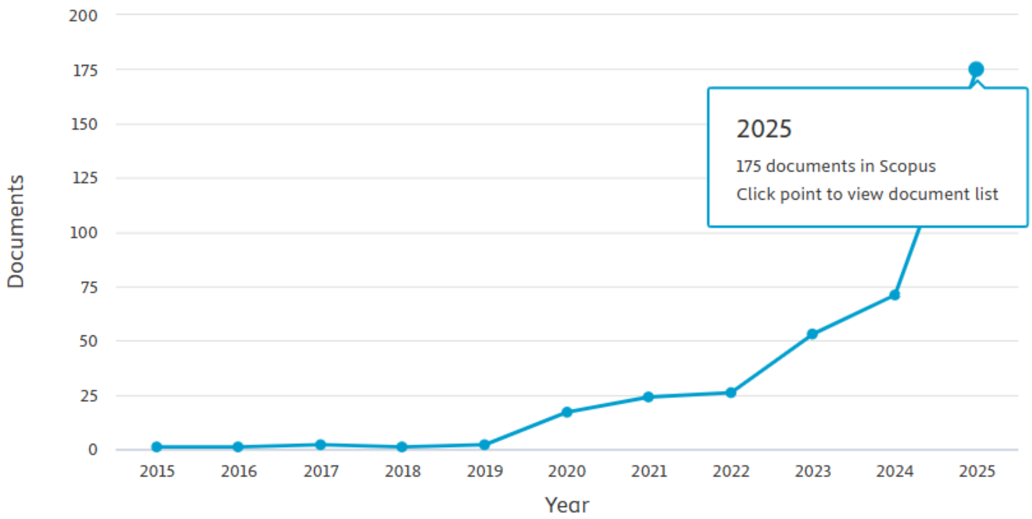

Figure 1. Publication growth trend in KM–AI (2015–2025)

The post-2020 surge is therefore not merely a volume effect; it also coincides with a shift in what the literature treats as the central challenge. Increasingly, AI-enabled KM is framed as an organisational capability-building issue rather than a purely technical deployment. In this regard, top management support is repeatedly linked to implementation success and the realisation of operational or strategic value (Ghani et al., 2022; Weinert et al., 2022). Workforce readiness features prominently as well. Studies frequently emphasise training and skills development as enabling conditions that shape whether AI tools lead to sustained improvements in knowledge sharing and knowledge use (Giffari et al., 2024; X. Hu et al., 2025). The trajectory in Figure 1 indicates a pronounced post-2020 acceleration, pointing to a rapidly maturing field that is increasingly oriented toward organisational KM applications. That said, publication growth alone does not reveal where this expansion is concentrated or which communities exert the strongest influence; the next subsection addresses this by examining the social structure of KM–AI scholarship (RQ2).

RO2: Social structure of KM–AI scholarship

Figure 2 uses a Three-Field Plot to connect affiliations, authors, and countries, providing a compact view of how KM–AI scholarship is distributed and where output is concentrated. The overall picture is international, but not evenly so. A relatively small set of recurring contributors appears prominently (e.g., Kuleto Valentin, Paun Dan, Zeng Yi), and publications are anchored in several national contexts, including the United Kingdom, Italy, India, and Romania. This is typical of an interdisciplinary area: participation expands over time, yet influence tends to cluster around active networks.

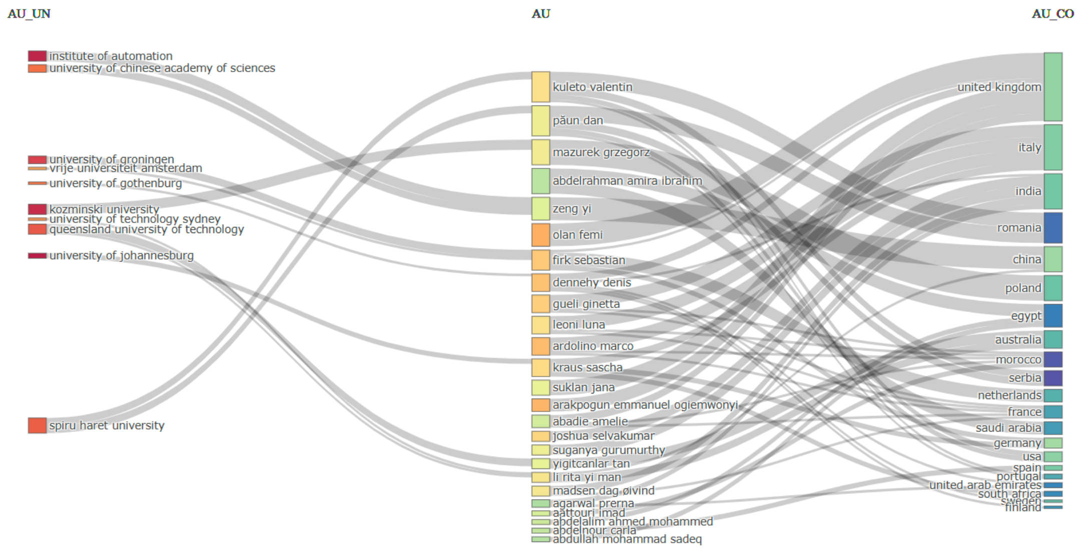

Figure 2. Three-Field Plot (Affiliations–Authors–Countries) in KM–AI research

Institutional visibility spans both technology-oriented organisations and business-facing universities. The prominence of the Institute of Automation and the University of Chinese Academy of Sciences alongside institutions such as Kozminski University, Vrije Universiteit Amsterdam, and the University of Gothenburg suggests a hybrid socio-technical research profile. This mix is substantive rather than incidental, since KM–AI research often requires technical capability to develop or apply AI approaches while also relying on organisational theory and implementation insight to interpret KM outcomes. At the country level, output is concentrated within a limited group, with Germany emerging as a leading contributor and strong representation from the United Kingdom and China, followed by the United States and Italy. This concentration matters because national ecosystems—industrial priorities, regulatory environments, and data access—can shape which problems are studied most frequently and which contexts become the default reference points for theorising. KM–AI scholarship is global in reach but anchored in a core set of countries, institutions, and author networks that likely influence agenda-setting and the diffusion of dominant themes. With these contributor and location patterns established (RQ2), the analysis now turns to the intellectual content of the field by mapping its conceptual structure and thematic clustering (RQ3).

RO3: Conceptual structure and thematic clustering

Figure 3 maps the conceptual structure of KM–AI research using author keyword co-occurrence, which shows how topics tend to cluster across publications and provides a practical indication of thematic proximity (Olczyk, 2016). As expected, “artificial intelligence” and “knowledge management” sit at the centre of the network and connect to multiple thematic groupings. From these anchors, the map separates into clusters that make the dominant streams and their connections easier to interpret.

One stream foregrounds human and organisational dimensions, bringing together keywords associated with innovation, human aspects, and technology-enabled work practices. This aligns with scholarship examining how AI adoption reshapes knowledge work and innovation behaviour, and why outcomes may differ across organisational contexts and governance arrangements (Dong et al., 2024). A second stream is more strongly oriented toward analytics and decision processes, clustering terms such as decision making, machine learning, and system integration. This reflects research that treats AI as an enabler of knowledge discovery and decision support, strengthening managerial inference through data-driven approaches (Moretto et al., 2022; Zeng et al., 2022). In addition, applied keywords such as sustainability and supply chain management appear as bridging elements, indicating contexts in which AI-enabled KM is investigated as a capability that supports resilience and longer-term performance priorities (L. Hu et al., 2024; Shahzad et al., 2020).

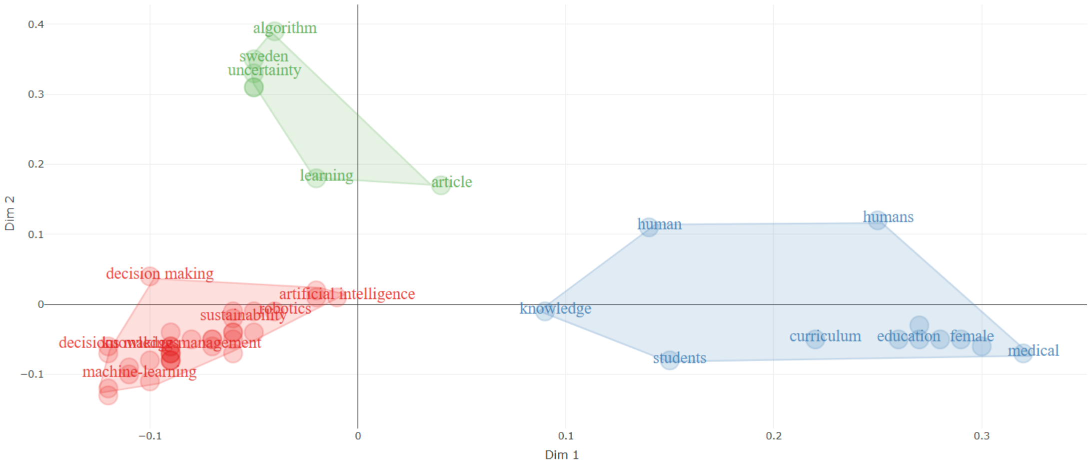

Figure 3. Co-occurrence network of author keywords in KM–AI research.

Read through a business and management lens, the conceptual landscape can be summarised into three pillars. First, a decision-and-analytics pillar positions AI as a mechanism for knowledge discovery and decision support (Moretto et al., 2022; Zeng et al., 2022). Second, a people-and-leadership pillar frames AI adoption as socio-technical change that shapes collaboration, knowledge-sharing routines, and innovative work behaviour (Dong et al., 2024; Q. Hu et al., 2019). Third, a governance-and-sustainability pillar emphasises that KM outcomes remain contingent on trust, risk management, and responsible knowledge processes, and that AI can either mitigate or intensify these issues depending on implementation choices (Bloodgood & K. Chen, 2021; Rahmawati & Riani, 2025; Zieba et al., 2022). Taken together, the clustering supports the view that AI-enabled KM value creation depends on alignment between analytics capability, human readiness, and governance arrangements. Figure 3 indicates that KM–AI research is structured around decision/analytics and machine learning, people/leadership and innovation, and governance/sustainability applications, with bridging topics linking these streams into a coherent organisational capability narrative. With the growth trajectory (RQ1), social structure (RQ2), and conceptual structure (RQ3) established, the next subsection integrates these findings and develops a focused research agenda aligned with the dominant thematic pillars.

Integrative implications and research agenda

Figures 1–3 portray a field that is not only expanding, but also beginning to organise itself. Growth is rapid, the most visible contributions come from a relatively concentrated set of research communities, and the thematic structure clusters around a few recurring streams. Viewed from a business and management standpoint, this points to a simple interpretation: the KM–AI nexus is increasingly treated as part of organisational capability building—shaping how firms generate, share, govern, and apply knowledge to support decision-making and performance.

From a managerial perspective, the evidence cautions against framing AI-enabled KM as a purely technical rollout. Leadership commitment matters because it affects prioritisation, resource allocation, and the removal of barriers that typically slow adoption (Ghani et al., 2022; Rahmawati & Riani, 2025; Weinert et al., 2022). Training investments are equally consequential; without them, AI tools may be used superficially and fail to translate into sustained changes in knowledge-related behaviours (Giffari et al., 2024; X. Hu et al., 2025). Trust remains central as well. When employees do not feel safe contributing knowledge—or do not trust what the system returns—platforms struggle to generate the contribution and reuse cycles that KM depends on (Lo et al., 2021).

On the research side, the thematic map highlights a recurring imbalance in the literature: claims about AI's promise for KM often advance faster than evidence on mechanisms and boundary conditions. The prominence of people- and governance-oriented clusters is especially telling, because it suggests that AI adoption outcomes are likely to be heterogeneous—varying with organisational readiness and the clarity of governance arrangements (Bloodgood & K. Chen, 2021; Dong et al., 2024; Zieba et al., 2022). To support cumulative knowledge development, Table 1 therefore summarises priority research questions aligned with the dominant thematic pillars identified in the keyword network.

Table 1. Research agenda for KM–AI: priority pillars and questions

Pillar	Research questions (RQ)
A. Decision and analytics *(AI as a KM capability for decisions)*	**RQ-A1**: When does AI-supported knowledge discovery translate into better decision quality, and when does it mainly increase speed without improving judgement? (Moretto et al., 2022; Zeng et al., 2022). **RQ-A2**: What role does explainability play in whether managers accept AI-supported knowledge recommendations, especially in high-stakes decisions? **RQ-A3**: How should organisations evaluate AI-enabled KM performance—what metrics capture value beyond usage counts (e.g., learning, decision outcomes, error reduction)?
B. People and leadership *(adoption, learning, and knowledge behaviour)*	**RQ-B1**: How does leadership support shape the link between AI adoption and knowledge-sharing routines, and which leadership behaviours matter most at different implementation stages? (Ghani et al., 2022; Q. Hu et al., 2019; Weinert et al., 2022). **RQ-B2**: What kinds of training investments actually change knowledge behaviour (contribution, reuse, cross-unit sharing), rather than only improving technical skills? (Giffari et al., 2024; X. Hu et al., 2025). **RQ-B3**: Under what conditions does AI become the "double-edged sword" for knowledge workers—raising productivity but weakening autonomy or learning? (Dong et al., 2024).
C. Governance and sustainability *(risk, responsibility, and long-run performance)*	**RQ-C1**: Which governance mechanisms reduce knowledge leakage and misuse in AI-enabled KM systems without choking knowledge flow? (Bloodgood & K. Chen, 2021; Zieba et al., 2022). **RQ-C2**: How do trust and perceived fairness influence willingness to share knowledge through AI-mediated platforms, especially when AI recommendations are opaque? (Lo et al., 2021). **RQ-C3**: In sustainability-oriented applications (including supply chains), how does AI-enabled KM support ongoing monitoring and learning, rather than one-off reporting? (L. Hu et al., 2024; Shahzad et al., 2020).

Another point becomes visible once the social-structure map is considered (Figure 2). Output is concentrated in a relatively small set of countries and institutions, and that concentration is not neutral. It can shape which empirical settings are most frequently studied and which assumptions quietly become “standard” in the literature. This is precisely why comparative work matters—across national contexts, industries, and organisational sizes—to test whether prevailing explanations of AI-enabled KM hold outside the ecosystems that currently dominate publication activity.

At the same time, the strength of bibliometric mapping is also its boundary: it offers a clear view of field-level structure—growth trajectories, influential actors, and thematic clustering—but it is not designed to establish causal mechanisms. As KM–AI research matures, progress will increasingly depend on designs that can unpack how capabilities are built in practice and how they translate into decision quality, innovation outcomes, and responsible governance. Mixed-method studies, comparative case research, field surveys, and (where feasible) experiments provide natural complements to bibliometric mapping for this purpose (Aria & Cuccurullo, 2017; Donthu et al., 2021; Rogers et al., 2020; Zanko, 2025).

CONCLUSION

This study mapped the development of research on artificial intelligence (AI) and knowledge management (KM), identified the main contributing communities, and clarified the thematic structure that organises the field. The findings show that KM–AI scholarship is in a period of rapid expansion and is increasingly framed around organisational applications, particularly those connected to decision support and knowledge-based capabilities. At the same time, knowledge production is international in reach but remains concentrated in a relatively limited set of countries, institutions, and author networks, which may shape the empirical settings and assumptions that become most visible in the literature. Conceptually, the field converges around three interlinked streams: decision-and-analytics (AI for knowledge discovery and decision support), people-and-leadership (adoption as socio-technical change affecting collaboration and knowledge sharing), and governance-and-sustainability (trust, risk management, and responsible knowledge processes). Taken together, the evidence suggests that AI-enabled KM value creation is best understood as a capability configuration, where analytics must be aligned with human readiness and governance arrangements.

For practice, organisations should approach AI-enabled KM as an organisational change program rather than a purely technical deployment. This includes sustained leadership commitment, workforce training, and trust-building mechanisms that encourage knowledge contribution and reuse. For future research, studies should specify mechanisms and boundary conditions more explicitly—for example, when AI improves decision quality rather than only speed, how explainability shapes acceptance in high-stakes contexts, and which governance designs reduce knowledge risks without constraining knowledge flows. Comparative research across industries and national settings is also encouraged to test the generalisability of prevailing models, complemented by mixed-method designs that can explain causal processes beyond field-level mapping.

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