Understanding the role of artificial intelligence in knowledge management systems: a systematic review using the antecedent, consequences and intervention framework

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Abstract

Purpose – This paper investigates the bibliometric parameters and content analysis of artificial intelligence in knowledge management systems, along with the development of a conceptual framework.

Design/methodology/approach – For this purpose, the study adopted the scientific procedures and rationales for systematic literature reviews framework to finalize the dataset downloaded from Scopus. Thematic analysis was conducted using the visualization of similarities viewer and Excel.

Findings – The study identified key journals, authors, institutions, keywords and other elements of the current literature. It recognized five main themes along with fifteen questions for future research. Additionally, it offers an antecedent, consequence and intervention (ACI) conceptual framework to advance this area. A comparison related to the existing socialization, externalization, combination and internalization and knowledge value chain models was also presented to emphasize the importance of the ACI framework.

Originality/value – The research raises several key questions concerning five distinct themes, suggesting intriguing directions for further investigation. The author acknowledges that other relevant papers might not have been included in the list of articles considered for review, although this criterion supports the article's quality motive.

Keywords Knowledge management, Artificial intelligence, ACI framework, Systematic review, Knowledge processes, Bibliometric analysis

Paper type Research article

1. Introduction-

Knowledge management (KM) is fundamentally composed of people, technology and processes, with people being the most critical element, accounting for 70% of performance (Geisler and Wickramasinghe, 2015). Processes, encompassing the creation and sharing of knowledge, make up 20%, while technology acts as a vital enabler, ensuring knowledge accessibility (Thakuri *et al.*, 2024). The rise of digital documents in the 20th century laid the groundwork for modern KM systems (Salloum *et al.*, 2019). These evolutions have been dramatically accelerated by artificial intelligence (AI), which is projected by the World Economic Forum to handle 52% of firm functions by 2025 (Arias-Pérez and Vélez-Jaramillo, 2022). This raises a critical and controversial question: will traditional KM strategies remain relevant in an era of rapid technological advancement? Or does AI's influence diminish the value of internal knowledge? In the 21st century, KM is universally recognized as essential for economic prosperity (Lei and Wang, 2020). It enables organizations to transition from individual to corporate knowledge, fostering institutional learning, growth and innovations (Chatterjee *et al.*, 2023). Knowledge-based enterprises are proving to be more resilient and competitive (Metaxiotis *et al.*, 2003). AI has emerged as a new component of this new landscape, enhancing

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information collection and sharing capabilities (Salloum *et al*., 2019). It has not simply disrupted KM; it has fundamentally redefined it. Today's AI-emblematic tools, from decision support systems to expert systems, have radically altered how we create, transfer and use knowledge (Coombs *et al*., 2020). Modern AI programmes can autonomously generate explicit knowledge, transfer it to third parties and even make independent decisions (Abbass, 2019). This challenges the long-held notion that only people can drive organizational knowledge, creating an intriguing and complex dilemma (Abubakar *et al*., 2019; Arias-Pérez and Vélez-Jaramillo, 2022).

Despite heightened research on artificial intelligence in knowledge management systems (AIKMS), a significant research gap exists. The existing literature suffers from extensive limitations in both conceptual depth and methodological rigor, leaving a fragmented and incomplete understanding of the AIKMS domain. For instance, while studies such as Pai *et al*. (2022) demonstrate the interdependence of AI and knowledge processes, their analysis is thematic and lacks a systematic framework that correlates AI capabilities with specific knowledge outcomes and enterprise performance. Similarly, de Oliveira and Rodrigues (2021) examine the convergence of AI and human behaviour from a neuroscientific perspective, but fail to extend these findings to a broader integrated model of organisational knowledge transformation. More recent works, including Taherdoost and Madanchian (2023) and Thakuri *et al*. (2024), are often confined to industry-specific applications or bibliometric relations, providing a summary description rather than a prospective model for effective integration. This fragmented conversation highlights a clear and urgent need for an integrative and diagnostic theory. This study aims to bridge this critical gap by introducing the antecedent, consequence and intervention (ACI) model (Paul and Roy, 2023). This novel framework combines central concepts like technological readiness and AI capabilities (automation, personalization, prediction) with quantifiable results such as innovation, decision quality and sustainability. The ACI model is strategically different from traditional KM models like socialization, externalization, combination and internalization (SECI) or knowledge value chain (KVC), as it is uniquely designed to incorporate dynamic variables, such as trust in AI, stakeholder pressure and digital literacy, that are essential for today's hybrid and uncertain organizational context. Therefore, to provide a comprehensive overview of AIKMS, this study employs a systematic literature review (SLR) based on the scientific procedures and rationales for systematic literature reviews (SPAR-4-SLR) protocol (Paul *et al*., 2021), using data from Scopus databases. The methodology tackles the important constraints of prior research by applying advanced bibliometric approaches and a thematic coding structure to synthesize the literature into the ACI framework. This research puts forth the following questions to resolve the aforementioned issues and strengthen the current domain.

RQ1. What is the publication trend in AIKMS?

RQ2. Who are the major contributors to the field of AIKMS?

RQ3. What are the existing themes in the AIKMS domain?

RQ4. What is the conceptual structure of AIKMS (ACI framework) and how does it differ from existing KM models?

RQ5. What are theme-wise future research questions in the AIKMS domain?

The remaining sections are organized as follows: Section 2 (methodology), Section 3 (performance and thematic analysis), Section 4 (discussion and conceptual framework), Section 5 (implications) and Section 6 (limitations and conclusion).

2. Methodology

The analysis employs the SPAR-4-SLR protocol by Paul *et al*. (2021), which comprises three stages: assembling, arranging and assessing, each of which comprises two sub-stages. The three stages of SPAR-4-SLR can be found in Figure 1.

Assembling

Identification
Review Domin: Artificial Intelligence in Knowledge Management Systems (AIKMS)
Research Question: Publication Trend (RQ1), Top contributor (RQ2), Major themes and conceptual structure (RQ3) & future directions (RQ4)
Source Type: Journal
Source Quality: Scopus

Acquisition
Search mechanism and material acquisition: Scopus
Search period: Up to 30th November 2024
Search keywords: TITLE-ABS-KEY ("AI" OR "Artificial Intelligence*" OR "Neural networks" OR "Large language model*" OR "Digital intelligence" AND "Knowledge sharing*" OR "Knowledge management*" OR "Knowledge hiding*" OR "Knowledge creation*" OR "Knowledge exchange*" OR "Knowledge sharing behaviour*") AND (LIMIT-TO (SUBJAREA , "BUSI")) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "re")) AND (LIMIT-TO (SRCTYPE , "j")) AND (LIMIT-TO (LANGUAGE , "English"))
Document type: Article and Review
Language: English
Search result: 385

Arranging

Organization
Organizing code: Article title, Journal title, Author name, Country or territory of affiliation, Affiliated institution, Author keywords, Number of citations, References

Purification
Exclusion Criteria: Articles not related to Artificial Intelligence in Knowledge Management Systems (AIKMS)
Final results: 151

Assessing

Evaluation
Analysis method: Performance analysis (Publication trend, author, article, journal, country)
Agenda proposal method: Thematic analysis, Conceptual Framework Formation, and future research direction

Reporting
Reporting conventions: Figures, Tables & Words
Limitation: Data is limited to the accuracy and completeness of Scopus

Figure 1. SPAR-4-SLR, adopted from Paul *et al*. (2021). Source: Authors

2.1 Assembling

In this stage, the authors searched and obtained the relevant literature on AIKMS using Scopus rather than the Web of Science because of its more expansive coverage (Panda *et al*., 2025). The search covered 1989 to December 2024, employed a structured strategy and yielded 385 peer-reviewed articles.

2.2 Arranging

In this stage, the authors organized the literature by filtering for English-language journal articles in the “Business, Management and Accounting” domain and by purifying and excluding 234 items that did not fit the AIKMS context, leaving 151 articles.

2.3 Assessing

In this stage, bibliometric analysis and network mapping were conducted in visualization of similarities (VOS) viewer, while also examining AIKMS research trends using bibliographic coupling and cluster analysis (Paul *et al.*, 2021). This also included discussions surrounding top-tier authors, publications and the impact of citations (Panda *et al.*, 2025). A thematic analysis was used to identify possible "future" research directions, informed by prior and emerging scholarly contributions. The study also identified key factors to construct the ACI framework.

3. Results

3.1 Performance analysis

Over 35 years (1989–2024), the authors identified 151 AIKMS publications, consisting of 140 articles and 11 reviews. The domain is currently experiencing an average growth rate of 5.38% per year with a total of 29.08 citations per document. Research has skyrocketed post-2018, amounting to approximately 80% of the articles published after 2018. The year 2024 is the most productive year with 39 publications. Anil Kumar is the most productive author with four papers and the most citations (238). The first eight institutions in this domain have published more than or equivalent to five papers, also including the top three countries identified U.S. (33), China (23) and the UK (23). The most productive journal is the *Journal of Knowledge Management* (13 articles and 367 citations), followed by Knowledge-Based Systems (9) and Knowledge Management Research Practice (5). Baskerville and Dulipovici (2006) and Castro *et al*. (2021) are the most cited documents in the domain of AIKMS. The most commonly used keywords are artificial intelligence (59), knowledge management (48) and knowledge sharing (20). The figures concerning the publication trend and top 10 authors, documents, countries, institutes, journals and keywords can be found in the supplementary file (SF 1 and 2).

3.2 Bibliographic coupling

Bibliographic coupling and thematic cluster analysis were used to analyze the dominant intellectual structures of AIKMS (Panda *et al.*, 2025). If one or more common documents are cited in the bibliographies of two papers, they are said to be bibliographically connected. There is a chance that the subjects of the two articles are related if they both refer to the same third work. A minimum of 10 citations in common was required for 75 papers to be eligible for coupling and using the VOS viewer, 53 documents were grouped into six clusters. All six different clusters are visible in the Figure available in the supplementary file (SF 3).

3.2.1 Theme 1 – AI's impact on KM dynamics. AI has shifted from being an enabler of automation to being a strategic neighbour of organizational knowledge, behaviours and systems. In early research by Kim and Trimi (2007), while they researched the role of Internet technologies and the people in consulting firms, AI was still at a stage of slower adoption. AI can now solve knowledge hiding and inefficiency, reflecting on the KM component of AI as an enabler of automation through emotion analytics and predictive modelling (Abubakar *et al.*, 2019), formalizing knowledge at the cost of using tacit values (Arias-Pérez and Cepeda-Cardona, 2022) and mediating knowledge sharing (Arias-Pérez and Vélez-Jaramillo, 2022). AI, utilizing deep learning, connects assets to competitive advantage (Mostafiz *et al.*, 2022), while developing personalization to reduce overload (Nguyen and Malik, 2022; Shaikh *et al.*, 2023). AI finds use as a tool to engage (Duong *et al.*, 2023), increase shared memory (Zhang *et al.*, 2024), to leverage for recall (Liu and Li, 2022), facilitate remote communications (Coombs *et al.*, 2020), support performance in small and uncertain environments (Chatterjee *et al.*, 2023; Soleimani *et al.*, 2022) and to advance market dynamism (Lei and Wang, 2020).

3.2.2 Theme 2 – integrating AI and KM for innovation and sustainability. The nexus of AI and KM is increasingly driving innovation and sustainability. With KM being connected to performance (Delen *et al*., 2013), drivers such as leadership alignment and cross-functional collaboration (Chatterjee *et al*., 2023) support the convergence of AI with KM and customer relationship management. Decision-making is enhanced with AI integration (Harlow, 2018) and sustainability, connecting KM with green human capital (Khan *et al*., 2024a, b). However, cognitive awareness remains important (Saviano *et al*., 2023), with context-aware AI as a better option (Sundaresan and Zhang, 2022). Adaptive AI makes KM more scalable (Nguyen *et al*., 2023), with uses in IoT-supported logistics (Yuen *et al*., 2018) and supply chain robustness (Mostafiz *et al*., 2022). Threats, including psychological impacts (Abbass, 2019), necessitate strategic, rather than technical, integration to guarantee long-term development and sustainable changes.

3.2.3 Theme 3 – AI-driven KM for decision-making and organizational learning. AI's journey in KM has matured from mere efficiency tools to cognitive decision-making and learning partners. Seminal papers (Zhu *et al*., 1997) describe AI's role in codifying knowledge orchestration, while other papers (Fowler, 2000; Metaxiotis *et al*., 2003) detail how adaptive decision support systems were developed. Wagner (2006) argues that they could offer open access and flexible flows of knowledge. Recent papers push AI's strategic implications into chapters relating to marketing potential (De Bruyn *et al*., 2020), real-time learning and flexibility (Shaikh *et al*., 2023). AI contextualizes knowledge and strategy related to sustainability and it is suggested that AI aids the decision quality under uncertainty (Liu and Li, 2022). As a portfolio, these studies demonstrate that AI is an agent of active change in implementing organizational learning, adaptation and strategic decision-making rather than static operational items.

3.2.4 Theme 4 – organizational performance and innovation through AI-enhanced KM for sustainable enterprise performance. AI-fused KM supports sustainable performance and innovation. AI maximizes decisions and foretells innovation outcomes and impacts every stage of the knowledge lifecycle (Jarrahi *et al*., 2023). Success depends on delineated roles and AI trustworthiness (Chowdhury *et al*., 2022) and customized settings that enhance satisfaction and retention (Malik *et al*., 2021). Ethical benefits comprise reducing AI hiring bias through knowledge sharing (Soleimani *et al*., 2022). Strategically, AI–KM links knowledge to fundamental missions (Benabdellah *et al*., 2021), utilizes networks and enhances supply chain resilience (Leoni *et al*., 2022). Applications range from fashion ecosystems (Liu and Li, 2022) to neural network–oriented KM innovation (Zhao *et al*., 2022), substantiating AI–KM's contribution to driving enterprise flexibility, performance and innovation across industries.

3.2.5 Theme 5 – redefining KM with generative AI and chatbots. Generative AI technologies such as ChatGPT are transforming the way people and organizations interact with knowledge sharing. Al-Emran *et al*. (2023) had linked behaviour drivers such as performance expectancy and perceived threat as essential for chatbot adoption. Building on this, Duong *et al*. (2023) noted that positive knowledge-sharing intentions are reflected in ChatGPT usage by students. Extending beyond individual behaviour, Sumbal *et al*. (2024) proved how ChatGPT integration into KM systems supports better decision-making and instant knowledge access. In response to the evolving practices, Korzynski *et al*. (2023) called for reimagining KM theory in light of generative AI, highlighting the management work shift along with present generative AI as a cornerstone facilitator of dynamic, adaptive and collaborative knowledge systems.

4. Discussion

This bibliometric analysis shows a steady growth pattern in AIKMS research (RQ1). From 1989 to 2018, there were very few publications, not exceeding ten per year. Between 2019 and 2024, there were 60 publications, with 2024 having the highest single-year output (39 papers), indicating rising interest in scholarly work, mainly fuelled by the evolving technological role in KM. The performance analysis (RQ2) is briefly discussed in Section 3.1. For RQ3, the thematic analysis focused on highly cited articles (≥10 citations); attention was given to themes involving the role of AI and KM in dynamic contexts, as well as topics like innovation, decision making, sustainability and tools such as generative AI and Chatbots. These areas suggest the increasing significance of this field.

4.1 Methodology, country and context related to AIKMS

The current study also synthesizes different article types (methodological perspective), industry perspective (context) and country perspectives to understand the growth of AIKMS.

4.1.1 Methodological perspective (article types). AIKMS demonstrates a broad and diverse methodological foundation. Each of these methods naturally aids in understanding and improving KMS due to the inherent complexity of both AI and KMS fields, especially when considering KMS development and implementation within specific contexts. In this regard, case studies (e.g. Rae *et al*., 2024; Sumbal *et al*., 2024) are likely the best choice because they aim to provide rich contextual insights into AI challenges and how situational factors influence AI system deployment in KMS environments. The broader literature review (Hao and Demir, 2024; Thakuri *et al*., 2024) and individual literature reviews each expand the body of knowledge by examining the theoretical evolution to identify potential gaps, thus outlining future research directions. Qualitative research (Olan *et al*., 2022; Malik *et al*., 2021), as a methodological category, investigates behaviours related to trust, resistance and managers' readiness concerning the development and deployment of AI technologies. Conceptual papers (Jarrahi *et al*., 2023; Fowler, 2000) are distinct from but complement empirical research, especially in areas lacking empirical data, by creating models and frameworks that clarify theories within this emerging field. Empirical studies (Khan *et al*., 2024a, b; Liu and Li, 2022) aim to generate generalizable insights and contribute to KMS by employing statistical testing and validation to evaluate AI's impact on the knowledge process. Collectively, these methods form an integrated, layered approach that explores KMS through contextual, theoretical and empirical lenses, highlighting opportunities to identify gaps between current academic theories and practical implementations of AI systems. Brief details of the paper-specific methodologies are available in the supplementary files (see details ST 1).

4.1.2 Context (sector-specific distribution). AIKMS demonstrates its importance across various sectors, highlighting its role in enhancing knowledge within organizations. The service industry makes up the largest share ($n = 14$), representing knowledge-intensive and customer-facing functions (Chatterjee *et al*., 2023; Olan *et al*., 2022), followed by the technology sector ($n = 10$), which has adopted AI to support research and development (R&D) and automation (Chanda, 2024; Botega and Da Silva, 2020). Education ($n = 9$) shows that AI is mainly used for academic collaboration or administration (Al-Emran *et al*., 2023; Zhang *et al*., 2024). Construction ($n = 7$) aims to improve knowledge flow around projects and enhance safety (Khan *et al*., 2024a, b). Multi-sector studies in this domain ($n = 6$) reveal the diverse adaptability of AI KMS (Sumbal *et al*., 2024). Manufacturing ($n = 5$) research mostly focuses on predictive maintenance (Leoni *et al*., 2022). The IT ($n = 4$) and banking ($n = 3$) fields appear in other studies, along with SME/family firms ($n = 3$) and hospitality, where AI is used to develop better smart indexing and personalization (Mostafiz *et al*., 2022). Healthcare, defense and public administration are examined in other niche sectors (Shaikh *et al*., 2023; Jeni *et al*., 2019). The details of sector-specific studies are available in the supplementary files (see details ST 2).

4.1.3 Country (geographic distribution). The international literature on AIKMS shows a broad global interest. China leads with 14 published studies (e.g. Zhang *et al*., 2024; Zhao *et al*., 2022), aligning closely with its digital transformation goals. Fourteen studies lack country affiliation (e.g. Hao and Demir, 2024) and tend to be conceptual. The USA ranks second with 13 contributions (e.g. Chen, 2024; Wagner, 2006), reflecting strong institutional and academic capacity, although this may mask greater involvement from other countries. India and the UK each have 10 studies (e.g. Chatterjee *et al*., 2023; Rae *et al*., 2024). Nine studies are multi-country collaborations (Olan *et al*., 2022; Soleimani *et al*., 2022), indicating cross-border interest. Emerging economies such as Pakistan (four studies), Colombia, Malaysia and Vietnam (three studies each) are also involved. Other developed countries, including Germany, Canada, South Africa and Japan, have produced several studies. Countries like Brazil and Ukraine have also contributed in the form of conceptual research. These trends highlight the importance of AIKMS and reflect socio-technical differences across regions and the details are available in supplementary files (see details ST 3).

The global research landscape contextualizing AIKMS demonstrates a difference between developed and developing countries. Developed economies such as the USA, United Kingdom, Germany, Japan and Canada tend to explore and assess the application of AI in KMS in use cases that emphasize AI's potential in advancing experience and knowledge processes toward innovation, providing a competitive advantage and embracing AI for advanced knowledge processes available in a KMS such as predictive analytics (Wagner, 2006; Kim and Trimi, 2007; Bilgram and Laarmann, 2023; Rae *et al*., 2024). Countries with a strong digital infrastructure and research ecosystem typically focus on KMS that assist users and organizations as an innovation practice. Conversely, published empirical literature from developing countries (e.g. India, Pakistan, Colombia, Vietnam and Malaysia) tends to identify the role of AI in KMS as a mechanism to mitigate barriers due to infrastructural limitations, improve organizational operational efficiency and improve digital inclusion (Chatterjee *et al*., 2023; Mostafiz *et al*., 2022). For example, in India, published studies (Chanda, 2024; Jeni *et al*., 2019) show that AI has increased utilization and improved management of resources (i.e. knowledge workers). Despite constraints such as limited funding, levels of digital literacy, there is evidence that interest in AI-KMS has also improved internationally, providing evidence to suggest that AI-KMS is a strategic priority in a variety of socio-economic contexts.

4.2 Conceptual framework

Based on the thematic analysis, the authors curated an ACI framework (Paul and Roy, 2023) for further enhancement of this field. The ACI framework (as shown in Figure 2), in detail, consists of antecedents (independent variables), intermediaries (moderators and mediators) and consequences (dependent variables). This study feels a need to develop a comprehensive view of AIKMS using the ACI framework (RQ4), as the previous review papers have not given any framework.

Antecedents are the primary drivers of facilitating KM. These include AI capabilities, i.e. machine learning, natural language processing, computer vision, etc. which form the technological foundation. AI integration in KMS ensures seamless blending of AI functionalities with knowledge repositories and workflows. AI-based knowledge insights enable organizations to mine, interpret and utilize knowledge more effectively. Additionally, AI-augmented knowledge processes improve how knowledge is created, stored and shared. While AI-enabled KS fosters dynamic interactions among employees. Finally, the use of GenAI and chatbots revolutionizes traditional communication by automating and personalizing knowledge exchanges.

The effectiveness of this transformation depends on several moderators that influence the strength and direction of these relationships. Organisational readiness will determine whether an organisation is prepared enough to absorb and capitalise on AI-driven changes. Environmental dynamism shapes the urgency and adaptability required for AI-KM integration. Leadership support plays a critical role in legitimizing and championing the change process. Simultaneously, digital literacy among employees determines their comfort and effectiveness using AI tools. Other key moderators – stakeholder pressure and trust in AI systems, become crucial for user acceptance and sustained engagement. Through these pathways, the antecedents impact a set of key mediators – the organizational processes that directly bridge technology and outcomes. The mediators include enhanced knowledge processes, improved knowledge integration, greater organisational agility, dynamic capability development and increased user engagement with AI systems. Together, they translate the AI adoption in KMS into better decision-making, innovation, sustainability and overall organisational performance.

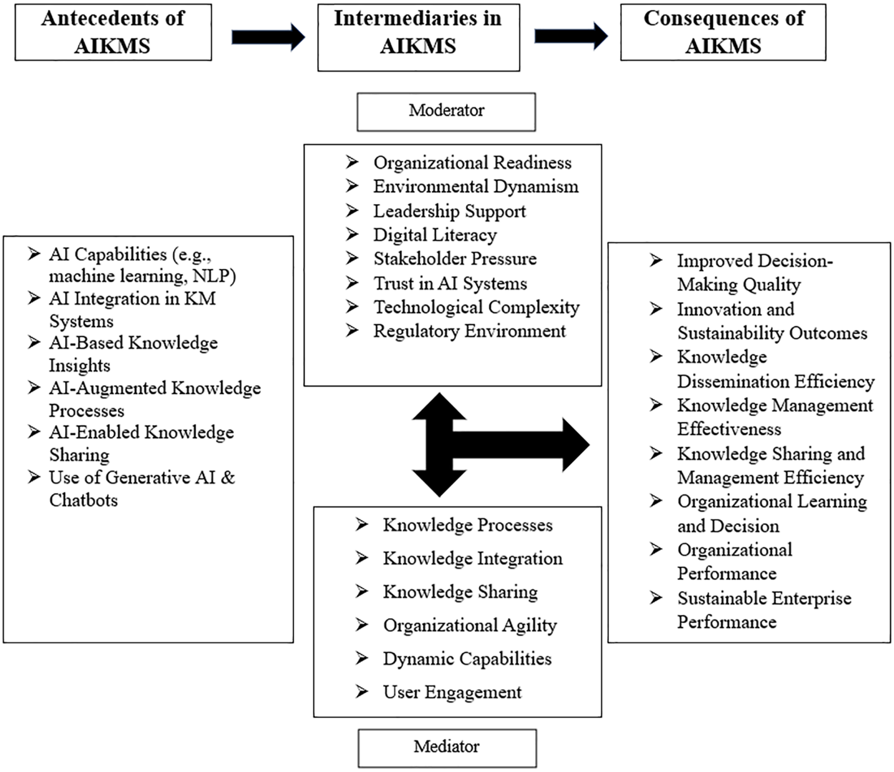

Figure 2. ACI framework for AIKMS domain. Source: Authors

The outcomes are improved knowledge dissemination efficiency, which ensures faster and broader access to information. Whereas innovation and sustainability outcomes flourish, organisations leverage better knowledge processes for creativity and responsibility. At a broader level, organisational learning deepens, organizational performance improves and sustainable enterprise performance is achieved. The framework (Figure 2) sheds light on key antecedents, consequences and intermediary factors.

The ACI model provides a future-oriented improvement in the domain of KM, perfectly adopting AI with KMS. Its multi-dimensional framework analyzes context factors (antecedents), mediating processes (intermediaries) and organizational outcomes (consequences), offering a systemic approach that differs from more traditional models like SECI (Nonaka, 1994; Nonaka and Takeuchi, 1995) and the KVC (Chyi Lee and Yang, 2000). SECI describes tacit-to-explicit knowledge conversion through cyclical mechanisms, whereas KVC describes KM as a linear value-creation process. They both are primarily human-centered, static and specific in handling environmental factors or technological shocks. ACI, on the other hand, integrates organization readiness, management support, stakeholder pressure and compliance requirements in a systematic approach, essential in the current dynamic digital economy. It incorporates AI-specialized features, such as machine learning, natural language processing, AI-driven insights, generative AI tools and chatbot-enabled knowledge sharing, placing AI not just as an enabler but also as a natural intermediary. These features enable knowledge creation and sharing via human and intelligent system interactions, coupled with user engagement and trust, something lacking in conventional KM systems.

A key distinction is ACI's performance orientation. Unlike SECI's emphasis on knowledge evolution or KVC's focus on value addition, ACI explicitly links knowledge processes to tangible outcomes such as innovation, decision-making quality, learning effectiveness and sustainable enterprise performance. This enables organizations to measure the return on investment of AI-driven KM initiatives and plan targeted interventions. Its flexible and modular design makes its application possible in regulated and rapidly changing sectors such as healthcare, finance and technology services, coping with environmental dynamism and technological intricacy. By solving challenges in AI integration, stakeholder dynamics and changing contexts, ACI gives a holistic, dynamic and technologically sensitive method to today's KM, deserving further empirical support.

Finally, the critical contribution is the theme-wise future research questions (RQ5), which will lay the foundation for future research. The study has suggested a total of 15 theme-wise future RQs for the advancement of this domain. The figure in the supplementary file (SF 4) will give a brief idea about this.

5. Implications

5.1 Theoretical implications

This bibliometric review, which spans almost 20 years, significantly contributes to the proverbial theoretical landscape of AIKMS and documents conceptual and empirical advancements. As such, this review makes a meaningful contribution to scholarly discussions by mapping how AI has changed how we view knowledge systems and the implications for organizational elements. It also sets a benchmark for researchers to find gaps in the literature, as well as future research directions. The review identifies six key streams of research, including AI-based decision-making, machine learning-oriented knowledge capture knowledge acquisition and the role of AI in organizational learning. The themes identified, on the other hand, set the stage for theory-building and generating hypotheses, while the aggregation and synthesis of different studies also contribute to an expanding border of knowledge and contribute towards previous works.

5.2 Managerial implications

Managers will face transformational changes and AI will change how knowledge works in organizations. For example, AI systems such as emotion-aware analytics can reduce knowledge hiding (Abubakar *et al.*, 2019) while personalized recommendations increase employee engagement (Nguyen and Malik, 2022). Subsequently, strategic organizational preparedness will be needed to use AI as part of workflows and existing organizational processes. Changes of this magnitude may require leadership buy-in and collaboration with other departments (Chatterjee *et al.*, 2023). For example, utilizing AI to support real-time environmental/dream planning relies on a coordinated network of knowledge and engagement. As AI will increasingly replace human–human interaction, it becomes imperative to establish robust oversight mechanisms that critically address ethical implications while safeguarding avenues for meaningful human cognitive engagement (Saviano *et al.*, 2023). Organizations must and will treat AI as a cognitive partner for decision-making (Liu and Li, 2022) and align AI tools with organizational goals. This notion of employee or citizen experiences in which organizations may reduce bias in hiring and decision-making (Malik *et al.*, 2021; Soleimani *et al.*, 2022) will also demand a certain amount of trust installed into AI systems. The adoption of generative AI and chatbots will also require agencies to address the behavioural determinants of perceived usefulness (Al-Emran *et al.*, 2023) and deploy real-time learning mechanisms (Sumbal *et al.*, 2024). This presents opportunities to advocate a human-oriented (and more extroverted) managerial approach towards AI-KMS.

5.3 Public policy, economic and ethical implications

The impact of AIKMS has serious implications for public policy, economic growth and ethics. On a policy and economic level, AI-KMS improves the quality of decisions and performance of enterprises, making it an enabler of national innovation (Paul and Roy, 2023). The USA's leadership in AIKMS research (Rae *et al*., 2024; Wagner, 2006) provides strong motivation to align national habitual AI agendas and knowledge-based approaches for development. Public policy funding and investment in digital infrastructures, frameworks for digital interoperability and ethical standards for AI are required. In economic terms, AI enhances efficiency in services and manufacturing (Lei and Wang, 2020; Liu and Li, 2022). Moreover, public sector investment in AI R&D as well as developing digital literacy capacity is required (Abbass, 2019; Shaikh *et al*., 2023). AI-KMS is being adopted in emerging nations like India and Malaysia, indicating that AI-KMS for SMEs can support them to improve digital capability and equity in access to digital technology and applications (Chatterjee *et al*., 2023; Mostafiz *et al*., 2022). There are recommendations for countries with emerging economies and organisations to develop AI-KMS for education, healthcare and government.

The benefits of AIKMS are, however, accompanied by ethical challenges. The ACI suggests two main moderators, namely (1) trust and (2) digital literacy, which offer significant value, but there are concerns about data privacy, algorithmic bias and excluding tacit knowledge (Coombs *et al*., 2020; Soleimani *et al*., 2022). In cases where society's digitization level is relatively low, such as in Pakistan and Vietnam (Nguyen and Malik, 2022; Subramanian *et al*., 2023), implementing ethical AI-KMS models requires a high level of informed collaboration.

6. Conclusion and limitation

This bibliometric review served two main purposes: (1) to illuminate the AIKMS domain's thematic analysis and conceptual framework and (2) to identify current research gaps and directions. Results show that, although still limited, AIKMS studies have increased both in number and quality over the past five years, with significant potential to influence various organizational outcomes. The resulting ACI framework offers a strong foundation for future empirical research and the five emerging themes and 15 theme-wise future research questions provide valuable pathways for further exploration and development in the field.

This study has limitations because it only uses the dataset from Scopus. Future research could include Web of Science and PubMed to identify different patterns and trends. Using broader keyword searches might produce larger datasets and exploring other academic fields like computer science, social sciences and arts would extend the relevance beyond business, management and accounting. Additionally, only English-language articles and reviews were included, while other document types and languages were excluded, which could broaden the scope and depth of future analyses.

Supplementary material

The supplementary material for this article can be found online.

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