Artificial Intelligence in Knowledge Management: Identifying Intellectual Milestones and Emerging Domains

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Abstract: Research exploring the integration of knowledge management and artificial intelligence has grown significantly over the past two decades, driven by the transformative potential of intelligent technologies in reshaping how organizations create, share, and apply knowledge. Despite this expansion, the field remains conceptually fragmented, with limited synthesis across theoretical and practical contributions. This study offers a comprehensive bibliometric analysis of 1,650 peer-reviewed publications indexed in the Web of Science from 1975 to 2024. By employing performance metrics, co-citation and keyword co-occurrence analyses, timeline visualizations, and citation burst detection; the study maps the intellectual landscape and thematic evolution of this interdisciplinary domain. The results reveal four core thematic areas: the strategic application of artificial intelligence in human resource management, hybrid decision-making frameworks, innovation-driven supply chain transformation, and the use of intelligent systems in hospitality and service delivery. These clusters illustrate the field's conceptual diversity and the convergence of technological and managerial perspectives. Burst-detection analysis pinpoints 2020–2023 as a tipping period, when landmark publications sharply accelerated theoretical diversification and research momentum across the KM–AI domain. Theoretically, the study refines the Knowledge-Based View by introducing the contingencies of algorithmic transparency and inter-organizational power asymmetry, advancing a paradox-aware lens that reconciles augmentation vs. transformation and optimization vs. resilience tensions. Practically, cluster-specific evidence is translated into adaptable principles for HR leaders, supply-chain managers, and service innovators, emphasizing phased AI deployment, transparency-driven trust, and balanced efficiency–resilience strategies, while informing sector-specific governance standards and paradox-aware curricula for policymakers and educators. By identifying key research trajectories, influential contributions, and emerging areas of inquiry, this work provides a structured overview of the field's development and lays the foundation for future investigations into the evolving relationship between knowledge management and artificial intelligence.

Keywords: Knowledge management, Artificial intelligence, Machine learning, Intelligent systems, Bibliometric analysis, Co-Citation analysis, Science mapping, CiteSpace

1. Introduction

In an era increasingly defined by data proliferation and algorithmic decision-making, organizations face mounting pressure to extract strategic value from their knowledge resources. Knowledge Management (KM), which emerged in the 1990s as a discipline focused on the creation, sharing, storage, and application of knowledge (Nonaka & Takeuchi, 1995), is undergoing a profound transformation through the integration of Artificial Intelligence (AI). Advanced AI technologies—such as machine learning, natural language processing, and intelligent agents—have introduced new paradigms in how knowledge is captured, classified, and operationalized across firms (Duan, Edwards & Dwivedi, 2019; Ma & Yu, 2010; Del Giudice & Maggioni, 2014).

This convergence has catalyzed growing academic interest in understanding how AI augments KM systems, enabling knowledge discovery from unstructured data, automating knowledge workflows, and personalizing decision support. At the same time, it introduces complex challenges that disrupt traditional KM assumptions—particularly concerning the unpredictable behavior of learning algorithms and the opacity of AI-driven reasoning processes (Cavaleri, 2004; Jarrahi, 2018).

The educational sector has emerged as a relevant test bed for AI–KM integration, with developments ranging from smart learning environments (Dmitrenko et al., 2022) and data-driven quality assessment (Bondar et al., 2022) to AI-powered speech recognition tools (Pronina & Piatykop, 2022) and IoT-based health monitoring systems (Klochko et al., 2022). These cases illustrate broader KM–AI challenges such as AI-enabled decision support, large-scale knowledge discovery, and intelligent system integration in complex organizational

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settings. Similar advancements are observed in AI-assisted human resource management, knowledge-driven supply chain optimization, and intelligent service delivery systems.

Recent contributions have explored this intersection from various angles. Some focus on the role of AI in enabling knowledge-intensive business processes and innovation (Marques & Ferreira, 2020), while others investigate how knowledge workers interact with AI-enabled systems in dynamic, data-saturated environments (Haenlein & Kaplan, 2019). Educational institutions, in particular, have served as important test beds, with studies examining how digital platforms facilitate knowledge sharing during crises (Papanikolopoulou Arco, 2022), how interactive technologies enhance knowledge transfer in specialized technical domains (Kanivets et al., 2022), how student response systems improve knowledge engagement (Holovnia et al., 2022), and how intelligent navigation systems support institutional knowledge access (Gryzun, Shcherbakov & Bida, 2022). Scholars such as Dwivedi et al. (2021) advocate for integrative models capturing the interplay between human cognition, machine intelligence, and organizational learning.

Despite these advances, the KM–AI literature remains fragmented at conceptual, theoretical, and methodological levels, with divergent definitions, foundational assumptions, and research designs (Rodríguez, Edwards and Bertone, 2020; Centobelli, Cerchione & Esposito, 2022). This lack of coherence hampers cumulative knowledge building and inhibits the development of robust, integrative frameworks. Addressing such fragmentation requires a synthesis method capable of identifying conceptual clusters, intellectual structures, and thematic trends across a diverse body of work.

Bibliometric mapping is particularly well-suited to this objective because it allows for a systematic, quantitative synthesis of large scholarly corpora, capturing both the intellectual foundations and emerging frontiers of a research field. Compared to traditional narrative or systematic reviews, bibliometric analysis can reveal the structural relationships between concepts, authors, and institutions, offering an evidence-based map of the domain's evolution.

Accordingly, this study addresses the following central research question:

What is the current state of research at the intersection of Knowledge Management and Artificial Intelligence, and what emerging trends are shaping this domain?

To provide a more precise analytical lens, this overarching question is examined through three sub-research questions:

- What are the intellectual foundations of KM–AI research?
- Which thematic clusters and research fronts have emerged over time?
- How have collaboration patterns and knowledge flows evolved across authors, institutions, and countries?

The aims of the study are therefore to: (1) consolidate dispersed research by mapping its intellectual and thematic structures, (2) identify gaps and fragmentation patterns, and (3) highlight future research frontiers. Theoretically, the study seeks to contribute to the development of an integrated conceptual framework that bridges AI and KM perspectives. Managerially, it offers actionable insights for designing AI-enabled KM systems that enhance decision quality, optimize knowledge flows, and foster organizational learning.

The remainder of the paper is structured as follows: Section 2 reviews the theoretical evolution of the KM–AI research domain. Section 3 presents the methodology, including data collection and scientometric techniques. Section 4 outlines the current state of KM–AI research based on publication trends, citation patterns, and collaboration networks. Section 5 examines thematic evolution through co-citation and keyword co-occurrence analyses. Section 6 explores the intellectual structure of the field via timeline visualizations and cluster analysis. Section 7 synthesizes the findings, identifies research frontiers, and proposes future research directions.

2. Theoretical Evolution of the KM–AI Research Domain

The integration of AI into KM has garnered increasing scholarly attention over the past two decades, prompting a reexamination of how knowledge is created, shared, and applied in data-intensive organizational environments. While KM emerged as a distinct research field in the early 1990s, grounded in foundational works such as Nonaka and Takeuchi (1995), its conceptual development was initially shaped by organizational learning theory (Argyris & Schön, 1978) and the resource-based view (RBV) of the firm (Barney, 1991; Grant, 1996). These frameworks positioned knowledge as a key strategic asset, emphasizing its role in enabling innovation and sustaining competitive advantage.

As digital transformation intensified and AI technologies became increasingly integrated into enterprise systems, scholars began to question the sufficiency of traditional KM theories. Cavaleri (2004), for example, noted that conventional KM systems were often ill-equipped to detect tacit, emergent, or non-linear knowledge patterns—dimensions that are now more accessible through AI techniques such as machine learning, natural language processing, and semantic analysis. To better reflect the complexity of AI-enhanced knowledge processes, researchers have progressively adopted diverse theoretical lenses.

Among these, sociotechnical systems theory has been influential in exploring how AI interacts with human knowledge workers and institutional contexts (Jarrahi, 2018). Simultaneously, complexity theory and systems thinking have been mobilized to conceptualize knowledge flows as dynamic, adaptive, and continuously reconfigured through feedback loops enabled by AI. In addition, paradox theory has helped frame the tensions between automation and human cognition, particularly in scenarios where AI augments rather than replaces knowledge work (Haenlein & Kaplan, 2019). When combined, these lenses provide a holistic framework: sociotechnical systems theory situates AI within human–organizational contexts; complexity theory explains the adaptive, emergent nature of AI-enabled knowledge flows; and paradox theory captures the tensions between automation and human agency. Together, they enable a richer understanding of AI not merely as a technological tool but as an active partner in organizational knowledge generation.

Despite this theoretical diversification, several recent reviews suggest that the field remains fragmented and lacks an overarching conceptual foundation (Dwivedi et al., 2021). One recurring critique is that AI is still predominantly treated as a tool or infrastructure, rather than as a partner in knowledge generation (Rodríguez, Edwards and Bertone, 2020). This ontological framing limits the development of integrative perspectives capable of capturing the co-evolution of human and machine intelligence in organizational settings.

To address this limitation, researchers have increasingly relied on systematic literature reviews and science mapping techniques to trace the evolution of KM–AI research and clarify its emerging structure. For example, Del Giudice and Maggioni (2014) examined KM dynamics in inter-organizational networks, highlighting the role of digital technologies in facilitating knowledge transfer. Later, Marques and Ferreira (2020) focused on the transformation of KM practices in higher education, while Centobelli, Cerchione & Esposito (2022) proposed a multi-dimensional framework for embedding AI into organizational knowledge systems.

In parallel, bibliometric methods have played a growing role in consolidating the intellectual architecture of the field. Early efforts by Ma and Yu (2010) identified key research paradigms within KM through citation-based analysis. Building upon this, Rodríguez, Edwards and Bertone (2020) and García-Peñalvo et al. (2021) employed co-word and co-citation techniques to map the diffusion of AI concepts—such as deep learning, recommender systems, and ontological reasoning—into KM literature. Unlike previous KM–AI bibliometric studies, which have typically focused on either technological trends or conceptual mapping in isolation, our work integrates multiple theoretical perspectives—sociotechnical systems, complexity, and paradox theories—into the science mapping process itself. This allows us to address the specific problem of conceptual fragmentation by examining how technological, organizational, and cognitive dimensions intersect, rather than treating them as separate analytical layers. Furthermore, our study extends the temporal scope to nearly five decades (1975–2024) and incorporates managerial implications, positioning it as a bridge between theoretical synthesis and practical decision-making.

Educational contexts have provided rich empirical grounds for testing these theoretical frameworks. For instance, studies on belief revision and epistemic modeling illustrate how formal logic approaches can be applied to educational knowledge systems (Kozachenko, 2022), while the implementation of STEM technologies in educational settings exemplifies how complexity theory principles manifest in knowledge-intensive learning environments (Kukharchuk et al., 2022). Additionally, the intersection of economic analysis and educational knowledge management highlights the importance of understanding market-driven knowledge requirements in educational institutions (Abuselidze & Zoidze, 2022).

These foundational studies have laid the groundwork for identifying thematic clusters and research fronts focused on AI's role in knowledge discovery, intelligent decision support, and automated classification. However, as Dwivedi et al. (2021) and Centobelli, Cerchione & Esposito (2022) emphasize, the proliferation of theories and methodologies now requires a synthesis-driven approach that bridges technical, organizational, and cognitive perspectives. The present study contributes to this ongoing effort by offering a comprehensive bibliometric analysis of 1,650 publications indexed in the Web of Science Core Collection from 1975 to 2024, with the aim of tracing the intellectual evolution and mapping the emerging knowledge structure of the KM–AI domain.

This theoretical fragmentation underscores the need for a systematic, quantitative synthesis of the KM–AI knowledge base. Bibliometric analysis offers a unique capability to integrate these dispersed insights and systematically address the conceptual and methodological gaps identified above.

3. Methodology

3.1 Data Collection

To address the research question concerning the evolution and intellectual structure of the literature at the intersection of KM and AI, this study adopted a scientometric approach grounded in principles of transparency, reproducibility, and methodological rigor. Scientometrics enables the quantitative analysis of scientific literature based on bibliographic metadata and offers clear advantages over traditional narrative reviews—particularly in capturing the performance, collaboration networks, and thematic structures of a research domain (White & McCain, 1989; Zupic & Čater, 2015).

The Web of Science (WoS) Core Collection was selected as the data source due to its extensive coverage of peer-reviewed journals and its well-established use in bibliometric analyses. Its reliable citation indexing and multidisciplinary breadth make it a preferred database for tracing knowledge evolution across scientific fields.

To retrieve relevant documents, a topic search (TS) query was formulated to capture the overlap between KM and AI-related literature. The following search string was used:

TS = (("knowledge management" OR "KM") AND ("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "intelligent systems"))

The query was conducted across all document types and publication years from 1975 to 2024, capturing nearly five decades of scientific output. This initial search yielded 1,986 records.

To ensure dataset quality and relevance, a multi-step filtering process was applied. Non-research content such as editorials, proceedings abstracts, and non-peer-reviewed material was excluded. Duplicate entries were removed, and a manual relevance screening based on the titles and abstracts was conducted to retain only articles clearly situated within the scope of KM–AI integration. After this cleaning and validation phase, a total of 1,650 publications were retained and served as the foundation for the bibliometric analyses described in the following sections.

3.2 Data Analysis

In this study, the scientific article served as the primary unit of analysis. We employed a bibliometric methodology to investigate the intellectual structure, thematic developments, and collaboration patterns in the literature situated at the intersection of KM and AI. Bibliometric analysis provides a systematic means of examining research trends, citation dynamics, and authorial networks, making it particularly suitable for identifying both historical roots and emerging research frontiers (Zupic & Čater, 2015).

To conduct the analysis, we utilized CiteSpace (Chen, 2006), a widely adopted software tool in the field of scientometrics and science mapping. CiteSpace supports the exploration of bibliographic records and their cited references, offering capabilities such as co-citation network construction, keyword co-occurrence mapping, and timeline visualizations. These functionalities are instrumental in detecting intellectual milestones, identifying structural turning points, and highlighting temporal patterns of scholarly influence.

While other tools—such as VOSviewer, HistCite, BibExcel, and Gephi—offer comparable features, CiteSpace was selected for its robust algorithms in citation burst detection, cluster labelling (via LLR and LSI), and its focus on the temporal evolution of knowledge domains. Its algorithmic foundation, particularly the pathfinder network scaling, enhances the interpretability of complex citation structures by filtering out redundant links and highlighting the most meaningful connections.

The outputs generated through CiteSpace allowed us to construct visual representations of the KM–AI research landscape, revealing its core thematic clusters, influential authors and publications, and temporal trajectories. These knowledge maps facilitated a deeper understanding of the field's developmental trajectory, from foundational theories to current research hotspots, while also enabling the identification of underexplored yet rapidly emerging areas of inquiry.

4. The Current Status of KM-AI field

4.1 Research Trends at a Disciplinary Level

To investigate the disciplinary evolution and knowledge diffusion patterns within the intersection of KM and AI, we conducted a dual-map overlay analysis of journals. This technique provides a macro-level visualization of citation flows across scientific domains, enabling a better understanding of how KM–AI research is intellectually positioned within the broader academic landscape.

The dual-map overlay, generated using bibliometric software, displays citing journals on the left and cited journals on the right. Each node represents a journal, and the connecting arcs indicate the directional flow of citations between disciplinary domains. These arcs are color-coded to reflect distinct citation trajectories, revealing how knowledge produced in the KM–AI domain draws from, and contributes to, various scientific fields.

Following the guidance of Lin, Chen & Fang (2023), this method captures shifts in disciplinary influence by identifying statistically significant citation paths. Table 1 reports the top domain-level associations, ranked by z-score, a statistical measure of the strength of citation linkage. The most significant citation path originates from journals in Psychology/Education/Health, which cite extensively from literature in Psychology/Education/Social Sciences ($z = 5.87$). This is followed by strong connections from the same citing cluster to the Systems/Computing/Computer Science domain ($z = 4.78$). Additionally, journals in the Mathematics/Systems/Mathematical cluster cite both Systems/Computing/Computer ($z = 2.43$) and Economics/Economic/Political domains ($z = 2.18$).

As visualized in Figure 1, the map reveals two dominant citation trajectories: one linking computational and mathematical sciences to computer and information systems, and another connecting educational and psychological research with social and organizational sciences. These dual pathways suggest that KM–AI research is inherently interdisciplinary, grounded simultaneously in technical foundations (e.g., AI methods, data processing) and human-centric disciplines (e.g., education, organizational behavior, management).

This hybrid knowledge base underscores the evolving nature of the KM–AI field, which increasingly depends on the integration of algorithmic capabilities with social, behavioral, and institutional insights. The convergence of these domains reflects both the technological sophistication and the managerial relevance of contemporary research on knowledge and intelligence systems.

Table 1: Citation trends at a domain level

Citing region	Cited region	Z-score
Psychology/Education/Health	Psychology/Education/Social	5.87
Psychology/Education/Health	system/computing/computer	4.78
Mathematics/systems/mathematical	system/computing/computer	2.43
Mathematics/systems/mathematical	economics/economic/political	2.18

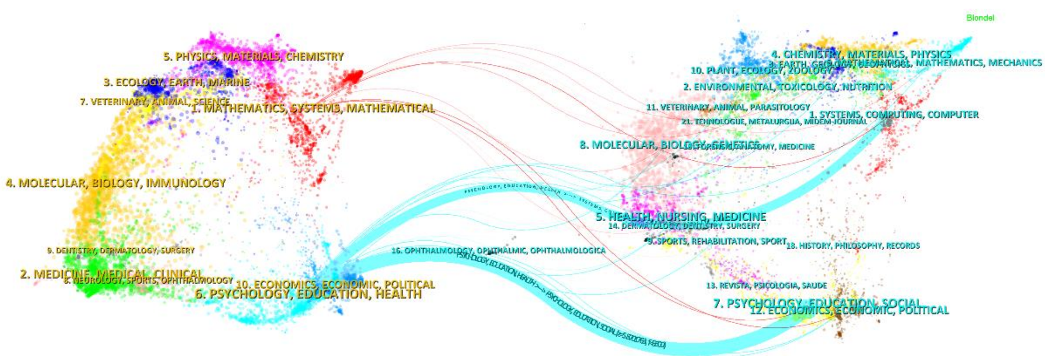

Figure 1: Dual-map overlay of cited and citing references on KM-AI field

4.2 Publication and Citation Pattern Analysis

A longitudinal examination of publication and citation trends offers valuable insight into the intellectual development and scientific consolidation of research at the intersection of KM and AI. As illustrated in Figure 2, both the volume of publications and their citation impact have increased markedly over the past five decades, with a particularly pronounced acceleration beginning in 2017.

From 1975 to the early 2000s, the field remained in its embryonic phase, characterized by low publication output—fewer than 10 articles annually—and exploratory contributions. During this period, scholarly efforts focused primarily on the conceptual foundations of KM and early applications of AI in expert and knowledge-based systems. The literature was sparse and largely fragmented.

Between 2010 and 2016, a steady development phase emerged. The number of annual publications grew consistently, reflecting the growing relevance of AI-related technologies—such as machine learning and big data analytics—to KM systems. Citation activity also increased, indicating broader academic engagement and diffusion.

The most dynamic growth occurred after 2017, marking the field's rapid expansion phase. Publication output more than doubled between 2018 and 2024, reaching a peak of over 300 articles in 2024. Citation counts followed a similar trend, culminating in more than 12,000 citations in 2023 alone. A slight decline observed in 2024 and 2025 is likely attributable to database indexing delays and the typical citation lag of recently published works.

In total, the dataset comprises 1,650 peer-reviewed articles indexed in the Web of Science Core Collection from 1975 to 2024, collectively cited 34,147 times, including 32,395 citations excluding self-citations. These articles appear in 25,212 citing documents, with an average of 22.58 citations per article and an overall H-index of 83. These metrics signal both high academic visibility and the field's consolidation as a multidisciplinary research front.

Despite its relatively recent momentum, the field's quantitative indicators underscore its maturity and impact. The growing citation base and increasing publication volume reflect a transition from theoretical groundwork to more applied and systemic research, drawing from disciplines such as computer science, information systems, organizational theory, and cognitive science.

While this analysis relies solely on WoS-indexed literature—excluding conference proceedings and grey literature—the findings nonetheless offer a robust overview of a rapidly evolving field with strong scholarly engagement and intellectual momentum.

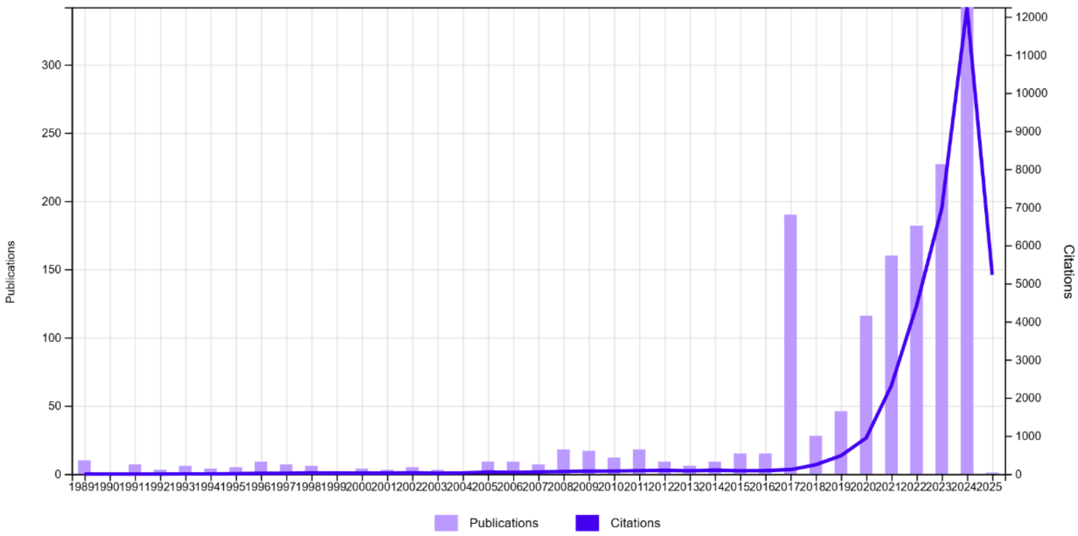

Figure 2: Times cited and publications over time

4.3 A Collaboration Analysis of Major Contributors to CS Field

As emphasized by Katz and Martin (1997), scientific collaboration refers to the process through which researchers collectively produce new knowledge. In the context of KM and AI—a field defined by its cross-disciplinary character—collaborative research is especially important, as it fosters the integration of technological, managerial, and organizational perspectives.

To examine collaboration patterns in this domain, we conducted a co-authorship network analysis using bibliographic data extracted from the Web of Science. The resulting maps illustrate three layers of collaboration: individual (author-level), institutional, and country-level. In these visualizations, node size reflects productivity (e.g., number of publications), while link thickness indicates the strength of collaborative ties. Node color captures temporal evolution, with warmer tones representing more recent activity. The overall network density (0.0025) suggests a low degree of cohesion, indicating that only a small fraction of potential collaborations have been actualized.

4.3.1 Co-authorship network

Identifying the most prolific authors is key to understanding the field's emerging intellectual core. Following Price's law, we expected a core group of approximately √1650 ≈ 40 authors to contribute roughly 50% of the field's publications. However, our data reveal that the top 40 authors account for only 14.5% of total output, suggesting that KM–AI remains a dispersed and maturing domain.

As shown in Table 2, S. Gupta leads with 14 publications, followed by S. Kumar and A. Malik with 11 each. Other key contributors include Y. Zhang, S. Bag, D. Vrontis, and P. Budhwar—scholars known for their work in digital transformation, business analytics, and intelligent knowledge systems. Their thematic alignment around AI-enabled innovation reflects the interdisciplinary nature of this research space.

Table 2: Most productive authors in CS domain

Authors	Record Count	% of 1 650
Gupta S	14	0.848
Kumar S	11	0.667
Malik A	11	0.667
Zhang Y	9	0.545
Bag S	8	0.485
Vrontis D	8	0.485
Budhwar P	7	0.424
Dwivedi YK	7	0.424

Authors	Record Count	% of 1 650
Kar AK	7	0.424
Kraus S	7	0.424

Despite the overall fragmentation of the global co-authorship network in the KM–AI research domain, two significant and thematically coherent groups of researchers have emerged. The first group (Figure 3a) is centered around Surajit Bag, S. Gupta, Arpan Kumar Kar, and M. S. Rahman, with frequent co-authorship from S. Kumar, Ajay Kumar, Maheshwari, and Leoni. Their collective body of work focuses on AI-enabled supply chains, sustainable digital transformation, and knowledge-based performance improvement, particularly in the context of emerging markets. Their contributions are regularly published in respected journals such as Technological Forecasting and Social Change, Industrial Marketing Management, Journal of Knowledge Management, and The International Journal of Logistics Management. For example, Bag et al. (2021) examined the role of AI in enhancing supply chain resilience, while Gupta and Rahman (2023) explored the dynamics of AI-driven knowledge ecosystems. The regularity of their collaborations and thematic consistency suggests a moderately cohesive and focused research agenda concerned with operational excellence through intelligent systems.

The second group (Figure 3b) includes Vijay Pereira, Shahriar Akter, Abhishek Behl, Sheshadri Chatterjee, and Samuel Fosso Wamba, with additional collaborations involving J. J. Ferreira, Mahdiraji, and Zaman. Their work appears in high-impact journals such as Human Resource Management Review, Technovation, International Marketing Review, and IEEE Transactions on Engineering Management. This group is primarily concerned with organizational AI adoption, knowledge transformation, and consumer behavior analytics, often framed through the lenses of strategic agility, digital platformization, and innovation management. Pereira, Mellahi and Collings (2023), for instance, proposed an AI-based framework for strategic HRM, while Akter et al. (2023) contributed to the literature on intelligent business model innovation. The group is marked by international, cross-disciplinary collaboration spanning information systems, marketing, and strategic management, underscoring the multidimensional nature of KM–AI research.

Despite the scholarly productivity and thematic coherence observed within the two leading research communities, the KM–AI field remains structurally fragmented. Cross-group collaboration is still limited, with many scholars publishing within institutionally or regionally siloed networks. This structural dispersion poses significant barriers to theoretical integration, knowledge transfer, and the cumulative advancement of the field.

This observation underscores an urgent need to move from parallel specialization to integrated collaboration. While the two groups each advance distinct areas of KM–AI scholarship—supply chain innovation and strategic HRM—the lack of cross-pollination prevents the field from reaching its full integrative potential.

To overcome this fragmentation, future research should prioritize the cultivation of cross-institutional and interdisciplinary linkages. Strengthening connectivity across research clusters can accelerate conceptual synthesis, promote methodological innovation, and support the co-development of actionable, practice-oriented frameworks that align technological capabilities with knowledge-based organizational strategy. These mechanisms align with broader trends in science policy, such as EU Horizon collaborative consortia and NSF-funded AI institutes, which actively promote transdisciplinary integration.

Specific, actionable mechanisms to promote such integration include:

- establishing thematic research consortiums that formally bridge the two identified author clusters through shared agendas and longitudinal collaboration;
- launching joint doctoral training programs across institutions to foster early-stage interdisciplinary knowledge exchange and methodological cross-pollination;
- designing multi-institutional grant proposals that explicitly require co-investigators from both communities; and
- convening structured workshops or symposia focused on synthesizing insights from supply chain innovation and strategic HRM to develop integrated, cross-domain research agendas.

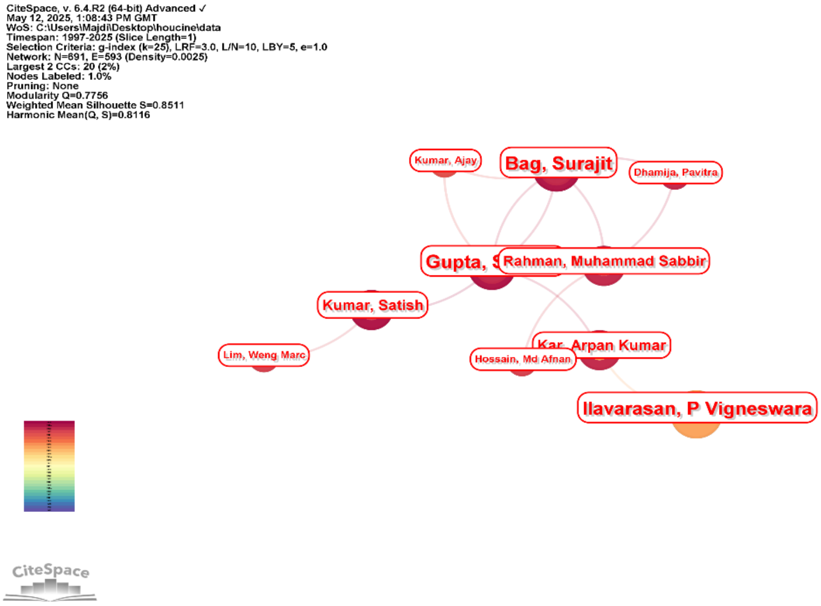

Figure 3a: Co-authorship cluster around Bag, Gupta, Kar, Rahman

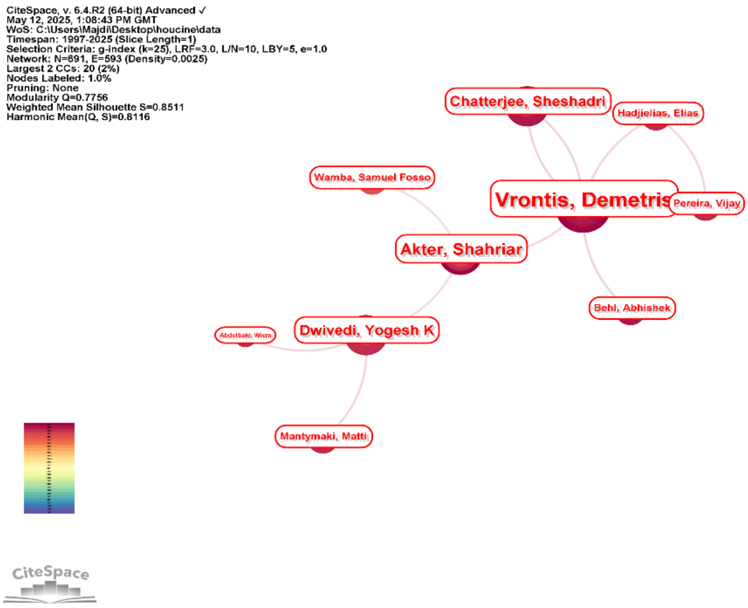

Figure 3b: Co-authorship cluster around Vrontis, Dwivedi, Akter, Wamba

4.3.2 Co-institute co-country network

Understanding collaboration patterns at both the institutional and national levels provides critical insights into the geographic concentration and organizational distribution of research at the intersection of KM and AI. The results indicate that the most active contributors to this domain are countries currently in advanced stages of digital and scientific infrastructure development. These nations are home to the majority of leading institutions that drive scholarly output in the KM–AI space.

As shown in Table 3, China stands out as the most prolific country, accounting for 18.61% of all publications in the dataset. It is followed by the United States (14.67%), India (13.46%), and England (11.64%). Other notable contributors include Italy, France, Australia, Germany, Spain, and Canada, each representing more than 3% of total publications. Collectively, these countries form the backbone of global KM–AI research, with regional clusters of activity concentrated in Asia, North America, and Western Europe.

The dominance of China, the USA, and India reflects the growing convergence between emerging innovation ecosystems and traditional academic strongholds. Researchers based in these countries have demonstrated the capacity to produce high-impact studies either independently or through domestic institutional networks. However, the landscape remains heavily inward-oriented, with collaboration often limited to national boundaries.

This trend is further illustrated in Figure 4, which visualizes the institutional collaboration network. The majority of nodes appear isolated, suggesting that most institutions operate independently, with minimal co-authorship or formal partnerships across organizations. While certain academic systems—such as India's IIM and IIT networks or China's Academy of Sciences—exhibit internal cohesion, their ties to international partners remain relatively weak and infrequent.

Table 4 lists the most productive institutions, with the Indian Institute of Management (IIM) System leading (36 publications), followed by Indian Institutes of Technology (IIT) and Jaypee Institute of Information Technology (JIIT). Other productive contributors include the Chinese Academy of Sciences, University of Johannesburg, and several institutions in Europe such as Aston University and the University of London.

Despite the presence of several high-output institutions and national research hubs, the overall structure of collaboration in KM–AI research remains fragmented. Most partnerships are domestically oriented, with limited durable connections across countries or institutional systems. This insularity restricts the global diffusion of novel insights and hampers the development of integrated theoretical models that can address the interdisciplinary nature of the field.

Promoting broader cross-institutional and international collaboration is therefore essential to accelerate theoretical convergence, foster knowledge diversity, and advance impactful innovation in KM–AI. These goals align with current global priorities in science policy, including open science, transnational funding frameworks, and inclusive digital infrastructures.

To operationalize these efforts, we propose the following collaborative mechanisms:

- Establishing international KM–AI research networks that formally link leading institutions across key regions (e.g., Chinese Academy of Sciences, IIM/IIT systems in India, top US universities, and European centers such as Aston University and the University of London);
- Creating multinational funding schemes requiring tri-continental research partnerships to stimulate broader intellectual exchange;
- Launching rotating international fellowships, enabling scholars to spend extended time at partner institutions to foster long-term collaboration and mentorship;
- Hosting an annual global KM–AI symposium, rotating across major research centers to encourage face-to-face networking and joint agenda-setting;
- Developing shared digital research infrastructures, including standardized datasets, interoperable collaboration platforms, and open-access publishing pipelines that transcend national boundaries.

These initiatives would not only bridge institutional and geographic divides but also establish a more cohesive and resilient global research ecosystem capable of driving interdisciplinary innovation in the KM–AI domain.

Table 3: Major productive countries

Countries/Regions	Record Count	% of 1 650
PEOPLES R CHINA	307	18.606
USA	242	14.667
INDIA	222	13.455
ENGLAND	192	11.636
ITALY	119	7.212
FRANCE	110	6.667
AUSTRALIA	109	6.606
GERMANY	97	5.879
SPAIN	61	3.697
CANADA	60	3.636

Table 4: Major productive institutions

Affiliations	Record Count	% of 1 650
INDIAN INSTITUTE OF MANAGEMENT IIM SYSTEM	36	2.182
INDIAN INSTITUTE OF TECHNOLOGY SYSTEM IIT SYSTEM	30	1.818
JAYPEE INSTITUTE OF INFORMATION TECHNOLOGY JIIT	28	1.697
CHINESE ACADEMY OF SCIENCES	26	1.576
UNIVERSITY OF JOHANNESBURG	21	1.273
ASTON UNIVERSITY	18	1.091
INDIAN INSTITUTE OF TECHNOLOGY IIT DELHI	18	1.091
UNIVERSITY OF LONDON	18	1.091
HSE UNIVERSITY NATIONAL RESEARCH UNIVERSITY HIGHER SCHOOL OF ECONOMICS	17	1.030
UNIVERSITY OF CHINESE ACADEMY OF SCIENCES CAS	17	1.030

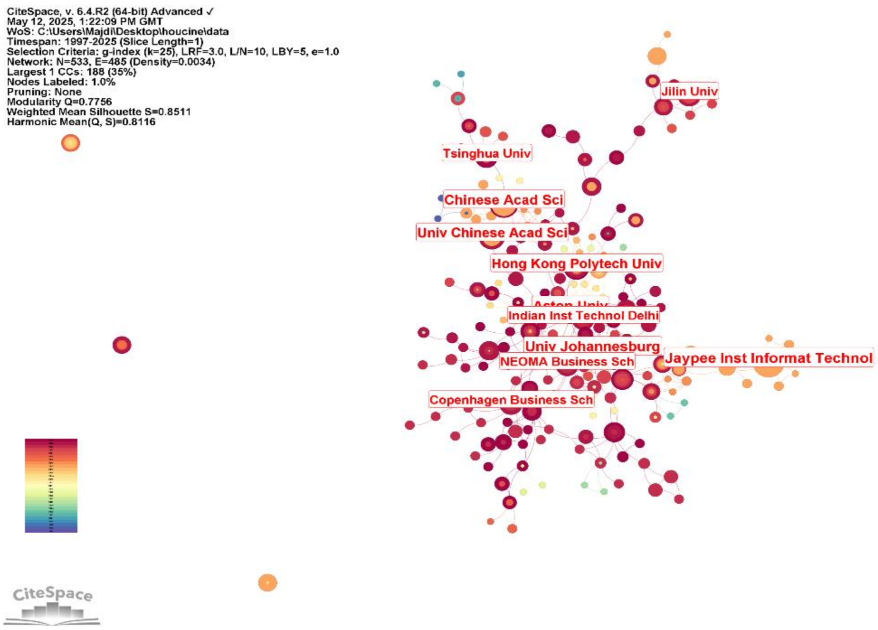

Figure 4: Most collaborative institutions

4.3.3 Keyword co-occurrence

The analysis of keyword co-occurrence provides valuable insights into the conceptual structure, research hotspots, and emerging themes of a scientific domain. Keywords serve as distilled representations of a study's focus, and their patterns of co-occurrence reveal how key topics converge, evolve, and delineate the intellectual frontiers of the field (Callon et al. 1983)

In the context of KM and AI, the co-occurrence network—visualized in Figure 5—comprises 796 nodes and 4,182 links, resulting in a network density of 0.0132. This density reflects a moderately interconnected structure, suggesting the presence of a well-formed conceptual core alongside a range of semi-autonomous thematic branches.

As shown in Table 5, the most frequently used keyword is "artificial intelligence", with 698 occurrences, underscoring its central role in the research corpus. It is followed by core terms such as "knowledge" (269), "management" (241), and "performance" (176), indicating sustained interest in the intersection of AI applications and knowledge processes—particularly as they relate to organizational effectiveness and value creation.

Other recurring keywords include "technology", "big data", and "innovation", which highlight the technological enablers driving knowledge transformations. Meanwhile, terms like "impact", "model", and "knowledge management" suggest a strong methodological and evaluative orientation within the literature.

The visual structure of the network reveals distinct topical clusters. For instance, terms such as big data, technology, and model frequently co-occur, reflecting a technically focused subdomain centered on AI architectures, data-driven modeling, and system design. In contrast, terms like performance, impact, and innovation are often grouped, pointing to research concerned with strategic, organizational, and outcome-oriented dimensions.

Overall, the keyword co-occurrence analysis reveals a robust conceptual nucleus at the intersection of AI and KM, framed by themes of performance and innovation. Around this core, the network branches out into specialized threads—ranging from big data analytics and intelligent modeling to digital transformation and knowledge-based decision-making. These findings confirm that the KM–AI domain is not only expanding in volume, but also diversifying in scope, evolving toward an increasingly interdisciplinary and application-driven frontier.

Table 5: Top 10 keyword

Frequency	keyword
698	artificial intelligence
269	knowledge
241	management
176	performance
164	technology
148	big data
147	innovation
146	impact
141	knowledge management
129	model

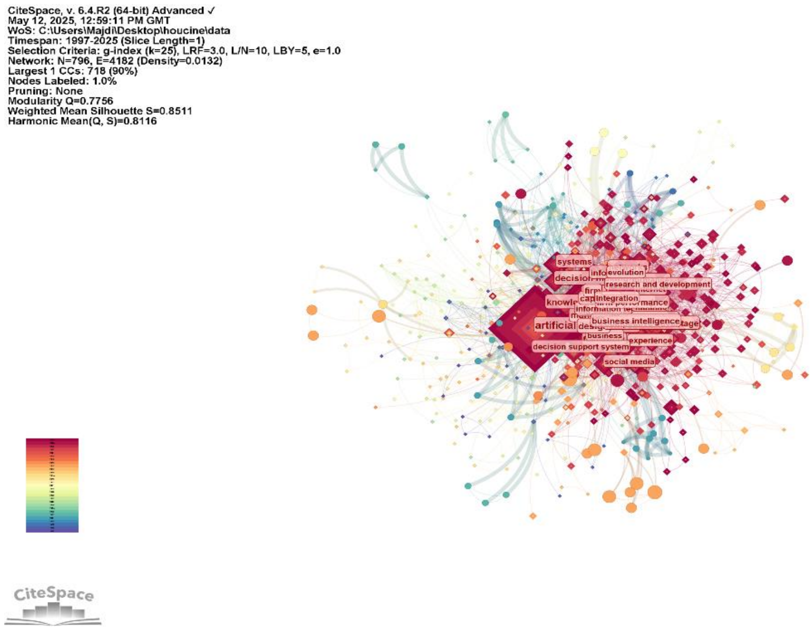

Figure 5: Keyword co-occurrence map

5. Scientometric Analysis: Research Hot Spots and Research Trend

5.1 Co-Citation Analysis

Co-citation analysis (CoA), originally developed by Small (1973), is a foundational method in scientometrics that enables the mapping of a field's intellectual structure. It operates on the premise that publications frequently cited together tend to share conceptual proximity, thus revealing core thematic domains and the evolution of scientific thought (Hjørland, 2013). This approach is particularly effective in identifying clusters of influence and research fronts within complex, interdisciplinary domains such as that of KM and AI.

In this study, we performed an author co-citation analysis to uncover the latent knowledge structure of KM–AI research. Using CiteSpace, we constructed a co-citation network based on the top 50 most cited authors per year, covering a time span from 1997 to 2025. The resulting network includes 1,086 authors, represented as nodes, with co-citation links visualized as edges. Node size reflects citation frequency, while link thickness represents the strength of co-citation between authors (Donthu et al., 2021; Zhang et al., 2021).

The temporal dynamics of the network are visualized using color-coded arcs, which indicate the year in which each co-citation relationship emerged. This temporal layer not only captures the historical progression of scholarly activity but also helps trace the intellectual evolution and the emergence of key research trajectories (Chen, 2012).

To assess the quality and structural coherence of the clusters produced, we used two key metrics:

- Modularity Q: Measures the clarity of separation between clusters. A value above 0.7 is generally considered a sign of well-delineated thematic groupings.
- Silhouette Score: Evaluates the internal consistency of each cluster, with scores approaching 1 indicating highly cohesive groupings (Argoubi & Masri, 2022).

Our analysis returned a modularity Q of 0.77, suggesting a well-structured network with clearly partitioned clusters. The top four clusters exhibited high silhouette values, indicating excellent internal consistency and thematic clarity.

As summarized in Table 6, four major co-citation clusters were identified, each reflecting a distinct subdomain of KM–AI research:

- Cluster 1 (Mean Year: 2018; Silhouette: 0.906; Size: 119): Focuses on the strategic integration of AI into human resource and organizational management, highlighting frameworks such as AI capability models and socio-technical alignment to enhance firm performance.
- Cluster 2 (Mean Year: 2009; Silhouette: 0.909; Size: 113): Concentrates on algorithmic HRM and human–AI collaboration, addressing themes such as algorithmic management, augmentation versus automation, and ethical implications in strategic decision-making.
- Cluster 3 (Mean Year: 1999; Silhouette: 0.998; Size: 86): Centers on AI adoption in supply chains, covering topics like knowledge-driven innovation, green logistics, and business model transformation through smart technologies.
- Cluster 4 (Mean Year: 2005; Silhouette: 0.965; Size: 52): Explores AI applications in hospitality and tourism, with a strong focus on service robotics, human–robot interaction, and customer experience management.

These clusters represent the thematic backbone of KM–AI research, illustrating how the field has evolved from foundational knowledge frameworks to nuanced, application-driven areas of inquiry. The co-citation network (Figure 6) provides a visual synthesis of this intellectual terrain, enabling scholars to identify influential authors, pivotal works, and emerging paths for future investigation.

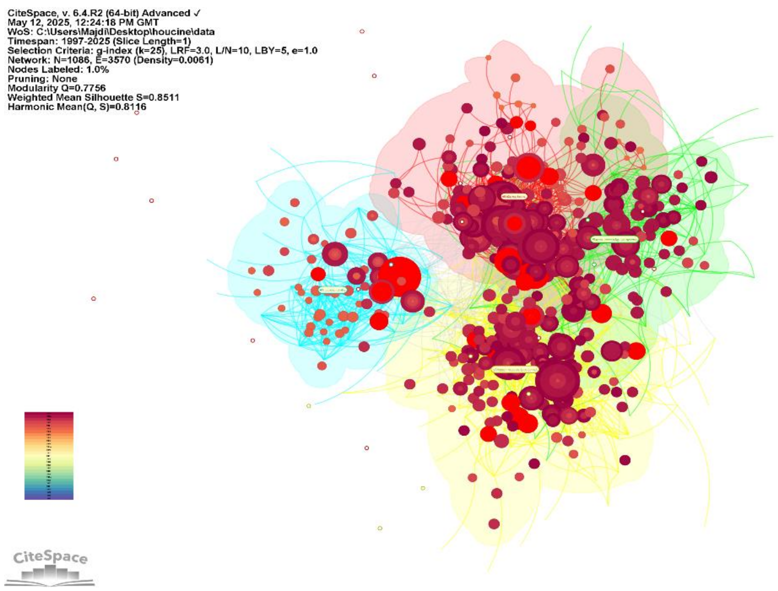

Figure 6: Co-citation map

Table 6: The 5 largest cluster

Cluster	ID	Size	Silhouette	Mean year
Strategic Integration of AI in Human Resource and Organizational Management	1	119	0.906	2018
Algorithmic HRM and Human–AI Collaboration in Strategic Management	2	113	0.909	2009
AI Adoption and Knowledge-Driven Innovation in Smart Supply Chains	3	86	0.998	1999
AI and Service Robots in Hospitality and Tourism Management	4	52	0.965	2005

5.2 Timeline-View Analysis

Figure 7 presents the timeline visualization of co-citation clusters in the KM–AI research domain. This representation offers a temporal dimension to the clusters previously identified in the co-citation network, illustrating how each thematic area has evolved over time. In this view, clusters are arranged horizontally, while their position on the vertical axis reflects their relative size—with the most substantial clusters placed at the top.

The colored lines represent the active citation period for each cluster, and the color gradient (from dark to light) denotes the chronological sequence, where darker tones indicate earlier activity and lighter colors reflect more recent citations. This format enables the identification of both enduring and short-lived research themes, offering a clear perspective on the developmental trajectory of the field.

The analysis reveals that several clusters demonstrate long lifespans exceeding 10 years, indicating sustained academic interest. These often correspond to foundational themes, such as the integration of AI in decision support systems, or theoretical discussions on knowledge creation and learning. In contrast, some clusters appear as short bursts, typically linked to emerging technologies or methodological innovations, which may reflect temporary research foci or developing subfields.

Of particular note is the observation that some clusters remain active beyond 2024, the final year included in our dataset. This signals that these areas are likely to constitute ongoing research fronts and may shape the next phase of KM–AI scholarship.

Compared to the static co-citation network, the timeline view offers a more intuitive understanding of thematic longevity and influence. It facilitates the detection of intellectual turning points, identifies periods of intensified scholarly attention, and distinguishes persistent foundational domains from transitory topics.

In the following section, we conduct a cluster-by-cluster analysis of the four most prominent thematic clusters, examining their leading authors, central documents, and conceptual contributions. These clusters form the intellectual backbone of the KM–AI research landscape and are instrumental in understanding its theoretical consolidation and future directions.

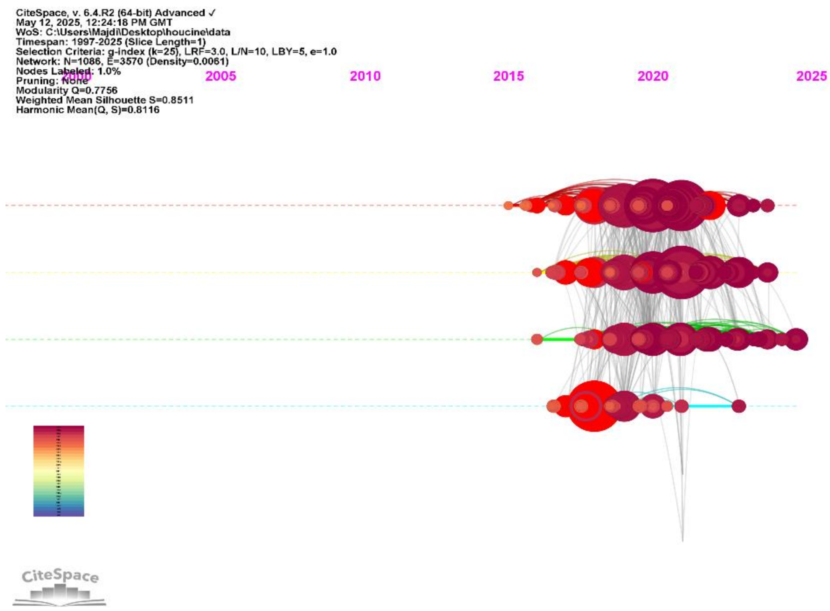

Figure 7: Network's timeline visualization

5.3 The Intellectual Base

Cluster analysis reveals hidden semantic themes and overlaps in research corpora by identifying groups of co-cited references that share conceptual foundations (Hossain, Ramakrishnan and Hecker, 2011; Waltman, van Eck & Noyons, 2010). Our analysis identifies four distinct thematic clusters (Q = 0.77, silhouette scores > 0.80) that represent the core intellectual foundations of KM–AI research over the 26-year period under investigation.

Rather than presenting these clusters by size, we discuss them in order of their theoretical significance and contribution to advancing KM–AI understanding. This ordering foregrounds the empirical patterns—both expected and unexpected—that emerge from the bibliometric mapping, including conceptual synergies within ostensibly opposed logics and unresolved theoretical tensions.

The four clusters contribute distinct but complementary theoretical insights: Cluster 2 provides the most fundamental reconceptualization by revealing paradoxes in human–AI collaboration that challenge traditional strategic management assumptions; Cluster 1 establishes the foundational capability frameworks that bridge KM and strategic HRM theories; Cluster 3 demonstrates how these theoretical advances manifest in complex operational contexts through AI-enabled supply chain innovation; and Cluster 4 offers sector-specific insights into service transformation that illustrate broader patterns of technology-mediated knowledge work.

Each cluster analysis combines quantitative evidence (citation bursts, centrality measures, temporal evolution) with qualitative interpretation, ensuring that theoretical propositions are grounded in empirical network structures. The gaps and tensions identified here directly inform the integrated theoretical contributions presented in Section 5.4. Table 7 summarises the structural characteristics of these clusters, which serve as the foundation for our theory-building discussion.

<u>Cluster 2: Algorithmic HRM and Human–AI Collaboration in Strategic Management</u>

Cluster 2 is the second-largest in the co-citation network, composed of 113 references, with a high silhouette value of 0.822, indicating strong thematic homogeneity. Its mean publication year is 2020, aligning with the 2020–2023 tipping period identified in our temporal analysis, and signalling a thematic area that is emergent yet rapidly consolidating. Quantitative network patterns reveal that several works in this cluster, particularly those addressing ethical governance, hold high betweenness centrality, suggesting their bridging role between HR analytics and broader KM–AI debates.

This cluster signals a strategic rethinking of HRM for the algorithmic era, emphasizing human–AI interaction, ethical issues, and the organizational fallout of automated decision-making. The citing documents—such as Kim (2025), Chowdhury (2023), Malik (2023), and Prikshat (2023)—reveal an expanding interest in multilevel theoretical frameworks that explore the capabilities, boundaries, and paradoxes of integrating AI into HR decision systems.

A distinguishing feature of this cluster is its normative and conceptual orientation. While Cluster 1 focuses more on capability development and performance impact, Cluster 2 dives deeper into critical and reflexive dimensions such as:

Algorithmic bias and fairness in HR decisions,

Redefinition of roles and identities in augmented workplaces,

Strategic ambidexterity and organizational paradoxes arising from human–AI coexistence.

Key cited references provide a rich theoretical backdrop:

- Raisch, Krakowski and Berente (2021) examine organizational ambidexterity and the challenges of managing contradictory tensions, highly relevant in AI-augmented HR contexts.
- Glikson & Woolley (2020) delve into human–AI collaboration, highlighting the social and psychological dynamics in AI-mediated team environments.
- Tambe, Cappelli and Yakubovich (2019) offer insights on AI-driven HR analytics, laying the groundwork for algorithmic decision-making.
- Jarrahi (2018) proposes a model of human–AI symbiosis, where decision power is shared between humans and intelligent agents.

The citing articles build upon these foundations to propose extended strategic frameworks. For instance, Malik (2023) conceptualizes AI-assisted HRM as a multifaceted system requiring ethical governance, data transparency, and hybrid decision-making protocols. Kim (2025) develops a research agenda for strategic HRM in algorithmic contexts, calling for new theoretical models that reconcile human judgment with machine logic.

An unexpected empirical insight emerging from this cluster is that efficiency gains—such as double-digit reductions in recruitment cycles and improved candidate–job fit (Tambe, Cappelli and Yakubovich, 2019; Kim, 2025)—often co-occur with stronger ethical safeguards like interpretability reports and applicant-facing explanations. This challenges the intuitive assumption that transparency requirements necessarily slow down performance, instead suggesting potential synergy between fairness and efficiency.

Yet, two paradoxes remain unresolved. First, Jarrahi's (2018) model of human–AI symbiosis clashes with analytics-driven frameworks that leave little room for human discretion, raising fresh questions about power sharing in hybrid decisions. Second, the call for organizational ambidexterity (Raisch, Krakowski and Berente, 2021) collides with algorithms' need for consistency, exposing a paradox between adaptive flexibility and rule-based automation.

Methodologically, many contributions rest on conceptual arguments: governance blueprints (Malik, 2023) or ethical guidelines (Kim, 2025) seldom undergo field validation or longitudinal testing. This "theory–practice gap" limits guidance for real-world transformation. Future work should combine quasi-experimental pilots, algorithm-audit protocols, and mixed-method designs to evaluate whether proposed safeguards actually mitigate bias and sustain ambidexterity.

Taken together, the network evidence and theoretical tensions in Cluster 2 form a critical input to the paradox-oriented theoretical refinements presented in Section 5.4, reinforcing the need to integrate ethical governance, performance optimisation, and human discretion in future KM–AI frameworks.

<u>Cluster 1: Strategic Integration of AI in Human Resource and Organizational Management</u>

Cluster 1 is the largest in the co-citation network, comprising 119 cited references, with a mean publication year of 2019 and a silhouette value of 0.815, indicating strong thematic consistency. Its works also display high betweenness centrality, suggesting a bridging role between knowledge management theory and applied strategic HRM. Spanning nearly a decade of research, this cluster represents a key intellectual foundation for understanding how AI capabilities are embedded in HRM to create organizational value.

The core themes emerging from the cluster include AI capability frameworks, AI–human collaboration, knowledge-based performance improvement, and the integration of socio-technical perspectives into strategic

HR planning and execution. The most frequently cited references—Davenport & Ronanki (2020), Dwivedi et al. (2021), Kaplan & Haenlein (2019), and Mikalef and Gupta (2021)—provide both theoretical and practical models for AI adoption, from strategic alignment and digital readiness to ethical governance and human–machine symbiosis. For example, Davenport & Ronanki (2020) demonstrate that AI can augment rather than replace HR decision-making, laying the groundwork for adaptive HRM systems.

A recurring theoretical anchor is the Knowledge-Based View (KBV), which positions AI capabilities as strategic knowledge assets. Chowdhury, Budhwar and Hammerschmidt (2022, 2023) and Malik (2023) merge KBV with socio-technical theory to examine how human–AI collaboration shapes business performance, employee experience, and strategic agility. Among citing works, Chowdhury, Budhwar and Hammerschmidt (2023) propose a robust AI capability framework for HRM, while Malik (2023) develops a strategic model emphasising organizational learning and workforce adaptability. Methodologically, the cluster shows a shift from early descriptive studies toward systematic reviews, conceptual modelling, and theory-building.

An unexpected empirical insight is that reported efficiency gains—such as 15–20 % faster decision cycles and lower administrative errors (Davenport & Ronanki, 2020; Mikalef and Gupta, 2021)—tend to materialise only in firms with strong learning climates, suggesting that technological capability alone is insufficient without cultural enablers.

Despite its foundational role, the cluster reveals two unresolved tensions. First, augmentation approaches (AI as assistant) conflict with transformation views advocating complete redesign of HR structures (Chowdhury, Budhwar and Hammerschmidt, 2023). Second, definitions of "AI capability" diverge: technology-centric perspectives (Mikalef and Gupta, 2021) emphasise infrastructure, while KBV-oriented studies (Chowdhury, Budhwar and Hammerschmidt, 2023; Kaplan & Haenlein, 2019) stress learning routines and culture. These definitional splits, compounded by differing performance metrics—intangible outcomes in KBV studies versus efficiency indicators in strategic-HRM work—complicate cumulative theory development.

Ethical considerations are frequently cited (Dwivedi et al., 2021) but rarely operationalised through concrete bias-mitigation or transparency mechanisms, leaving a gap between principle and practice. Furthermore, much of the literature remains conceptual, limiting empirical validation.

In sum, Cluster 1 establishes AI-enabled strategic HRM as a legitimate research frontier but exposes conceptual, methodological, and ethical gaps. Its bridging position in the network makes it pivotal for integrating KBV, socio-technical systems theory, and strategic HRM—connections further developed in Section 5.4, where we address the paradox of combining augmentation and transformation logics within coherent KM–AI frameworks.

Cluster 3: AI Adoption and Knowledge-Driven Innovation in Smart Supply Chains

Cluster 3 comprises 86 co-cited references, with a mean publication year of 2021 and a silhouette score of 0.803, indicating satisfactory internal consistency. Ranked third in prominence within the co-citation network, this cluster captures a rapidly expanding research front at the intersection of AI, knowledge management (KM), and supply chain innovation. Quantitative patterns — including high inter-cluster link density with strategic KM networks and strong betweenness centrality for Dubey et al. (2020) — suggest a shift from abstract capability discussions toward application-focused investigations, particularly in operations, logistics, and digital transformation contexts.

The most frequently cited works include Dubey et al. (2020) and Toorajipour, Sohrabpour and Ghasemaghaei (2021) on big data and AI in enhancing supply chain responsiveness and flexibility; Bag (2021) on resilience and performance; Di Vaio et al. (2020) on digital accountability and transparency; and Hair et al. (2019), which plays a methodological anchor role by providing partial least squares structural equation modelling (PLS-SEM) guidance widely adopted in empirical AI adoption and performance research.

The citing literature reinforces this thematic convergence. Shahzadi (2024) and Di Vaio (2024) provide systematic reviews of AI in supply chains and enterprise systems. Abdulmuhsin (2024) integrates KM and AI into a proactive green innovation model moderated by trust and sustainability imperatives, while Jorzik (2024) conceptualises how AI-driven innovation reshapes business models under digital pressure. These studies emphasise multi-level perspectives, combining firm-level capabilities with inter-organisational coordination and environmental responsiveness.

A distinctive — and somewhat non-intuitive — finding emerging from the cluster is the integration of resilience-oriented strategies within efficiency-optimisation paradigms (Bag, 2021; Dubey et al., 2020), suggesting these approaches may function synergistically rather than competitively. This aligns with dynamic capabilities theory but remains under-theorised in the AI–supply chain domain.

Critical gaps, however, remain. The tension between resilience-driven and optimisation-driven paradigms is rarely reconciled in theory, reflecting a broader fragmentation in AI supply chain scholarship. Methodologically, the widespread reliance on PLS-SEM, while ensuring statistical reliability, risks obscuring conceptual validity issues — especially when operationalising complex constructs like "AI adoption" or "knowledge integration." Moreover, the literature's focus on positive implementation outcomes risks selection bias, limiting insights into failure factors. The predominantly firm-centric lens also neglects power asymmetries and value distribution dynamics inherent in AI-enabled supply networks.

Overall, Cluster 3 marks substantial progress in operationalising AI–KM integration in supply chains but requires more systematic theoretical synthesis, methodological diversity, and critical examination of less successful cases to evolve into a robust, generalisable research stream.

<u>Cluster 4: AI and Service Robots in Hospitality and Tourism Management</u>

Cluster 4 comprises 52 co-cited references, with a high silhouette score of 0.927, indicating excellent thematic homogeneity. With a mean publication year of 2018, it represents one of the more mature research fronts in the KM–AI domain, focusing on the adoption and impact of service robotics and AI in hospitality, tourism, and customer service industries. Network metrics reveal low inter-cluster connectivity but high internal cohesion, signalling a specialised but relatively siloed domain.

The citing literature — including Chi, Denton and Gursoy (2020), McCartney (2020), Zhu and Xu (2020), and Belanche et al. (2020) — examines AI deployment in frontline service contexts, with particular attention to customer experience, service design, trust formation, and organisational readiness in technology-mediated environments. Chi, Denton and Gursoy (2020) provide a systematic review of AI in hospitality service delivery; McCartney (2020) develops a conceptual framework for service robots in hospitality and tourism; Zhu and Xu (2020) investigate how anthropomorphic design in robotic chefs influences food quality perceptions; and Belanche et al. (2020) outline a theoretical agenda for service robot implementation.

Key co-cited works anchor the cluster in established service and technology adoption theories: Lemon & Verhoef (2016) on customer experience management across touchpoints, Huang & Rust (2018) on AI's strategic role in service delivery, Wirtz et al. (2018) on the future of service with intelligent automation, and Gursoy et al. (2019) on technology acceptance and innovation in tourism and hospitality. Collectively, these studies integrate service-dominant logic, technology acceptance models, and human–machine interaction theories to explain shifting service encounter dynamics in AI-augmented environments.

A distinctive — and somewhat counter-intuitive — insight from this cluster is the coexistence of anthropomorphic design strategies aimed at enhancing emotional engagement (Zhu and Xu, 2020) alongside efficiency-driven models advocating minimal human-like features (Huang & Rust, 2018). This suggests that optimal design may be highly contingent on service context and cultural expectations, a nuance often overlooked in deterministic adoption models.

Despite its thematic maturity, Cluster 4 shows notable limitations. The literature is heavily skewed toward Western, high-income contexts, limiting cross-cultural generalisability. Employee perspectives — including displacement risks, skill adaptation, and workplace power dynamics — remain under-examined, leading to a customer-centric bias. Methodologically, the strong reliance on technology acceptance models ensures coherence but restricts theoretical innovation, reinforcing linear and context-agnostic adoption narratives.

In sum, Cluster 4 defines a well-bounded, sector-specific research front that advances understanding of AI-mediated service transformation, yet its broader KM–AI contribution is constrained by cultural bias, unresolved theoretical tensions between experiential and efficiency paradigms, and a systematic neglect of labour-related implications.

5.4 Theoretical Contributions and Strategic Implications

Our bibliometric analysis ($Q = 0.77$; silhouette scores > 0.90) identifies two cross-cutting tensions shaping KM–AI research since the 2020–2023 tipping period: augmentation vs. transformation logics and optimisation vs. resilience–sustainability paradigms. A notable, non-intuitive finding is that resilience-oriented work increasingly emerges within optimisation-focused clusters (Clusters 1 and 3), indicating potential synergies rather than strict opposition.

Theoretical advances.

Three key empirical patterns underpin our theoretical contributions:

- Algorithmic transparency — prominent in Cluster 2 (AI-enabled decision support), where citation burst analysis highlights foundational works on auditability and explainability — directly challenges the KBV assumption that codified knowledge is universally transferable.
- Inter-organisational power asymmetry — most visible in Cluster 3 (Data governance and knowledge flows), where high betweenness centrality nodes represent dominant platform actors — constrains the diffusion of AI-enabled knowledge capabilities.
- Unexpected theory convergence — co-citation mapping reveals paradox theory connecting with optimisation-focused literature, forming a latent bridge for integrating competing logics within KM–AI frameworks.

These findings collectively support refining the KBV to incorporate context-dependent governance mechanisms and shifting from contingency-only models toward paradox-oriented perspectives, recognising that firms often sustain opposing logics simultaneously.

Strategic implications.

Stable environments: Augmentation paths with explainable decision aids can deliver efficiency gains while preserving human oversight.

Turbulent contexts: Transformation paths centred on autonomous learning systems are viable when supported by mechanisms for bias monitoring and tacit knowledge transfer.

Supply chains: Phased strategies balancing cost-efficiency with disruption-readiness are promising, especially when transparent data governance reduces power asymmetry.

Policy and education.

Sector-specific AI governance, tested in regulatory sandboxes, and curricula addressing augmentation/transformation and optimisation/resilience as complementary rather than opposing logics can accelerate responsible AI adoption.

Grounded in quantitative network evidence, these contributions move beyond descriptive mapping to offer an empirically anchored, theoretically integrated, and practice-relevant framework for advancing KM–AI research.

Table 7: Clusters analysis

Cluster Label	Size	Silhouette	Mean year	Most citing articles	Most cited authors (in the cluster)
				Reference	**Reference**
Cluster 1: Strategic Integration of AI in Human Resource and Organizational Management	119	0.815	2019	Chowdhury, S (2023-JAN) Unlocking the value of artificial intelligence in human resource management through ai capability framework. HUMAN RESOURCE MANAGEMENT REVIEW DOI 10.1016/j.hrmr.2022.100899 Lee, MCM (2023-JAN) The implementation of artificial intelligence in organizations: a systematic literature review. INFORMATION & MANAGEMENT DOI 10.1016/j.im.2023.103816 Chowdhury, S (2022-JAN) Ai-employee collaboration and business performance: integrating knowledge-based view, socio-technical systems and organisationalsocialisation framework. JOURNAL OF BUSINESS RESEARCH, V144, P19 DOI	Davenport T (2020) J ACAD MARKET SCI V48 P24 2.5 10.1007/s11747-019-00696-0 Dwivedi YK (2021) INT J INFORM MANAGE V57 P0 2.5 10.1016/j.ijinfomgt.2019.08.002 Kaplan A (2019) BUS HORIZONS V62 P15 3.5 10.1016/j.bushor.2018.08.004 Mikalef P (2021) INFORM MANAGE-AMSTER V58 P0 2.5 10.1016/j.im.2021.103434 Duan YQ 2019 INT J INFORM MANAGE V48 P63 3.5 10.1016/j.ijinfomgt.2019.01.021

Cluster Label	Size	Silhouette	Mean year	Most citing articles	Most cited authors (in the cluster)
				10.1016/j.jbusres.2022.01.069 Malik, A (2023-JAN) Artificial intelligence (ai)-assisted hrm: towards an extended strategic framework. HUMAN RESOURCE MANAGEMENT REVIEW DOI 10.1016/j.hrmr.2022.100940	
Cluster 2: Algorithmic HRM and Human–AI Collaboration in Strategic Management	113	0.822	2020	Kim, S (2025-JAN) Strategic human resource management in the era of algorithmic technologies: key insights and future research agenda. HUMAN RESOURCE MANAGEMENT, V64, P18 DOI 10.1002/hrm.22268 Chowdhury, S (2023-JAN) Unlocking the value of artificial intelligence in human resource management through ai capability framework. HUMAN RESOURCE MANAGEMENT REVIEW DOI 10.1016/j.hrmr.2022.100899 Malik, A (2023-JAN) Artificial intelligence (ai)-assisted hrm: towards an extended strategic framework. HUMAN RESOURCE MANAGEMENT REVIEW DOI 10.1016/j.hrmr.2022.100940 Chowdhury, S (2022-JAN) Ai-employee collaboration and business performance: integrating knowledge-based view, socio-technical systems and organisationalsocialisation framework. JOURNAL OF BUSINESS RESEARCH, V144, P19 DOI 10.1016/j.jbusres.2022.01.069 Prikshat, V (2023-JAN) Ai-augmented hrm: literature review and a proposed multilevel framework for future research. TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE DOI 10.1016/j.techfore.2023.122645	Raisch S (2021) ACAD MANAGE REV V46 P192 2.5 10.5465/amr.2018.0072 Glikson E (2020) ACAD MANAG ANN V14 P627 3.5 10.5465/annals.2018.0057 Tambe P (2019) CALIF MANAGE REV V61 P15 3.5 10.1177/0008125619867910 Vrontis D (2022) Vrontis D 2022 INT J HUM RESOUR MAN V33 P1237 1.5 10.1080/09585192.2020.1871398 Jarrahi MH (2018) BUS HORIZONS V61 P577 3.5 10.1016/j.bushor.2018.03.007

Cluster Label	Size	Silhouette	Mean year	Most citing articles	Most cited authors (in the cluster)
Cluster 3: AI Adoption and Knowledge-Driven Innovation in Smart Supply Chains	86	0.803	2021	Shahzadi, G (2024-JAN) Ai adoption in supply chain management: a systematic literature review. JOURNAL OF MANUFACTURING TECHNOLOGY MANAGEMENT, V35, P26 DOI 10.1108/JMTM-09-2023-0431 Abdulmuhsin, AA (2024-JAN) Impact of artificial intelligence and knowledge management on proactive green innovation: the moderating role of trust and sustainability. ASIA-PACIFIC JOURNAL OF BUSINESS ADMINISTRATION DOI 10.1108/APJBA-05-2024-0301 Jorzik, P (2024-JAN) Ai-driven business model innovation: a systematic review and research agenda. JOURNAL OF BUSINESS RESEARCH DOI 10.1016/j.jbusres.2024.114764 Di, vaio A (2024-JAN) Digitalization and artificial knowledge for accountability in scm: a systematic literature review. JOURNAL OF ENTERPRISE INFORMATION MANAGEMENT, V37, P67 DOI 10.1108/JEIM-08-2022-0275	Hair JF (2019) EUR BUS REV V31 P2 4.5 10.1108/EBR-11-2018-0203 Dubey R (2020) INT J PROD ECON V226 P0 3.5 10.1016/j.ijpe.2019.107599 Bag S (2021) Bag S 2021 TECHNOL FORECAST SOC V163 P0 2.5 10.1016/j.techfore.2020.120420 Toorajipour R (2021) J BUS RES V122 P502 2.5 10.1016/j.jbusres.2020.09.009 Di Vaio A (2020) Di Vaio A 2020 J BUS RES V121 P283 2.5 10.1016/j.jbusres.2020.08.019
Cluster 4: AI and Service Robots in Hospitality and Tourism Management	52	0.927	2018	Chi, OH (2020-JAN) Artificially intelligent device use in service delivery: a systematic review, synthesis, and research agenda. JOURNAL OF HOSPITALITY MARKETING & MANAGEMENT, V29, P30 DOI 10.1080/19368623.2020.1721394 Mccartney, G (2020-JAN) Rise of the machines: towards a conceptual service-robot research framework for the hospitality and tourism industry. INTERNATIONAL JOURNAL OF CONTEMPORARY HOSPITALITY MANAGEMENT, V13, P17 DOI 10.1108/IJCHM-05-2020-0450 Zhu, DH (2020-JAN) Robot with humanoid hands cooks food better? effect of robotic chef anthropomorphism on food quality prediction. INTERNATIONAL JOURNAL OF CONTEMPORARY HOSPITALITY MANAGEMENT, V32, P17 DOI 10.1108/IJCHM-10-2019-0904 Belanche, D (2020-JAN) Service robot implementation: a theoretical framework and research agenda. SERVICE INDUSTRIES JOURNAL, V40, P23	Lemon KN (2016) J MARKETING V80 P69 4.5 10.1509/jm.15.0420 Huang MH (2018) J SERV RES-US V21 P155 3.5 10.1177/1094670517752459 Wirtz J (2018) SERV MANAGE V29 P907 2.5 10.1108/JOSM-04-2018-0119 Li J (2019) Li J 2019 TOURISM MANAGE V73 P172 3.5 10.1016/j.tourman.2019.02.006 Gursoy D (2019) INT J INFORM MANAGE V49 P157 4.5 10.1016/j.ijinfomgt.2019.03.008

6. Research Frontiers and Major Milestones

In a field marked by rapid technological change and increasing cross-disciplinary integration, identifying turning points and emerging trajectories is essential to understanding the evolution of KM and AI research. To this end, we employed Kleinberg's burst detection algorithm (Kleinberg, 2003) to identify references that experienced a sudden and intense increase in citations over a defined time span. These citation bursts signal works that have catalyzed academic attention and, consequently, represent significant milestones in the field's development.

The analysis uncovered ten references with the highest burst strengths (see Table 8), which together delineate key research frontiers and help illuminate the shifting intellectual landscape of the KM–AI domain. These bursts are distributed across multiple clusters, highlighting the field's thematic diversification. Three particularly influential contributions are examined below.

The first and strongest citation burst is associated with Huang and Rust (2018), published in *Journal of Service Research* and belonging to Cluster 4 (AI in hospitality and service contexts). With a burst strength of 17.26 lasting from 2020 to 2023, this work has played a central role in conceptualizing how AI transforms service encounters. It introduces a hierarchical model of AI applications in service settings and outlines the evolution from task automation to full cognitive service delivery. Its influence is especially pronounced in studies addressing service robotics, customer experience, and automation strategies in hospitality and tourism.

The second notable burst corresponds to Syam and Sharma (2018) in Industrial Marketing Management (Cluster 1). This study discusses the integration of AI and machine learning into strategic marketing decisions and organizational design. Though rooted in marketing, its broader organizational implications have significantly influenced work on AI-enabled strategic HRM, particularly in the development of capability frameworks and workforce transformation strategies. With a burst strength of 9.33 (2019–2022), it reflects growing interest in how AI reshapes managerial decision-making and resource allocation in knowledge-driven contexts.

A third turning point is identified in Jarrahi (2018), published in *Business Horizons* and assigned to Cluster 2. The article conceptualizes human–AI symbiosis in organizational decision-making, arguing for the complementary strengths of humans and intelligent systems. With a burst period from 2020 to 2022 and a strength of 7.80, the paper has become foundational for research on algorithmic management, hybrid decision-making models, and the ethical governance of AI-infused processes.

These burst references—together with others listed in Table 8—reveal a research trajectory that is increasingly oriented toward strategic implementation, organizational redesign, and ethical oversight. Their timing also reflects key inflection points, especially between 2020 and 2023, coinciding with a broader acceleration of digital transformation in organizational and societal contexts due to external pressures such as the COVID-19 pandemic.

In sum, the citation burst analysis not only validates the thematic clusters identified through co-citation mapping but also sharpens our understanding of the temporal dynamics and research momentum within the KM–AI field. These high-impact studies continue to shape scholarly discourse and will likely inform the next generation of research addressing AI's role in knowledge-intensive, service-oriented, and digitally transformed organizational environments.

Table 8: Top 10 burst references

Authors	Cluster	Year	strength	Begin	End	1996-2022
Huang MH, 2018	4	2011	31.23	**2013**	2016	
Syam N, 2018	1	2009	17.66	**2012**	2014	
Wirtz J, 2018	4	2018	14.41	**2020**	2022	
Jarrahi MH, 2018	2	2009	13.56	**2011**	2014	
Davenport TH, 2018	1	2018	11.51	**2020**	2022	
Von Krogh G, 2018	2	2007	9.54	**2009**	2012	
Hair JF, 2017	2	2011	9.35	**2012**	2016	

Authors	Cluster	Year	strength	Begin	End	1996-2022
Dwivedi YK, 2021	1	2016	8.47	**2019**	2022	
Makridakis S, 2017	2	2006	8.36	**2007**	2011	
Kumar V, 2019	1	2012	8.21	**2014**	2016	

7. Conclusion

The intersection of Knowledge Management and Artificial Intelligence has emerged as a strategically significant research frontier, reflecting accelerated technological change, shifting organizational paradigms, and interdisciplinary convergence. This study provides a comprehensive scientometric analysis of 1,650 publications indexed in the Web of Science Core Collection between 1975 and 2024, combining performance metrics, co-authorship and co-citation mapping, and keyword co-occurrence analysis in CiteSpace. These methods allowed us to chart the intellectual evolution, current structure, and emerging trends within the KM–AI research landscape.

Our findings reveal that the field has moved beyond its formative phase, exhibiting substantial growth since 2017 with increasing scholarly impact. This growth is evidenced by high citation rates and cohesive co-authorship communities. The intellectual structure centers on four dominant thematic clusters: AI-enhanced strategic human resource management, algorithmic HRM and human–AI collaboration, AI adoption in knowledge-driven supply chains, and AI-based service delivery in hospitality and tourism. These clusters reflect both theoretical diversification and application-oriented evolution.

The burst analysis revealed recent milestone publications that catalyzed intellectual shifts between 2020 and 2023. However, despite this growing maturity, the field faces persistent challenges including fragmentation, limited international collaboration, and conceptual dispersion across disciplines. These challenges directly inform our recommendations for future research directions. For example, longitudinal multi-tier case studies could test how algorithmic transparency moderates supply chain resilience, while large-scale audit protocols might quantify power asymmetry effects in AI-driven HR analytics.

Methodological note. This study relies on a scientometric approach using CiteSpace for network mapping and bibliometric indicators to capture the structural and dynamic aspects of the field. This methodological choice enables systematic, replicable insights but also imposes boundaries shaped by database coverage and citation-based metrics.

Limitations. The analysis is based exclusively on the Web of Science Core Collection, which—while offering high-quality, peer-reviewed sources—excludes relevant work indexed in other databases such as Scopus, IEEE Xplore, and Google Scholar. Grey literature, industry reports, and non-English publications were also excluded, potentially omitting valuable practitioner-oriented insights and non-Western perspectives.

Implications for stakeholders.

- Scholars: The mapped intellectual structure and identified gaps offer a basis for theory development that integrates algorithmic capabilities with human-centered knowledge processes, encouraging cross-disciplinary and longitudinal research designs.
- Practitioners: Sector-specific insights, particularly in HRM, supply chains, and service industries, provide actionable guidance for responsible AI deployment that aligns with organizational knowledge strategies.
- Policymakers: Findings highlight the need for regulatory frameworks that promote algorithmic transparency, mitigate power asymmetries, and foster international collaboration to ensure equitable AI benefits.

Given these findings, future studies should prioritize developing integrative theoretical frameworks that transcend disciplinary boundaries and bridge the gap between algorithmic capability and human-centered knowledge processes. The observed fragmentation necessitates greater emphasis on global and institutional collaboration to support knowledge diffusion and methodological innovation, and to tailor AI applications to specific knowledge-intensive contexts.

This systematic mapping of the KM–AI research domain consolidates prior work and provides a foundation for future inquiry. The findings support scholars, practitioners, and policymakers in navigating this rapidly evolving field and contribute to designing more intelligent, adaptive, and inclusive knowledge systems. By introducing algorithmic-transparency and power-asymmetry contingencies into the Knowledge-Based View, this study moves beyond descriptive mapping. Coupled with paradox-aware principles for practice, it sets a forward agenda for responsible, AI-enabled knowledge systems.

AI Statement: The author confirms that no generative artificial intelligence was used in the writing of this manuscript or in the creation of images, graphics, tables, or their corresponding captions.

Ethics Statement: This study does not require Institutional Review Board (IRB) approval, as it involves only the analysis of publicly available bibliometric data from the Web of Science Core Collection. No human subjects were directly involved in the research. All analyzed publications are accessible through legitimate academic databases, and no personal or sensitive information was collected or processed. The study adheres to standard practices in bibliometric and scientometric research, which typically fall outside the scope of human subjects research regulations. All data handling and analysis procedures followed established ethical guidelines for secondary data research.

References

Abdulmuhsin, A.A., Hussein, H.D., Al-Abrrow, H., Masa'deh, R. & Alkhwaldi, A.F. 2024, 'Impact of artificial intelligence and knowledge management on proactive green innovation: The moderating role of trust and sustainability', Asia-Pacific Journal of Business Administration, ahead-of-print, pp. 1–31. doi: 10.1108/APJBA-05-2024-0301

Abuselidze, G. & Zoidze, G. 2022, 'Economic analysis of factors associated with education and employment', in Proceedings of the 10th Workshop on Cloud Technologies in Education (CTE 2022), CEUR Workshop Proceedings, vol. 3364, pp. 24–37. doi: 10.55056/cte.565.

Akter, S., Behl, A., Chaudhuri, R. & Fosso Wamba, S. 2023, 'Business model innovation through AI: A multi-level framework', Technovation, vol. 125, Art. 102768. doi: 10.1016/j.technovation.2023.102768.

Argoubi, M. & Masri, H. 2022, 'Operations Research Case Study Papers for Africa: A Bibliometric Review', in *Africa Case Studies in Operations Research*, pp. 159–181, Springer, doi: 10.1007/978-3-031-17008-9_8.

Argyris, C. & Schön, D.A. 1978, Organizational learning: A theory of action perspective, Addison-Wesley, Reading, MA.

Bag, S. 2021, 'Artificial intelligence (AI)-driven supply chain resilience and performance', Technological Forecasting and Social Change, vol. 163, Art. 120420. doi: 10.1016/j.techfore.2020.120420.

Bag, S., Gupta, S., Kumar, S. & Dwivedi, Y.K. 2021, 'Role of artificial intelligence-driven big data analytics in improving operational performance: A case of manufacturing supply chains', Technological Forecasting and Social Change, vol. 170, Art. 120880. doi: 10.1016/j.techfore.2021.120880.

Bag, S., Wood, L.C., Xu, L., Dhamija, P. & Kayikci, Y. 2020, 'Big data analytics as an operational excellence approach to enhance sustainable supply chain performance', Resources, Conservation and Recycling, vol. 153, Art. 104559. doi: 10.1016/j.resconrec.2019.104559.

Barney, J. 1991, 'Firm resources and sustained competitive advantage', Journal of Management, vol. 17, no. 1, pp. 99–120. doi: 10.1177/014920639101700108.

Behl, A., Nigam, A. & Vrontis, D. 2024, 'Guest editorial overview: Mapping the future of consumer behaviour using disruptive technologies', Journal of Consumer Behaviour, vol. 23, no. 4, pp. 1854–1857. doi: 10.1002/cb.2309.

Belanche, D., Casaló, L.V., Flavián, C. & Schepers, J. 2020, 'Service robot implementation: A theoretical framework and research agenda', The Service Industries Journal, vol. 40, nos. 3–4, pp. 203–225. doi: 10.1080/02642069.2019.1672666.

Bondar, K., Shestopalova, O., Hamaniuk, V. & Tursky, V. 2022, 'Ukraine higher education based on data-driven decision making (DDDM)', in Joint Proceedings of the 10th Illia O. Teplytskyi Workshop on Computer Simulation in Education (CoSinE 2022), CEUR Workshop Proceedings, vol. 3358, pp. 53–72. doi: 10.55056/cte.564.

Callon, M., Courtial, J.P., Turner, W.A. & Bauin, S. 1983, 'From translations to problematic networks: An introduction to co-word analysis', Social Science Information, vol. 22, no. 2, pp. 191–235. doi: 10.1177/053901883022002003.

Cavaleri, S.A. 2004, 'Are learning organizations pragmatic?', The Learning Organization, vol. 11, no. 4, pp. 248–259. doi: 10.1108/09696470410538203.

Centobelli, P., Cerchione, R. & Esposito, E. 2022, 'Managing knowledge in the era of digital transformation: A systematic literature review and research agenda', Journal of Business Research, vol. 139, pp. 700–725. doi: 10.1016/j.jbusres.2021.09.061.

Chen, C. 2006, 'CiteSpace II: Detecting and visualizing emerging trends and transient patterns in scientific literature', Journal of the American Society for Information Science and Technology, vol. 57, no. 3, pp. 359–377. doi: 10.1002/asi.20317.

Chen, C. 2012, 'Predictive effects of structural variation on citation patterns', Journal of the American Society for Information Science and Technology, vol. 63, no. 3, pp. 431–449. doi: 10.1002/asi.21694.

Chen, C. 2020, Mapping Scientific Frontiers: The Quest for Knowledge Visualization, 2nd edn, Springer, Cham. doi: 10.1007/978-3-030-52340-5.

Chi, O.H., Denton, G. & Gursoy, D. 2020, 'Artificially intelligent device use in service delivery: A systematic review, synthesis, and research agenda', Journal of Hospitality Marketing & Management, vol. 29, no. 6, pp. 757–786. doi: 10.1080/19368623.2020.1721394.

Chowdhury, S., Budhwar, P. & Hammerschmidt, J. 2022, 'AI-employee collaboration and business performance: Integrating knowledge-based view, socio-technical systems and organisational socialisation framework', Journal of Business Research, vol. 144, pp. 19–34. doi: 10.1016/j.jbusres.2022.01.069.

Chowdhury, S., Budhwar, P. & Hammerschmidt, J. 2023, 'Unlocking the value of artificial intelligence in human resource management through AI capability framework', Human Resource Management Review, vol. 33, no. 1, Art. 100899. doi: 10.1016/j.hrmr.2022.100899.

Davenport, T.H. & Ronanki, R. 2020, 'Artificial intelligence for the real world', Harvard Business Review, vol. 96, no. 1, pp. 108–116.

Del Giudice, M. & Maggioni, V. 2014, 'Managerial practices and operative directions of knowledge management within inter-firm networks: A global view', Journal of Knowledge Management, vol. 18, no. 5, pp. 841–846. doi: 10.1108/JKM-06-2014-0265.

Di Vaio, A., Grimaldi, M. & D'Amore, G. 2024, 'Digitalization and artificial knowledge for accountability in SCM: A systematic literature review', Journal of Enterprise Information Management, vol. 37, no. 1, pp. 67–98. doi: 10.1108/JEIM-08-2022-0275.

Di Vaio, A., Palladino, R., Pezzi, A. & Kalisz, D.E. 2020, 'The role of digital innovation in knowledge management systems: A systematic literature review', Journal of Business Research, vol. 121, pp. 283–296. doi: 10.1016/j.jbusres.2020.08.019.

Dmitrenko, N.Ye., Voloshyna, O.V., Kizim, S.S., Mnyshenko, K.V. & Nahorniak, S.V. 2022, 'Smart education in the prospective teachers' training', in Proceedings of the 10th Workshop on Cloud Technologies in Education (CTE 2022), CEUR Workshop Proceedings, vol. 3364, pp. 38–53. doi: 10.55056/cte.568.

Donthu, N., Kumar, S., Mukherjee, D., Pandey, N. & Lim, W.M. 2021, 'How to conduct a bibliometric analysis: An overview and guidelines', Journal of Business Research, vol. 133, pp. 285–296. doi: 10.1016/j.jbusres.2021.04.070.

Duan, Y., Edwards, J.S. & Dwivedi, Y.K. 2019, 'Artificial Intelligence for decision making in the era of Big Data – evolution, challenges and research agenda', International Journal of Information Management, vol. 48, pp. 63–71. doi: 10.1016/j.ijinfomgt.2019.01.021.

Dubey, R., Gunasekaran, A., Childe, S.J., Blome, C., Papadopoulos, T. & Roubaud, D. 2020, 'Examining the role of big data and predictive analytics on supply chain sustainability', International Journal of Production Economics, vol. 226, Art. 107599. doi: 10.1016/j.ijpe.2019.107599.

Dwivedi, Y.K. et al. 2021, 'Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy', International Journal of Information Management, vol. 57, Art. 101994. doi: 10.1016/j.ijinfomgt.2019.08.002.

García-Peñalvo, F.J., Corell, A., Abella-García, V. & Grande-de-Prado, M. 2021, 'Knowledge management as a key element in the development of intelligent systems: Mapping the literature', Sustainability, vol. 13, no. 6, Art. 3061. doi: 10.3390/su13063061.

Glikson, E. & Woolley, A.W. 2020, 'Human trust in artificial intelligence: Review of empirical research', Academy of Management Annals, vol. 14, no. 2, pp. 627–660. doi: 10.5465/annals.2018.0057.

Grant, R.M. 1996, 'Toward a knowledge-based theory of the firm', Strategic Management Journal, vol. 17, special issue 2, pp. 109–122. doi: 10.1002/smj.4250171110.

Gryzun, L.E., Shcherbakov, O.V. & Bida, B.O. 2022, 'Development of the information system for navigation in modern university campus', in Proceedings of the 5th International Workshop on Augmented Reality in Education (AREdu 2022), CEUR Workshop Proceedings, vol. 3364, pp. 108–126. doi: 10.55056/cte.566.

Gupta, S. & Rahman, M.S. 2023, 'Exploring AI-driven digital ecosystems in knowledge management: A capability-based approach', Journal of Knowledge Management, vol. 27, no. 2, pp. 245–266. doi: 10.1108/JKM-09-2021-0703.

Gursoy, D., Chi, C.G., Lu, L. & Nunkoo, R. 2019, 'Consumers acceptance of artificially intelligent (AI) device use in service delivery', International Journal of Information Management, vol. 49, pp. 157–169. doi: 10.1016/j.ijinfomgt.2019.03.008.

Haenlein, M. & Kaplan, A. 2019, 'A brief history of artificial intelligence: On the past, present, and future of AI', California Management Review, vol. 61, no. 4, pp. 5–14. doi: 10.1177/0008125619864925.

Hair, J.F., Hult, G.T.M., Ringle, C.M. & Sarstedt, M. 2019, A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), 2nd edn, Sage Publications, Thousand Oaks, CA.

Hjørland, B. 2013, 'Citation analysis: A social and dynamic approach to knowledge organization', Information Processing & Management, vol. 49, no. 6, pp. 1313–1325. doi: 10.1016/j.ipm.2013.07.001.

Holovnia, O.S., Shchur, N.O., Sverchevska, I.A., Bailiuk, Y.M. & Pokotylo, O.A. 2022, 'Interactive surveys during online lectures for IT students', in Proceedings of the 10th Workshop on Cloud Technologies in Education (CTE 2022), CEUR Workshop Proceedings, vol. 3364, pp. 65–86. doi: 10.55056/cte.556.

Hossain, L., Ramakrishnan, V. & Hecker, R. 2011, 'Mapping the dynamics of research networks in the field of e-government', Journal of Organizational Computing and Electronic Commerce, vol. 21, no. 3, pp. 257–282. doi: 10.1080/10919392.2011.590005.

Huang, M.H. & Rust, R.T. 2018, 'Artificial intelligence in service', Journal of Service Research, vol. 21, no. 2, pp. 155–172. doi: 10.1177/1094670517752459.

Jarrahi, M.H. 2018, 'Artificial intelligence and the future of work: Human–AI symbiosis in organizational decision making', Business Horizons, vol. 61, no. 4, pp. 577–586. doi: 10.1016/j.bushor.2018.03.007.

Jorzik, P. 2024, ‘AI-driven business model innovation: A systematic review and research agenda’, Journal of Business Research, vol. 173, Art. 114764. doi: 10.1016/j.jbusres.2024.114764.

Kanivets, O.V., Kanivets, I.M., Gorda, T.M., Gorbenko, O.V. & Kelemesh, A.O. 2022, ‘Using a mobile application to teach students to measure with a micrometer during remote laboratory work’, in Proceedings of the 5th International Workshop on Augmented Reality in Education (AREdu 2022), CEUR Workshop Proceedings, vol. 3364, pp. 87–107. doi: 10.55056/cte.563.

Kaplan, A. & Haenlein, M. 2019, ‘Siri, Siri, in my hand: Who’s the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence’, Business Horizons, vol. 62, no. 1, pp. 15–25. doi: 10.1016/j.bushor.2018.08.004.

Katz, J.S. & Martin, B.R. 1997, ‘What is research collaboration?’, Research Policy, vol. 26, no. 1, pp. 1–18. doi: 10.1016/S0048-7333(96)00917-1.

Kim, S. 2025, ‘Strategic human resource management in the era of algorithmic technologies: Key insights and future research agenda’, Human Resource Management, vol. 64, no. 1, pp. 18–33. doi: 10.1002/hrm.22268.

Klochko, O.V., Fedorets, V.M., Mazur, M.V. & Liulko, Y.P. 2022, ‘An IoT system based on open APIs and geolocation for human health data analysis’, in Joint Proceedings of CoSinE & CSTOE 2022, CEUR Workshop Proceedings, vol. 3358, pp. 87–101. doi: 10.55056/cte.567.

Kozachenko, N.P. 2022, ‘Modelling of AGM-style doxastic operations in three-valued setting’, in Joint Proceedings of the 10th Illia O. Teplytskyi Workshop on Computer Simulation in Education (CoSinE 2022), CEUR Workshop Proceedings, vol. 3358, pp. 19–38. doi: 10.55056/cte.553.

Kukharchuk, R.P., Vakaliuk, T.A., Zaika, O.V., Riabko, A.V. & Medvediev, M.G. 2022, ‘Implementation of STEM learning technology in the process of calibrating an NTC thermistor and developing an electronic thermometer based on it’, in Joint Proceedings of the 10th Illia O. Teplytskyi Workshop on Computer Simulation in Education (CoSinE 2022), CEUR Workshop Proceedings, vol. 3358, pp. 39–52. doi: 10.55056/cte.560.

Lavidas, K., Voulgari, I., Papadakis, S., Athanassopoulos, S., Anastasiou, A., Filippidi, A., Komis, V. & Karacapilidis, N. 2024, ‘Determinants of Humanities and Social Sciences Students’ Intentions to Use Artificial Intelligence Applications for Academic Purposes’, Information, vol. 15, no. 6, Article 314. doi: 10.3390/info15060314.

Lee, M.C.M. & Trimi, S. 2023, ‘The implementation of artificial intelligence in organizations: A systematic literature review’, Information & Management, vol. 60, no. 1, Art. 103816. doi: 10.1016/j.im.2023.103816.

Lemon, K.N. & Verhoef, P.C. 2016, ‘Understanding customer experience throughout the customer journey’, Journal of Marketing, vol. 80, no. 6, pp. 69–96. doi: 10.1509/jm.15.0420.

Leoni, L. & Behl, A. 2024, ‘Artificial intelligence capabilities and supply chain resilience: A knowledge-based view’, International Journal of Operations & Production Management, vol. 44, no. 5, pp. 911–940. doi: 10.1108/IJOPM-05-2022-0282.

Lin, C., Chen, C. & Fang, W. 2023, ‘Mapping scientific knowledge diffusion using dual-map overlays: A review and synthesis’, Journal of Data and Information Science, vol. 8, no. 2, pp. 1–15. doi: 10.2478/jdis-2023-0010.

Ma, Z. & Yu, K. 2010, ‘Research paradigms of knowledge management: A bibliometric analysis’, Online Information Review, vol. 34, no. 1, pp. 134–153. doi: 10.1108/14684521011024120.

Malik, A. 2023, ‘Artificial intelligence (AI)-assisted HRM: Towards an extended strategic framework’, Human Resource Management Review, vol. 33, no. 1, Art. 100940. doi: 10.1016/j.hrmr.2022.100940.

Marques, D.P. & Ferreira, J.J. 2020, ‘Digital transformation in higher education: The role of knowledge management’, Education and Information Technologies, vol. 25, no. 4, pp. 3381–3406. doi: 10.1007/s10639-020-10127.

Mikalef, P. & Gupta, M. 2021, ‘Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance’, *Information & Management*, vol. 58, no. 3, p. 103434, DOI: 10.1016/j.im.2021.103434.

Papanikolopoulou Arco, L.J. 2022, ‘Possibilities and limitations of social media in education processes during the pandemic: The teachers perspective’, in Proceedings of the 10th Workshop on Cloud Technologies in Education (CTE 2022), CEUR Workshop Proceedings, vol. 3364, pp. 54–64. doi: 10.55056/cte.552.

Pereira, V., Mellahi, K. & Collings, D.G. 2023, ‘Strategic HRM in the era of AI: A capability framework’, Human Resource Management Review, vol. 33, no. 1, Art. 100857. doi: 10.1016/j.hrmr.2021.100857.

Prikshat, V., Malik, A., Sharma, P. & Pereira, V. 2023, ‘AI-augmented HRM: Literature review and a proposed multilevel framework for future research’, Technological Forecasting and Social Change, vol. 189, Art. 122645. doi: 10.1016/j.techfore.2023.122645.

Pronina, O. & Piatykop, O. 2022, ‘The recognition of speech defects using convolutional neural network’, in Joint Proceedings of the 10th Illia O. Teplytskyi Workshop on Computer Simulation in Education (CoSinE 2022), CEUR Workshop Proceedings, vol. 3358, pp. 73–86. doi: 10.55056/cte.554.

Raisch, S., Krakowski, S. & Berente, N. 2021, ‘Artificial intelligence and management: The automation–augmentation paradox’, Academy of Management Review, vol. 46, no. 1, pp. 192–210. doi: 10.5465/amr.2018.0072.

Rodríguez, A., Edwards, J.S. & Bertone, S. 2020, ‘The role of artificial intelligence in knowledge management: A systematic review and future research agenda’, Journal of Knowledge Management, vol. 24, no. 7, pp. 1617–1637. doi: 10.1108/JKM-12-2018-0775.

Shahzadi, G. & Akhtar, N. 2024, ‘AI adoption in supply chain management: A systematic literature review’, Journal of Manufacturing Technology Management, vol. 35, no. 1, pp. 26–48. doi: 10.1108/JMTM-09-2023-0431.

Small, H. 1973, ‘Co-citation in the scientific literature: A new measure of the relationship between two documents’, Journal of the American Society for Information Science, vol. 24, no. 4, pp. 265–269. doi: 10.1002/asi.4630240406.

Syam, N. & Sharma, A. 2018, ‘Waiting for a sales renaissance in the fourth industrial revolution: Machine learning and artificial intelligence in sales research and practice’, Industrial Marketing Management, vol. 69, pp. 135–146. doi: 10.1016/j.indmarman.2017.12.019.

Tambe, P., Cappelli, P. & Yakubovich, V. 2019, ‘Artificial intelligence in human resources management: Challenges and a path forward’, California Management Review, vol. 61, no. 4, pp. 15–42. doi: 10.1177/0008125619867910.

Toorajipour, R., Sohrabpour, V. & Ghasemaghaei, M. 2021, ‘Impact of artificial intelligence and data analytics on supply chain sustainability: A systematic review’, Journal of Business Research, vol. 122, pp. 502–516. doi: 10.1016/j.jbusres.2020.09.009.

Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A. & Trichina, E. 2022, ‘Artificial intelligence, robotics, advanced technologies and human resource management: A systematic review’, International Journal of Human Resource Management, vol. 33, no. 7, pp. 1237–1266. doi: 10.1080/09585192.2020.1871398.

Waltman, L., van Eck, N.J. & Noyons, E.C.M. 2010, ‘A unified approach to mapping and clustering of bibliometric networks’, Journal of Informetrics, vol. 4, no. 4, pp. 629–635. doi: 10.1016/j.joi.2010.07.002.

White, H.D. & McCain, K.W. 1989, ‘Bibliometrics’, in M.E. Williams (ed.), Annual Review of Information Science and Technology, vol. 24, Elsevier, Amsterdam, pp. 119–186.

Wirtz, J., Patterson, P.G., Kunz, W.H., Gruber, T., Lu, V.N., Paluch, S. & Martins, A. 2018, ‘Brave new world: Service robots in the frontline’, Journal of Service Management, vol. 29, no. 5, pp. 907–931. doi: 10.1108/JOSM-04-2018-0119.

Zhang, J., Yu, Q., Zheng, F., Long, C. & Lu, Z. 2021, ‘Comparing keywords plus of WoS and author keywords: A case study of patient adherence research’, Journal of the Association for Information Science and Technology, vol. 72, no. 10, pp. 1224–1235. doi: 10.1002/asi.24406.

Zhu, D.H. & Xu, X. 2020, ‘Robot with humanoid hands cooks food better? Effect of robotic chef anthropomorphism on food quality prediction’, International Journal of Contemporary Hospitality Management, vol. 32, no. 11, pp. 3473–3493. doi: 10.1108/IJCHM-10-2019-0904.

Zupic, I. & Čater, T. 2015, ‘Bibliometric methods in management and organization’, Organizational Research Methods, vol. 18, no. 3, pp. 429–472. doi: 10.1177/1094428114562629.

