Journal of Advances in Information Technology, Vol. 16, No. 4, 2025

A Systematic Review of Improving Knowledge Management with Generative AI and Large Language Models

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***Abstract*—The development of Generative Artificial Intelligence (GAI) and Large Language Models (LLMs) has transformed the field of Knowledge Management (KM) by enabling precision in transferring knowledge as well as improving decision-making processes and operational efficiency. This paper systematically reviews 58 peer-reviewed publications from 2019 to early 2024 to comprehensively understand how these technologies impact knowledge management practices across numerous industries. The roles of GAI and LLMs were examined by using the Prisma methodology. VOSviewer and Power BI were used to visualize and analyze the data. Our research identified impacts and identified related gaps, including the need for advanced anonymities of techniques, AI-related technology development, and robust ethical mechanisms. In detail, trust emerges as a key factor that impacts and encompasses technological, organizational, and interpersonal dilemmas to empower knowledge management processes. This review emphasizes the crucial importance of strategic data management and cross-disciplinary approaches in addressing and responding to existing challenges. By bridging the gaps in ethics and trust-building in the practical adoption of these technologies, organizations can utilize GAI and LLMs to create an impactful and transparent KM system while maintaining sustainable and inclusive KM practices. Further, this paper provides a detailed investigation on the transformative potential of GAI and LLMs in KM and proposes strategies for future research to address existing gaps and optimize and broaden the fields of applications.**

***Keywords*—Knowledge Management (KM), knowledge sharing, Generative Artificial Intelligence (GAI), Large Language Models (LLMs)**

Manuscript received November 5, 2024; revised December 27, 2024; accepted January 20, 2025; published April 27, 2025.

I. Introduction

Knowledge Management (KM) in an organizational strategy is essential for creating, storing, and transferring knowledge. The integration of Generative Artificial Intelligence (GAI) and Large Language Models (LLMs) offers unique solutions to traditional challenges and reveals new insights into organizational performance. KM is traditionally concerned with the effective collection, management, organization, and distribution of knowledge. The development of GAI and LLMs—exemplified by systems such as ChatGPT, Microsoft Copilot, and Google Gemini has ushered in a new era in which knowledge creation and dissemination are not only mechanistic but also dynamic and generative, akin to human cognitive and functional processes [1–3]. These models, pretrained on vast datasets and corpus and predicted on complex deep learning algorithms, have shaped the KM practices of many businesses across sectors and domains [4, 5]. As Gartner [6] describes, KM is crucial across many industries, driving innovation and efficiency. This definition encapsulates a few critical elements that emphasize the strategic approach that businesses take toward managing their intellectual property, including businesspeople; it emphasizes that KM is not only a sole concept but a business process that involves structured methods to formalize and manage intellectual assets. Gartner suggests that KM processes are established and well designed to bridge silos within organizations, thereby enhancing collective intelligence and understanding of knowledge in various business domains as well as emphasizing the tacit and uncaptured knowledge of people.

The integration of such technologies in KM processes has heavily impacted foundational theories in the field.

The year 1990 saw the presentation of Nonaka's SECI Model (including Socialization, Externalization, Combination, and Internalization), and subsequent publications [7–9]. Those publications provide a solid framework for KM and how tacit and explicit knowledge interchange and align with Artificial Intelligence (AI)'s capabilities to transfer, code, program and contextualize knowledge proactively. Similarly, Zack [10] stated his perspectives on knowledge strategies with organizational objectives, mentioning "integrative and interactive". This provides an understanding of how organizations and enterprises can utilize AI to customize their decision-making processes based on knowledge. Drucker [11] was focused on the knowledge economy and emphasized the importance of intellectual property management, which is particularly pertinent to the age of AI. In the west, Davenport and Prusak [12] also highlighted the knowledge flow and investigated that KM practices were explored in multinational businesses. Those practices are aligned with SECI model in which KM priorities organizational performance and effectiveness, building cultural collaboration and technological implementation. Furthermore, recent research has investigated the commercial value of AI, dynamic knowledge tracking and sharing in KM [13–15].

Significant gaps remain in the present literature on KM. Currently, most KM research focuses on traditional KM systems and procedures, such as static approaches to data capture, storage, retrieval, and distribution. While KM frameworks have been shown to improve organizational performance, they fail to handle modern challenges such as managing unstructured and semi-structured data, real-time knowledge development, and a lack of new information technology. Although modern technologies have demonstrated the potential in KM, significant gaps exist in their adoption including knowledge validation, trust building, data privacy and ethical considerations remain underexplored in the current literature. The modern and complicated nature of corporate management has necessitated the development of more dynamic KM systems that provide systematic insights into how these emerging technologies, GAI and LLMs, may represent the pressing demands. This gap highlights the crucial need for more thorough and in-depth studies into the underlying and transformative effects of GAI and LLMs in KM settings.

In addition to the growing adoption of GAI and LLMs as well as their apparent benefits, prior research has not adequately investigated and explored social impacts, ethical considerations, knowledge trustworthiness, and validation processes in AI-produced KM systems [7–9]. These challenges are identified as AI outputs biases, the risk of overlapping knowledge and knowledge redundancy or encountering difficulties to make sure that generated knowledge are aligned with organizational goals. While Gartner's Hype Cycle for Data Management [16] emphasizes the "Innovation Trigger"-the transformative potential of GAI to predict a shift in the maturity of knowledge intensive practices as industries should consider to adapt to their offerings, there is limited proofs on how organization can practically implement and retain these innovations across industries.

To fully capture these innovations and how these information technologies impact KM, the following research questions are proposed to be answered:

- RQ1: How do GAI and LLMs improve KM processes? This RQ aims at exploring how GAI and LLMs enhance KM processes including: knowledge creating, sharing, and managing in organizations.
- RQ2: To identify challenges including trust-building, ethical considerations and most important knowledge validation in conjunction with the adoption of GAI and LLMs, what are the difficulties and challenges associated with knowledge validation including trust, ethics?
- RQ3: What are existing opportunities and risks when integrating GAI and LLMs into KM? Thus, we comprehend current research findings to provide actionable insights into the opportunities and risks in terms of integrating GAI and LLMs in KM.
- RQ4: To summarize future research and discuss how to bridge the gaps to optimize GAI and LLMs in KM systems, what are potential research directions?

To uncover how these technologies can enhance or improve KM processes, we conducted a systematic review of 58 papers based on the PRISMA statement, version 2020 [17]. These papers cover the period from 2019 to early 2024 and are peer reviewed publications that apply GAI and LLMs to different industries from healthcare, education to businesses.

II. Method

A. Eligibility Criteria

The present systematic review of the literature is conducted in accordance with the PRISMA standards. Through the utilization of several digital academic resources (ScienceDirect, Web of Science (WoS), Scopus, and IEEE Xplore), pertinent articles and publications were located. The final compilation of selected articles for review, which reveals the results of the following search terms: knowledge management, generative artificial intelligence, and large language models, is comprised of a comprehensive compilation of peer-reviewed publications from reputable publishers, which finally identified 400 papers in total (as shown in Fig. 1).

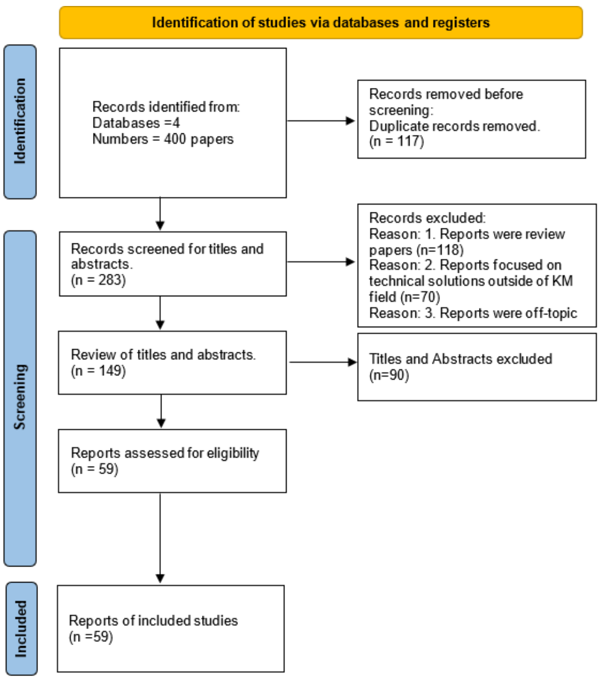

Fig. 1. Prisma diagram statement.

For the search strategies, we employ the full syntax of a search as follows:

- WoS: (“Knowledge Management” AND (“LLMs” OR “AI” OR “Collaborative AI” OR “Knowledge Sharing”)): 87
- ScienceDirect: (“Knowledge Management” AND (“Large Language models” OR “AI” OR “Collaborative AI” OR “Knowledge Sharing”)) (2019-2024): 250.
- Scopus: TITLE-ABS-KEY (knowledge AND management AND generative AND ai AND large AND language AND models) AND PUBYEAR i 2018 AND (LIMIT-TO (DOCTYPE, “ar”)): 9.
- IEEE: (“Knowledge Management” AND (“LLMs” OR “AI” OR “Collaborative AI” OR “Knowledge Sharing”)) Filters Applied: JournalsEarly Access Articles2019–2024: 49.

B. *Inclusion Criteria*

To determine the outlook of GAI and LLMs in KM, we apply the following inclusion criteria:

- Subject focus: research which is relevant and focusing on GAI and LLMs in KM. Papers with more discussion from the application to entire KM processes (application of LLMs in KM: Papers detailing the use of LLMs in enhancing KM processes).
- Sectoral scope: reports addressing interdisciplinary and cross sectoral approaches and applications of GAI and LLMs
- Publication date: studies published within the last five years (2018–2023) and early 2024 (January) to capture the most recent developments in the field.
- Language and review status: articles written in English that have undergone a peer-review process to ensure the credibility and quality.
- Ethical, regulatory, and privacy considerations: Studies that consider the ethical, regulatory, and privacy implications of using AI in KM.
- Domain-specific applications: papers that explore the applications of collaborative AI and LLMs in specialized domains, especially those that align with digital research libraries and organizational knowledge hubs.
- Technological and methodological innovations: Research presenting new technological and methodological advancements in the integration of AI into KM systems.
- Empirical research: empirical studies that provide data-driven insights into the application of AI and LLMs in KM.

C. *Exclusion Criteria*

To concentrate on the significant studies related to the outlook of GAI and LLMs in KM, we employ the following exclusion criteria:

- Non-English and non-peer reviewed papers were removed.
- Non-relevant to KM framework: studies that are solely discussing digital transformation in specific sectors such as primary care, retail, or health care without focusing on addressing KM practices will also be excluded.
- Papers consisting of systematic review, literature review, or scoping reviews were removed.
- Papers with technical focus outside KM were also removed.
- Off-Topic discussions that do not directly pertain to the use of AI and LLMs in KM were removed.

To provide a comprehensive overview of the subject matter, 400 publications were first identified through the implementation of the chosen keywords and search algorithms. After eliminating duplicate articles (117 in total), 283 papers remained for screening of titles and abstracts in the final selection. A detailed description of the decisions regarding record exclusion are discussed here:

- Topical Relevance: 118 papers focused on systematic, literature, and scoping reviews which were excluded to prioritize original research papers that contained original research.
- Technical Focus Outside KM: the exclusion of 72 papers from the systematic review was based on their primary focus on AI applications in specialized fields such as energy, seaports, construction, and healthcare, which did not directly investigate the influence of Generative AI and LLMs on KM processes. We removed these papers because their content deviated from the central research aim, which is to understand how AI technologies specifically contribute to an impact KM strategies, practices, or systems. The exclusions include papers focused on specialized applications that often discuss AI's impact on subject-specific domain processes and outcomes rather than on general KM practices or strategies. This could be illustrated by papers on AI in healthcare or even a highly specialized medical approach discussing the optimization of operational efficiency or predictive maintenance rather than how those technologies curate, share, manage, or create knowledge across organizations. There are also papers touching on digital transformation, but they focus more on labour markets and freelance work than how those organizations manage and leverage their knowledge. While KM has been thoroughly investigated and implemented into many fields, as well as the implementation of new technologies such as GAI and LLMs, many papers discuss specific technological challenges and opportunities that are not inclusive and relevant to KM strategies on the use of how AI can improve and affect knowledge processes, including sharing and supporting decision-making processes in more typical organizational contexts.
- Reports were off-topic discussions: 36 papers were excluded because they were not directly concerned with the impact of GAI and LLMs on KM processes. Papers discuss sustainability indexes related to corporate practices or involving technology integration situated within community services rather than KM within organizations. Some papers even go deeper into biomedical research, which likely doesn't address the use of AI in organizational knowledge processes. Some other examples could refer to the modelling and evaluation of data dissemination on the Internet, robotics, and object manipulation in the domain of adaptation in a specific context. In short, while these papers may be leveraging AI and related technologies, they do not specifically address how GAI and LLMs impact and influence KM in terms of the strategic and operational aspects of the systematic review.

III. Data Collection Process

A. Data Collection and Extraction

Four databases are chosen including Web of Science, IEEE, Scopus, and Science Direct to conduct the search. Table SI in Supplementary demonstrates how data is extracted to get insights from objectives, key findings, method used, application areas and limitations from each selected paper.

B. Data Items- Bibliographic Analysis

Fig. 2 visualizes, showing a growing interest and surge in research activities in the field over the year. Research focus clusters suggest that certain topics gain prominence in particular years. For example, 2023 shows a strong focus on "technology related topics" indicating a trend towards integrating advanced technological aspects in KM. Furthermore, the interconnected nodes in the year 2024 indicate a significant interest in LLMs, GPT and AI. This year highlights a vibrant and rapidly evolving field where many researchers are dedicated to improving the capabilities of KM through these technologies, ensuring their positive impacts and exploring innovative applications.

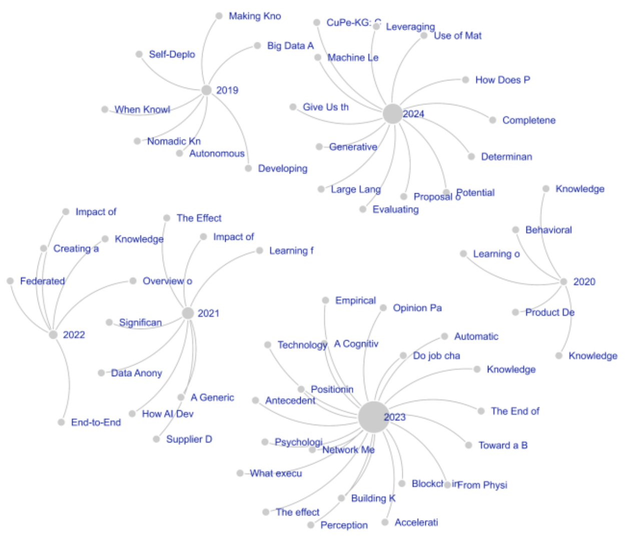

Fig. 2. Years of publications (generated by Power BI).

The word cloud Fig. 3 represents keywords showing connections or co-occurrences in the research. In this chart, links represent connections shown between keywords in research studies and node sizes intricate the frequency as well as the importance of the research topic. All the colors' clusters indicate a group of keywords that appear together. The central nodes (knowledge management clusters) are the largest and most central ones, indicating their critical significance and frequent co-occurrence with related topics. This topic shows strong connections to knowledge sharing, organizations, enterprises and innovation. Its links show the important role in organizational and business contexts. The other clusters (artificial intelligence in green) have formed a distinct cluster with associated topics such as ML, LLMs, data-driven systems, and neural networks. This trend has shown itself to be a growing field with strong and increasing connections to job characteristics and knowledge management. Obviously, from the chart there are visible links between the red clusters (knowledge management) and green clusters (artificial intelligence) such as the integration of advanced AI technologies into knowledge-based management systems and how AI has impacted on the knowledge processes such as knowledge sharing, learning, and organizational performances. Besides, smaller clusters representing emerging topics focusing on computer architecture, wireless communication, and data storage as well as technology aided knowledge management systems. These emerging topics contain computational techniques and ML showing its niche yet role in modern knowledge management approaches. The chart also describes visible clusters, but there are gaps between AI-connected topics and traditional knowledge management approaches shown in red/orange clusters. While research with focus on knowledge management remains dominant attention in the area, the integration of technology infrastructure (such as AI, GAI, LLMs, and data systems) into the whole KM process is a potential evolving area to further future research.

Fig. 4 shows the distribution of cited articles from various journal sources. The IEEE Transactions on Engineering Management have the highest number of articles, indicating significant interest in engineering management within digital knowledge management research. The IEEE Access journal also displays a significant number of articles, demonstrating the prominence of research in this field.

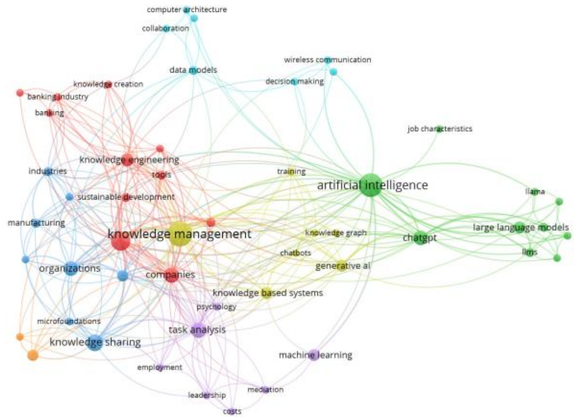

Fig. 3. Word-cloud (generated by VOSviewer).

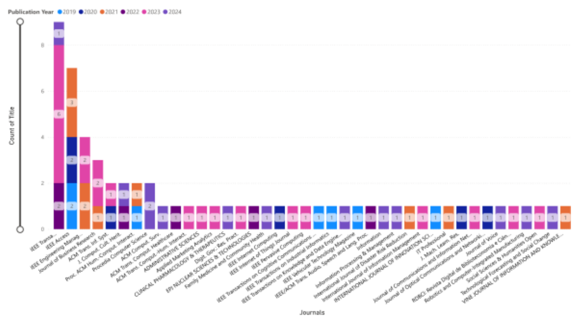

Fig. 4. Publications by journals (generated by Power BI).

C. Topmost Cited Articles

Table I significant highlights and contributions to KM across various studies, showing the indicators and impacts on the fields. In this table, key papers focus on AI-driven knowledge management and sharing system, GAI innovations and applications span diverse geographical locations. Various metrics are used such as citation counts (TC: Total Citations), Highly Influential Citations (HIC) underscore the importance of interdisciplinary nature of KM research.

TABLE I. TOPMOST CITED PAPERS

CR	Document	Year	First author's country	Source	DT	TC	HIC	BC	MC	RC	OA
1	A Generic Approach for Wheat Disease Classification and Verification Using Expert Opinion for Knowledge-Based Decisions	2021	Waleej Haider/Pakistan	IEEE Access	A	30	3	13	4	NA	O
2	A Cognitive Assistant for Operators: AI-Powered Knowledge Sharing on Complex Systems	2023	Samuel Kernan Freire/The Netherland	IEEE pervasive computing	A	12		6	3	2	N

3	Accelerating Innovation with Generative AI: AI-Augmented Digital Prototyping and Innovation Methods	2023	Volker Bilgram/Germany	IEEE Engineering Management	A	59	2	31	3	NA	N
4	Antecedents of Online Knowledge Seeking of Employees in Technical R&D Team: An Empirical Study in China	2021	Wenyao Zhang/China	IEEE Engineering Management	A	14	1	6	2	NA	N
5	Assessing the Utility of ChatGPT Throughout the Entire Clinical Workflow: Development and Usability Study	2023	Arya Rao/MIT-USA	Journal of Medical Internet Research	A	5	109	17	9	3	N
6	Automatic Skill-Oriented Question Generation and Recommendation for Intelligent Job Interviews	2023	Chuan Qin/China	ACM Transactions on Information Systems	A	18		12	2	NA	N
7	Behavioral Selection Strategies of Members of Enterprise Community of Practice—An Evolutionary Game Theory Approach to the Knowledge Creation Process	2020	Dan Wang/China	IEEE Access	A	5		2	2	NA	O
8	Big Data Adoption and Knowledge Management Sharing: An Empirical Investigation on Their Adoption and Sustainability as a Purpose of Education	2019	W. Al-rahmi/Malaysia	IEEE Access	A	69	2	33	8	5	O
9	Business value appropriation roadmap for artificial intelligence	2020	A. Mishra/India	VINE Journal of Information and Knowledge Management Systems	A	38	3	18	3	NA	N
10	Creating a Knowledge Graph for Ireland's Lost History: Knowledge Engineering and Curation in the Beyond 2022 Project	2022	C. Debruyne/Belgium	ACM Journal on Computing and Cultural Heritage (JOCCH)	A	10	1	7	2	NA	O
11	CuPe-KG: Cultural perspective–based knowledge graph construction of tourism resources via pretrained language models	2024	Zhanling Fan/China	Information Processing & Management	A	3	1	1	NA		O
12	Developing a conceptual framework of knowledge management	2019	Rayees Farooq/Oman	International Journal of Innovation Science	A	70	7	29	3	2	N
13	Do job characteristics shape academics' affective commitment and knowledge sharing behavior in the institutes of tertiary education?	2023	Dewan Niamul Karim/Malaysia	Social Sciences & Humanities Open	A	4	1	3	NA	1	O
14	Empirical analysis of the influencing factors of knowledge sharing in industrial technology innovation strategic alliances	2023	Meixia Wang/China	Journal of Business Research	A	30	1	NA	NA		O
15	Impact of information hiding on circular food supply chains in business-to-business context	2021	S. Mangla/UK	Journal of Business Research	A	30	NA	3	NA	NA	O
16	Knowledge Graphs to Empower Humanity-Inspired AI Systems	2020	Hemant Purohit/USA	IEEE Internet Computing	A	14	NA	8	NA	NA	N
17	Knowledge management in optical networks: architecture, methods, and use cases [Invited]	2019	M. Ruiz/France	Journal of Optical Communications and Networking	A	12	NA	2	3	NA	N
18	Knowledge Sharing in Roadmapping: Toward a Multilevel Explanation	2022	Elisabeth Krull/UK	IEEE Transactions on Engineering Management	A	8	1	3	1	NA	N
19	Learning from past earthquake disasters: The need for knowledge management system to enhance infrastructure resilience in Indonesia	2021	K. Pribadi, M. Abduh/Indonesia	International Journal of Disaster Risk Reduction	A	53	4	21	NA	NA	O
20	Learning or forgetting? A Dynamic Approach for Tracking the Knowledge Proficiency of Students	2020	Zhenya Huang/China	ACM Transactions on Information Systems	A	77	1	28	5	NA	O

21	Leveraging error-assisted fine-tuning large language models for manufacturing excellence	2024	Liqiao Xia/China	Robotics and Computer-Integrated Manufacturing	A	18	4	NA	NA	NA	O
22	Machine Learning in Modeling Disease Trajectory and Treatment Outcomes: An Emerging Enabler for Model-Informed Precision Medicine	2023	N. Terranova/Middle East	Clinical pharmacology and therapy	A	17	6	NA	NA	NA	O
23	Making Knowledge Tradable in Edge-AI Enabled IoT: A Consortium Blockchain-Based Efficient and Incentive Approach	2019	Xi Lin/China	IEEE Transactions on Industrial Informatics	A	145	6	66	17	1	N
24	Network Meets ChatGPT: Intent Autonomous Management, Control and Operation	2023	Jingyu Wang/China	Journal of Communications and Information Networks	A	19	1	11	3	NA	N
25	Opinion Paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy	2023	Yogesh K. Dwivedi/UK	International Journal of Information Management	A	949	36	245	25	11	O
26	Representation Learning for Dynamic Graphs: A Survey	2019	Seyed Mehran Kazemi/Canada	The Journal of Machine Learning Research	A	391	28	226	67	2	N

Note: DT: Document types; A: Article; TC: Total citations; HIC: Highly influential citations; BC: background citations; MC: Methods citations; RC: Results citations; OA: Open access. N: Not Open Access, O: Open Access); NA: Not Available.

D. *Method Analysis*

Fig. 5 and data extraction from Supplementary Table I highlight the distribution of methods among given topics and their corresponding results. This radial chart shows the counts of topics (dark blue) and Counts of Results (light blue) by accompanied methods. In this chart, methods are listed around the circles while dark blue represents the Count of topics where each method has been applied, and light blue shows the counts of results attributed to those methods. As can be seen from the chart, the longest bars indicate the widely used methods across research topics and results including Structural Equation Modelling (SEM), PLS-SEM Analysis (partial least Squares SEM), Survey Questionnaires and Content Analysis). These applied methods appear as major tools in both quantitative and qualitative analysis. Some methods such as Confirmatory Factor Analysis (CFA), Field Surveys, and Post-hoc Indirect Effect Analysis are highly effective in delivering measurable outcomes.

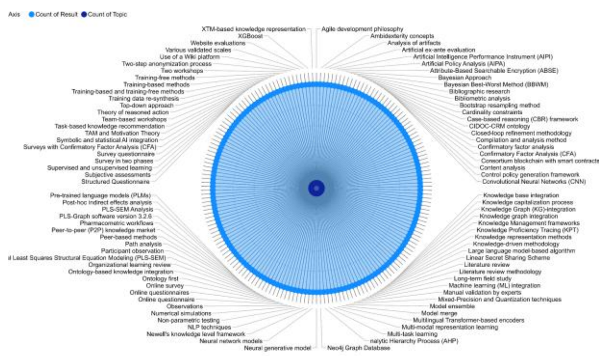

Fig. 5. Methods (generated by Power BI).

Some methods such as Neural Network Models, Graph-Enhanced Algorithms, Human Evaluation, and Multi-tasking. Those methods are emerging or niche approaches with potential for conducting future research. For some methods, the bars for Counts of Topics are longer than count of results, showing disparity between topics and results such as survey-based methods. Emerging methods and techniques like NLP, ML integration, and neural networks are used but underutilized.

IV. Findings

A. *Identified Gaps in KM with GAI and LLMS*

There are seven clusters in Fig. 6, providing insights into thematic distribution and relationships among 363 keywords in identifying research gaps from the set of chosen papers. Central theme also the knowledge sharing gaps act as the core nodes, connecting all clusters. This graph indicates its interdisciplinary relevance to bridge different thematic areas. Besides, inter-cluster links show strong connections and overlapping research. Cluster 2 shows organizational culture linking with cluster 1 via leadership and training. Cluster 5 connects with Cluster 3 (bias). Therefore, research gaps are identified as follows:

- Understanding knowledge sharing when working in a team and its effectiveness on overall working environment regarding supervisory and cultural challenges [4, 12–16].
- Examining longitudinal impacts on organizational and intellectual properties to overcome limitation of cross-culture working environments [1, 5, 13, 15, 17–21].
- Methodological bias and sampling are critical in improving data reliability to reduce systemic bias [1, 20, 22, 23].
- Knowledge sharing to ensure research quality to explore transparency and knowledge validation to foster collaborative knowledge sharing and knowledge [4, 7, 12, 15, 17, 20, 24–34].
- Technology assimilation and emotional factors are addressed to express embarrassment reactions when it comes to adapt new technologies to technically adaptable and to practice sustainability and green are also emerging areas to focus [1, 4, 14, 22, 25, 29, 30, 34–42].
- Resource-intensive knowledge management deals with issues in static knowledge management systems, discovering tacti knowledge conversion supporting strategic knowledge validation and creation [1, 8, 13, 20, 21, 22, 24, 36, 40, 43–45].
- Supplier development and knowledge transfer regarding mechanism, ethical considerations, building trust and network of collaboration frameworks are called for future [1, 19, 28, 33, 36, 43, 46–51].

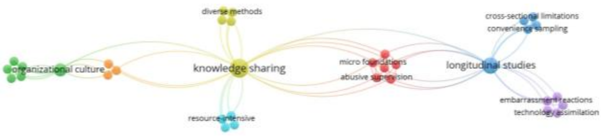

Fig. 6. Research gaps (generated by VOSviewer software).

B. *Knowledge Management Approaches*

KM is framed as a multifaceted strategy that enhances organizational effectiveness while securing a competitive advantage, particularly tacit knowledge which is often challenging to capture and share due to its nature [38]. Those emphasizes are not only orienting learning, sharing knowledge, memorizing organizational performance, and reusing knowledge, but they also help optimize business processes and innovation capabilities [40, 41, 52]. This approach is not just about managing knowledge; it is also about how to leverage and drive sustainable business value and adapt to market change, as well as the innovative wave of technologies. Farooq [32] described KM components that delves deeply into creating value and competitive advantages, highlighting and emphasizing a broad range of interconnected frameworks where the KM process and each of these elements feed into strategic advantage in a more dynamic capabilities and adaptability, which underscores KM's role in boosting and, at the same time, fostering organizational agility and resilience, especially in the era of digital transformation. Huang [14] discusses KM in this context, where the ability to quickly adapt and respond to technological changes is essential.

KM is intricately interconnected with AI technologies [2, 9] discussing how these technologies have transformed traditional KM practices by enabling sophisticated data analysis, predictive data, and proactive data management. Al-driven KM goes beyond traditional barriers and boundaries [23, 53] allowing for ongoing learning and training based on new data and interactions. These activities, in turn, enhance the decision-making process and boost operational effectiveness. While the latter views AI as optimizing KM practices by improving information processing and organizational learning capabilities, the former discusses the use of LLMs in managing network traffic data dynamically, improving the opportunities and capabilities of KM through AI environments. This reflects a shift from data repositories to a more proactive, dynamic, and intelligent system that evolves alongside organizational needs and adapts to the future challenges of the information age. Pribadi [49] puts his research on emphasizing KM as crucial for the operation of resilient infrastructure in a specific context of disaster-prone areas, demonstrating KM's roles in strategic planning and operational execution.

In other words, Gao [34] focuses on a semi-structured approach to KM, which is crucial for managing complexities in dialogue systems that interact with both structured and unstructured data. Those perspectives deal with KM as comprehensive systems that control and manage the entire life cycle of knowledge, from capturing, creating, distributing, and finally applying information. With the focus on generating structured frameworks, ensuring knowledge is not only preserved but also accessible, actionable, and insightful across the organization. This systematic approach to KM is essential for maintaining the relevance and effective usability of knowledge in organizational settings. In context-specific knowledge management [29, 54] tailors on KM effective management and dissemination of radioactive waste management, and [55] discusses KM in the context of preserving and utilizing traditional architecture knowledge through the researched Eco-Diar flatform. Those approaches are tailored to the specific organizational, educational training [14], and strategic needs of different fields and requirements. This adaptability of KM practices is to make sure that KM strategies are directed and planned directly aligned with the specific and unique challenges as well as objectives of various sectors, improving operational efficiency and tailoring strategic decision making.

In brief, these definitions of KM (as covered in Fig. 7) are essential for comprehending the conceptual significance and for determining how KM practices are perceived and implemented. KM can be described as a deliberate and methodical process that encompasses the generation, acquisition, distribution, and utilization of knowledge across many domains and organizational settings. This technique improves innovation, competitiveness, and operational efficiencies. The system utilizes both conventional methods and cutting-edge technology such as LLMs, AI, and GAI to actively generate and manage knowledge.

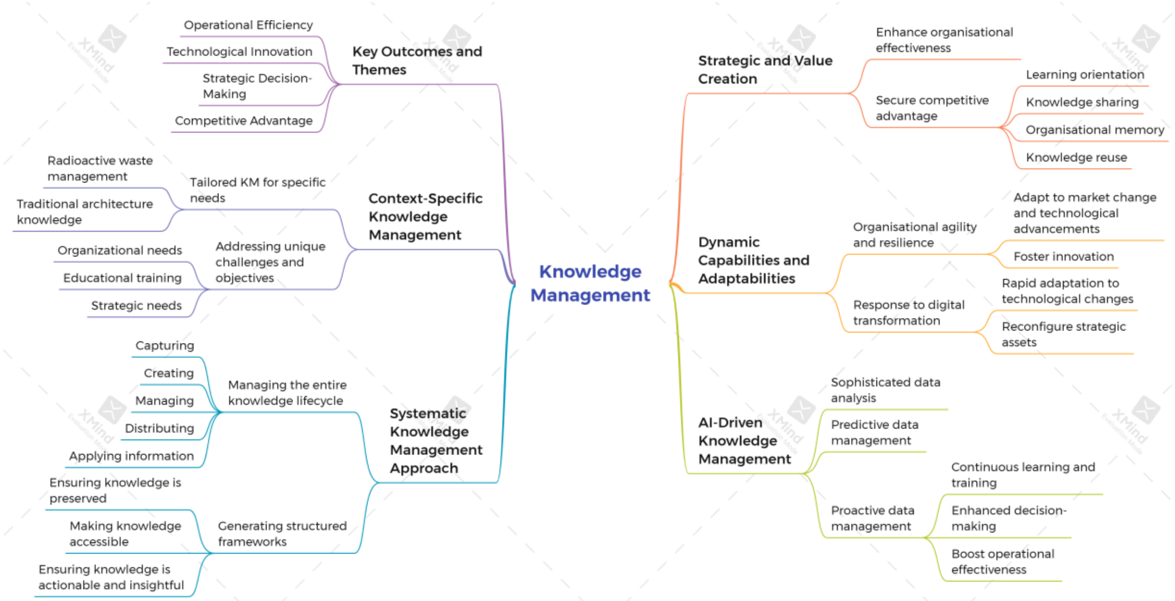

Fig. 7. KM-Thematic analysis (generated by Xmind software).

C. Technology Adoption

1) Adoption of AI and LLMs in KM

Various industries (Tables I and II) including healthcare, banking, technology, telecommunications, and others, have implemented GAI and LLMs to enhance their performance. The exploration of technology provides evidence in answering RQ1. According to Haider [19] the use of decision trees resulted in a 28% increase in accuracy and a 4.3% improvement in efficiency. The advancement has resulted in a more precise and prompt detection and categorization of wheat diseases, enhanced disease control, and increased agricultural crop productivity. The utilization of Machine Learning (ML), General Artificial Intelligence (GAI), interpretable techniques like SHapley Additive exPlanations (SHAP), and wearable devices in healthcare has improved the accuracy of predicting illness progression and treatment results [51]. Furthermore, there has been a notable enhancement in the effectiveness of clinical trial designs, resulting in a significant reduction of sample sizes by 30%. According to Mishra [15], a significant majority of executives in business-related fields, approximately 85%, are of the opinion that AI can be beneficial in various aspects of business. These include improving customer segmentation, optimizing operations, and logistics, enhancing the human resource function, increasing efficiency, and aligning key applications with the transformative potential of AI in knowledge management and related business processes. Adoption rates are highest in the domains of technologies, healthcare, finance, and manufacturing. Specific applications and approaches, such as aiding decision-making processes, automated content development, and increased customer assistance, are clearly observed. Efficiency gains and operational performance improvements are achieved through faster information retrieval, enhanced decision-making, and automation of routine processes [35] The application of these technologies into KM systems shows significant improvements in enhancing working collaboration and decision-making process. The results have also been highlighted in Table II with their transformative impact on KM settings and practices.

TABLE II. TECHNOLOGY ADOPTION

Categories Industry	Decision Support Systems	Automated Content Generation	Knowledge Discovery and Data Mining	Customer Service Enhancements	Predictive Analytics and Data Modelling	Clinical Trial Optimization	Risk Mitigation
Pharmacy and Healthcare [2, 29, 44, 56]	×	×	×	NA	×	×	×
System Engineering [57, 58]	×	×	×	NA	×	NA	×
Business [9, 14, 31]	×	×	×	×	×	NA	×
Manufacturing and Telecommunication [12, 17, 32, 37, 43, 45, 46]	×	×	×	NA	×	NA	×
[5, 59]	×	×	×	NA	×	NA	×
Clinical trials [5, 29, 44]	×	NA	NA	NA	×	×	×
Innovation Management and Education] [2, 4, 5, 16, 24, 26, 38, 39]	×	×	×	NA	×	NA	×
Tourism [29]	×	×	×	NA	×	NA	×
Public Policy [42, 60]	×	×	×	×	×	NA	NA
AI Development [2, 19, 24, 29, 33, 39, 56, 60]	×	×	×	NA	×	NA	×

Note: × (indicates the presence of technology adoption in the corresponding category). NA: Not available

The year 2023 marked significant advancement and popularization in applying LLMs across various sections and KM practices' enhancement. These tailored LLMs for fields such as tourism, education, and manufacturing are investigated with domain-specific fine-tuning (red cluster shown in Fig. 8 and Table III). Research in this period emphasizes enriching metadata architectures and error-assisted finetuning to improve content credibility, reliability, and accuracy. Furthermore, the year 2024 demonstrates a significant shift in the advancement of these technologies, particularly in the fields of tourism and manufacturing. While ethics, trust, domain-specific fine-tuning, and knowledge validation remain challenging in integrating AI-generated knowledge into entire KM processes.

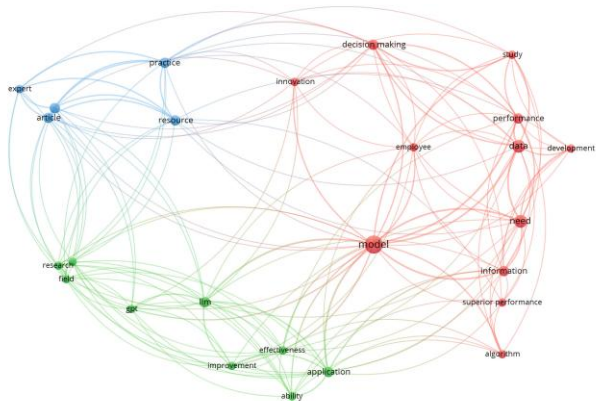

Fig. 8. Network visualization of topic occurrence (generated by VOSviewer).

TABLE III. GAI AND LLMS IN 2023–2024

Study	Year	Novel Contribution	Practical Insights	Most Emphasized issue
[18]	2023	NA	NA	Ethical concerns, Operator development, over-reliance, critical thinking, problem solving, privacy risks, data misuse, data management plans, intellectual property, tacit knowledge ownership
[3]	2023	Early innovation phrases: exploration, ideation, prototyping, faster iterations, cost reduction, no coding skills required, bridging conceptual and functional gaps	Workflow improvement, task delegation with AI agents, reduced human workload, enhancing data-driven decision making	Implementation and trust, organizational data misuse, hinders critical thinking, transparency, tacit knowledge ownership (intellectual property rights)
[20]	2023	Robust knowledge architecture, data and content management, metadata-enriched LLMs, mitigating hallucinations, improving content reliability	Business value assessment of GAI, target use case evaluation, structured knowledge and data, managing large volumes of documents, streamlined decision-making, metadata integration, tailored AI for business scenarios.	Necessity of human oversight, specific to policies and processes, enhancing retrieval, content accuracy, maximizing AI value impact
[23]	2023	Intelligent system for job interviews, skill-oriented interview questions, distantly supervised model, minimal human annotation, data driven approach, high quality training instances, recommender system	Skill extraction, large scale data processing, minimal manual effort, data -driven neural models, targeting questioning, leveraging query logs, precision in recommendations	Lack of AI explainability
[29]	2024	Tourism knowledge graphs, innovative cultural perspective, cultural type identification, applicability of ChatGPT, enriched knowledge graphs, annotated	Cultural integration, link between tourism resources and traditional culture, high quality annotated dataset,	Lack of historical tourism focus, challenges in ontology design,

		dataset, challenges of PLMs, FT-ERNIE outperforming ChatGPT	improved identification, recognition and classification,	annotation challenges, AI performance, ChatGPT limitations in cultural context,
[35]	2024	AI chatbot performance (ChatGPT, Llama, Bilateral Vocal Fold Paralysis treatment), Chat GPT: 50% accuracy, Llama: 15% accuracy, complexity in BVFP management, AI limitations in clinical decision making (specialized fields, expert consensus)	Standardized treatment protocols, gaps in AI knowledge and expertise, risks of harmful assertions, potential for medical malpractice (AI tool safety) clinical judgment and expertise cannot be replaced, supportive role of AI in decision-making	AI inadequacy (incorrect BVFP treatment protocols, knowledge and expertise gaps in AI models), medical safety concerns, call for guidelines and standardization, expert consensus needed
[37]	2023	Information quality model, integrating dimensions: intrinsic, contextual, representational, accessibility. Focus on decision making efficiency, generative conversational AI, empirical examination of content quality factors.	Decision making efficiency, information credibility, user concerns on believability, trust and transparency, ethical framework, handling organizational information securely, bias and fairness in AI interactions.	Ethical concerns, bias, fairness, transparency, interpretability, sensitive regulatory data handling, information credibility, need for ethical framework, secure and ethical use of conversational AI, controversies in ethical and legal dimensions.
[47]	2023	LLM-based algorithm, designed for disinformation detection, focus on generated videos and photos, Llama model integration, task specific- instructions, fake news detection application, human judgement comparison, fine tuning challenges, limited computational power, self-instruction method, 70,000 instructions, 30 alignment seed tasks.	Disinformation detection, Llama model in improving accuracy in fake news detection, computational constrains optimization, distinguishing credible vs false information, enhanced detection deepfake techniques	Rapid dissemination, social media as disinformation breeding ground, difficulty in discerning credible information, detection limitations, parameter-efficient methods for Optimization, resources constraints in model tuning
[49]	2023	Error assisted fine tuning, adapting LLMs to manufacturing domain, scientific novelty, fine-tuning process enhance adaptability and performance, domain specific queries, interactive prompting procedure, ensures syntactic correctness, enhances accuracy and effectiveness, engine utility, feasible programming solutions, tailored LLMS for manufacturing sector.	Intricate domain knowledge required, LLM limitations, general knowledge base, lack of domain specific adaptability, fine-tuned LLM for reliable programming, improved predictive accuracy, enhance engagement with engineers' queries	Reliability and effectiveness of LLMs, limited capability in programming languages, lack of domain expertise, refinement for better accuracy, addressing sector specific needs
[1]	2023	Generative AI applications, transforming education, business and society, interdisciplinary research, exploring AI implications across fields, curriculum design and student learning, productivity enhancement, automating mundane tasks, focus on creative and complex activities, ChatGPT limitations, real time data access issues, bias in output, policy development, ethical considerations and potential misuse, regulation and publishing policies, research revision	Personalized, on demand learning, feedback and guidance for students, enhancing knowledge validation and learning outcomes, automating routine tasks, improved customer service efficiency, reducing task time, enhancing managerial effectiveness	Ethical concerns, privacy, autonomy, decision-making, accountability gaps, AI systems responsibility for errors, transparency, risk of misuse, deepfake and misinformation, legal issues, copyrights and intellectual property

NOTE: NA: Not available.

KM plays a complex function in enhancing organizational effectiveness and gaining advantages by highlighting the significance of tacit knowledge [1, 2, 9, 18, 24, 40, 56]. Simply said, KM plays a crucial role in improving creativity, competitiveness, and organizational efficiency in many environmental contexts. This process encompasses the activities of producing, collecting, managing, distributing, and utilizing knowledge using both conventional and advanced approaches, including GAI and LLMs. This approach not only supports organizational strategies but also enhances learning, sharing, and value creation to adapt to change. It connects notions of organizational capacity with GAI, and LLMs.

2) Human elements in AI and technology-driven knowledge management

In responding to RQ2, the findings have identified important challenges in establishing trust and validating of knowledge. These visualizations (illustrated in Figs. 8 and 9) analyze trust factors and their impacts on KM processes. The creation is based on the count of key trust insights extracted from 35 papers providing a source for data visualization and analysis. While the first chart concentrates on "Count of Trust Factor Categories", describing the prevalence of different factors influencing the process including technological, organizational, and interpersonal trust. The second diagram focuses on the "Impact of KM processes", showing how specific trust-related insights, for example, collaboration, motivation, and transparency directly impact and effect on KM outcomes like KM creation, utilization, and exchange.

a) Interpersonal trust

This factor (Fig. 10) pertains to the conviction that coworkers and colleagues possess qualities of trustworthiness, dependability, and competence, as evidenced by the works of [1, 28, 45, 58]. Trust at high levels minimizes concerns about exploitation or criticism when sharing knowledge. In dynamic organizational settings, effective sharing practices enable the utilization and control of advanced technologies, promoting the exchange of ideas and knowledge and fostering trust among colleagues [3, 27]. Besides, the interpersonal trust with elements such as cross-functional collaboration, peer-feedback mechanisms and team dynamics also impact on knowledge exchange since it directly associates with psychological safety and interpersonal incentives [7, 15, 29–31, 44].

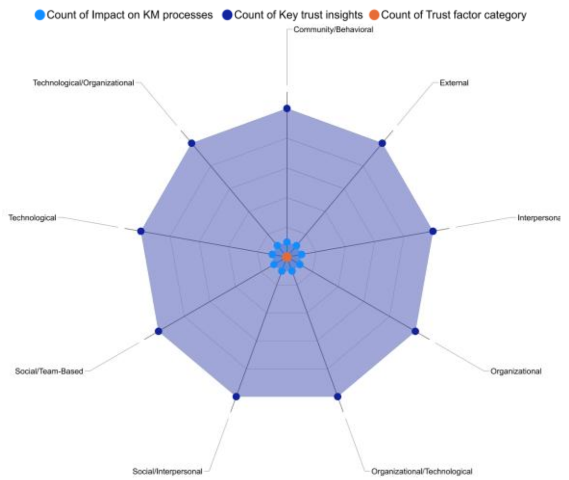

Fig. 9. Trust factors (generated by Power BI).

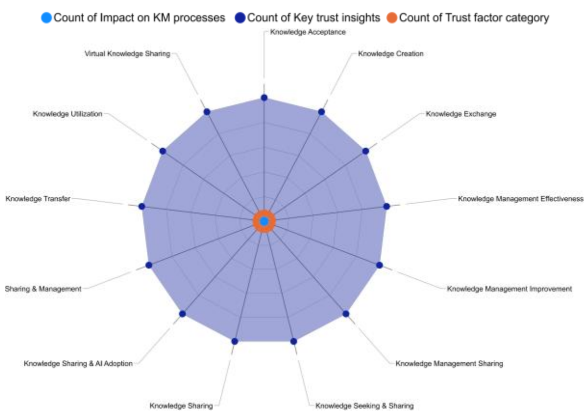

Fig. 10. Trust impacts (generated by Power BI).

b) Organizational trust

While organizational trust is of a multifaceted nature, trust in the organization boosts employees' confidence in various aspects such as overall organizational performance, leadership, strategies, policies, and cultures. As a result, employees feel more assured in sharing their knowledge without fear of negative consequences and safeguarding their contributions [9, 21, 26]. Through the establishment of equitable and transparent policies, adherence to ethical standards, and the implementation of incentive schemes for employee well-being, leadership consistently emphasizes the importance of knowledge sharing and ensures that such contributions are duly recognized and rewarded [16, 17, 25, 44, 61, 62]. Other than that, formal structures as mentioned policies, governance along with organizational climate and employee advocacy could be taken into account as those formal structures and information mechanism always stay in parallel [28, 34, 40].

In 2023, Agarwal [61] proposed the concept of "psychological safety effects," which is a crucial aspect of human behaviour that is closely linked to trust. He stated that the work atmosphere creates a perception of safety for individuals to take interpersonal risks, such as confessing mistakes and discussing fresh ideas. The identical concept has also been referenced in the following source [4].

c) Social capital

The term "social capital" was used by Monti [36] to describe the interconnected networks of interactions among individuals inside a specific organization. The discussion has focused on three important concepts: "structural, relational, and cognitive dimensions." These concepts help us understand the patterns of connection between individuals. When it comes to the quality of relationships, it involves elements such as trust, norms, obligations, shared visions, common language, and mutual understanding, all of which play a role in fostering strong connections. Social capital is a fundamental factor that affects the degree and efficacy of information sharing [29, 32, 34] While structural, relational, and cognitive dimensions are heavily attributed to trust, cross-cultural communication and knowledge network are determined to have significant influence on globalized teams and social capital [20].

d) Motivation and incentives

As stated by [17, 63], there are two types of motivation: intrinsic and extrinsic. Intrinsic motivation is driven by personal satisfaction and a sense of achievement, which encourages individuals to share knowledge freely and consistently. On the other hand, extrinsic motivation focuses more on external incentives such as rewards, recognition, and career advancement opportunities.

3) Data analytics in KM

The utilization of big data in data analytics, as demonstrated [24] facilitates advanced analysis and efficient data management. This, in turn, promotes educational sustainability and enhances decision-making capabilities and creativity, as discussed in [42]. Data analytics is crucial for comprehending personnel by offering insights into various individual and contextual factors that impact the utilization of digital platforms [14, 30, 58, 61]. Therefore, AI related technologies and data analytics are emphasized as crucial elements of KM systems. AI enables the gathering, examination, and administration of vast amounts of data. The strategic utilization of data in analytics facilitates enhanced decision-making and promotes innovation by offering valuable insights and predictive analysis, hence enhancing performance outcomes. AI and analytics facilitate proactive data management, guaranteeing that knowledge is consistently refreshed and easily available.

4) Knowledge management systems

Agile development is a key part of making sure that systems can quickly change to new threats. For a crisis reaction to work well, it needs a customized Knowledge Management System (KMS) that can adapt to changing conditions by using current knowledge from the system to gather, share, and use knowledge. In this way, organizations can not only handle crises well, but they can also include specific knowledge and stakeholders in outlining the steps and answers for strong management [42, 48, 50].

In industry-specific knowledge management (Table IV) [46, 45], looks at how knowledge is hidden in the meat industry in Turkey and suggests ways to improve food supply chains' ability to be traced and be clear. These ways include knowledge management, innovation capacity, product innovation performance, and absorptive capacity. Researchers have investigated how ICT and behavioral control can be used in supplier development programs [63]. They found that allowing ICT and perceived behavioral control makes knowledge sharing more effective by reducing power distance and promoting uncertainty avoidance. [64] talks about knowledge management practices in the banking industry and suggests a complete method for coordinating business plans with knowledge creation so that knowledge can be recorded.

TABLE IV. KNOWLEDGE MANAGEMENT PLATFORMS

References	KM Platform	Elements
[65]	EURAD	Processes for knowledge sharing, for example interaction between the different Radioactive Waste Management (RWM)
[48]	ERI	Crisis management: earthquake resilient infrastructure
[55]	Eco-Diar	Construction: Proposes a knowledge-based platform for capitalizing on environmental knowledge in traditional Algerian architecture, aiming to support heritage preservation and energy reduction.
[23]	DuerQues	Skills-oriented generating question and answer platform

Knowledge Base (KB) agents in KMS use a four-step process to keep and retrieve knowledge: retrieval, reuse, review, and retention [24, 47, 62]. Many KMS use LLMs and NLP to create content-related context, like skill-based interview questions, clinical treatment outcomes, keeping track of student progress, agile development for crisis management, maintenance data sharing that needs data anonymization, optical networks for self-operation and group learnings [14, 26, 27, 29, 36]. In other situations, blockchain-based design makes it safe for IoT devices to share information. For example, federated learning in healthcare uses edge device training to improve patients' quality of life and lower the number of hospitalizations [5, 16, 26, 46, 49, 61]. Information quality models are needed to make sure that generative chat AI works well in the decision-making process and knowledge graph enhancement techniques, data augmentation, and retrieval augmentation make it easier for LLMs to model real [1, 5, 24, 27, 35, 48, 60].

D. Challenges

Great progress has been made in many disciplines and organizations to improve knowledge management and knowledge sharing to integrate products and services, increase productivity, and conduct research and development. However, KM still confronts various problems in its practical usage and applications (illustrated in Table V).

TABLE V. CHALLENGES

Categories	Subcategories	Challenges
Knowledge Management	Data anonymization [30]	Ensuring data privacy and security in maintenance data sharing
	Agile development [59]	Managing crisis with KMS
	Federated learning [5]	Enhancing patient outcomes through edge device training
	Blockchain integration [25]	Secure knowledge sharing across IoT devices with lightweight blockchain
	Knowledge graphs [43]	Improving factual language modelling ability of LLMs
	Information quality [37]	Ensuring effectiveness of generative AI in decision making
	Autonomous Operations [22]	Collective learning in optical networks
	Peer-to-peer knowledge markets [53]	Facilitating knowledge sharing in Edge AI IoT using blockchain for security and efficiency

Knowledge sharing and collaboration	Transparency [1, 45]	Overcoming information hiding challenges
	Cultural and technological barriers [13, 16, 20, 49]	Influencing in knowledge sharing in supplier and chain management
	Social network analysis [14, 30, 49]	Insights into knowledge consulting and sharing behaviors
	AI communication [19, 26, 34–36, 50, 66]	Extended planning periods, shared documentation
	Personalized knowledge graphs [43]	Managing integrated cognitive and social science research for humanity-inspired AI systems
	Big data adoption [24]	Enhancing sustainability and outcomes in educational settings
Educational knowledge proficiency	Knowledge hiding [41, 66]	Addressing negative impacts on innovation behaviors
Innovation and transfer	Intellectual leadership [67, 68]	Driving mass customization through adaptive new technologies
	AI development [2, 8, 13, 18, 19, 25, 27, 34, 37–42, 50]	Privacy, consent, and transparency issues
Ethical and practical considerations	Accuracy and credibility [1, 2, 13, 18, 21, 39]	Ensuring accuracy and contextual relevance in AI-generated information
	Privacy concerns [1, 26]	Supporting various organizational tasks with privacy, developing responsible ML systems
Organizational knowledge and ML	Work design characteristics [18]	Managing perceived autonomy, organizational support and psychological costs
Digital Voice Assistants	Organizational context [37]	Different organizational contexts on ML teaching systems requirements
Machine learning-based teaching system	Customer service [36, 61]	Enhancing service through NLP
Net-Language Models in Telecommunications	Task Automation [1–4, 8, 14, 15, 20, 24, 32, 37–39, 54, 57]	Automating repetitive tasks and predictive maintenance
	Fraud detection [48]	Analyzing customer data for fraud detection
	Sales and marketing optimization [1, 61]	Personalized customer engagement and sales forecasting.
	Privacy and data security [2, 5, 18, 61]	Ensuring patient confidentiality in clinical practice
Barrier in LLMs application	Inaccurate outputs [35]	Reducing biases and inaccuracies in AI-generated information
	AI competencies [2, 5, 18, 39, 55]	Integrating AI into medical care training
	Network optimization [59]	Modelling user responsiveness to network recommendations
Optimal self-development in wireless networks	Propagation models [52]	Improving models for faster convergence in optimization
	Joint optimization strategies [48, 52]	Coordinating multiple extenders for better network performance
	User education [1, 4, 8, 24, 25, 56, 60]	Educating about limitations and biases of GAI tools
Chat GPT and GAI tools	Regulation development 3, 20, 23, 25, 28–31, 34, 36, 37, 39–41, 47, 65, 66]	Balancing protection and innovation
	AI quality [12, 23, 38, 48]	Accessing high quality data for AI training
Briefing note creation with AI	NLP limitations [1, 2, 13, 24, 60]	Improving NLP systems for briefing note generation
	Knowledge sharing [1, 4, 7, 12, 13, 15, 17, 20, 24–35, 49, 50, 56]	Proving diverse perspectives
Diversity in virtual teams	Innovation [3, 20, 23, 25, 28–31, 34, 36, 37, 39–41, 47, 65, 66]	Enhancing innovation through knowledge sharing initiatives
	Medical making decision [2, 18, 22, 39]	Combing mathematical models with medical knowledge
Integration of Math and IT in medicine	Fuzzy set theory [58]	Applying fuzzy set theory and Bayesian methods in diagnosis.

The analysis of trust establishment validating knowledge has underscored their critical roles in the phases of successful adoption of LLMs and GAI. Human elements in AI and technology drive KM system (in responding to RQ2) identified trust -related challenges are multidimensional and challenges (Table V) in which trust mechanism, ethical frameworks and knowledge validation are essential in maximizing the potential of GAI and LLMs in KM.

V. Future Perspectives

A. Enhancing Data Privacy and Security-Detecting Hidden Bias

There is a strong emphasis on protecting sensitive data and ensuing data anonymity in certain fields, such as healthcare and educational settings. In other words, developing models or systems need to explain how the problems are approached; which datasets are being used; whether others have the ability to reference, audit or replicate those processes or not; and finally, why a certain technology is used [1, 16, 18, 27] Future research must focus on the development of advanced anonymization technologies to protect sensitive data while ensuring its utility for AI training and KM. This could explain why ensuring that AI systems comply with data privacy regulations and regular updates made to handle data are necessary [13, 38, 45].

B. Advanced Collaborative Platforms

The development of more organized and advanced collaboration platforms, utilizing AI and blockchain, to guarantee safe and effective information exchange are practical approaches such as KM in medical care, education, building and cultural heritage reservation, and disaster management. While ensuring knowledge sharing and cooperation, cultural and technology integration will be critical in incorporating varied cultural and technological practices to improve knowledge sharing across organizations 17, 20, 25, 59, 63] Innovation and information sharing, or transfer, are crucial for organizational growth and resilience in terms of knowledge management techniques, intellectual property, and leadership, as well as the integration of modern technology to promote innovation and enhance outcomes [3, 15, 24, 28, 50, 52, 54].

C. AI and Machine Learning Development-Reestablishing Trust

Future research will emphasize participatory approaches to AI development, ensuring that these systems are produced responsibly and with input from various stakeholders. This aims to ensure that AI-generated material is accurate, credible, and contextually relevant in vital domains like healthcare and education [1, 2, 8, 14, 18, 38, 47, 50, 52]. While AI-driven optimization continues to create approaches for network creation, system administration, and performance enhancement, blockchain technology could be used for safe and efficient knowledge exchange in IoT and other distributed systems. Cross-disciplinary techniques are increasingly being used to stimulate and integrate various technologies successfully [16, 29, 37, 50, 52, 59]. Trust remains a critical bottleneck to the technological adoption of GAI and LLMs in the entire KM processes, accuracy concern where LLMs can produce misleading and inaccurate information [1, 20, 31, 39, 66]. Knowledge validation proposed by RAG models [1, 14, 20, 50, 58] and technological competence [3, 26, 37] in the development and delivery of its product and services are considered keys to establishing organizational trust.

While developing, improving, and integrating advanced AI into existing systems, there is an increased need to focus on ethical guidelines for AI trust. These programs have addressed both public and scientific anxiety over the loss of control over this change. As a result, it is not just consumers or clients who want a clear vision for AI. This complicates the entire landscape of stakeholders surrounding AI, whereas openness and responsibility in AI will ensure that sophisticated or AI-powered algorithms are thoroughly tested, explainable, and aligned with the basic goals of companies. In the long run, it allows organizations to control of their knowledge management systems and AI models [1–3, 14, 18, 21, 24, 28, 38, 39, 61].

D. Educational Training and Interactive Learning Systems

Educational institutions and businesses will revise their frameworks and curricula to incorporate AI and big data technology to ensure that users are equipped for future work. Specifically, specialist training programs for professionals to keep up with rapid technological changes in their industries. The design and deployment of interactive ML systems should be carefully adapted to various organizational, educational, and business contexts [3–5, 17, 19, 25, 29, 38, 42].

E. Ethical Considerations in AI Adoption in KM

The creation of comprehensive ethical frameworks is essential to guide the development, usage, and integration of AI, addressing challenges such as bias, transparency, and explainability, ensuring that AI systems are deployed in accordance with ethical standards and respect for privacy, consent, and credibility. In particular, the literature review in the period from 2023–2023 (shown in Tables III and IV) highlights significant challenges in technological adoption. In specific industries, take banking and healthcare for example, utilizing LLMs outputs could possibly reinforce organizational disparities and inequalities involving in the decision-making process. Authors [1, 42, 64, 68, 69] concerned industries like banking, healthcare and education where LLMs inputs and output are used for extremely sensitive tasks such as clinical consulting or even credit scoring. While several works [1, 41] emphasized the nature of LLMs (black-box), lack of explainability and transparency are contributed to complicating credibility and trust. Especially in the field of healthcare where doctors and practitioners are demanding clarity and precision in diagnosing and recommendations from AI systems [35].

Research into strategies is necessary for identifying and reducing errors in training data and algorithms. Thus, research into strategies for detecting and reducing errors in training data and algorithms is necessary [2, 5, 11, 13, 15–17, 20, 26, 31, 37, 38, 40, 41, 47, 52, 55–58, 68].

Leadership must step up to be formally warned about not only ethical uncertainties surrounding AI, but also to establish a clear vision of companies and organizations' values, communicate them internally, and ensure that the use of any additional technologies is consistent with these values. Importantly, digital ethics must be embedded into entire KM process to have a good impact not only on businesses but also on society [3, 16, 28, 40, 41, 55].

In responding to RQ3, the findings and future perspectives have highlighted the opportunities in integrating Gai and LLMs to leverage KM practices. The opportunities those technologies have brought include enhanced knowledge sharing, more precision in knowledge creation with applications of LLMs to improve knowledge output and save time. Furthermore, these technologies also improve the accuracy of generating knowledge by rapidly providing insights and automating tasks. These activities lead to better decision-making. Importantly, LLMs and GAI allow scalability and efficiency, exceeding traditional ways of sharing knowledge to manage large datasets and workflows. Their supportive technologies include the use of personalized knowledge graphs, context driven chatbot conversations, and dynamic-real time recommendations.

However, to address associated risks, organizations also have also encountered bias in AI systems with trust-related issues remaining the large proportion among users, stakeholders. Besides, ethical consideration and knowledge validation obstacles can also affect the fairness and reliability of the knowledge processes.

VI. Conclusion

Academic and professionals have extensively discussed the concepts of knowledge management and sharing, particularly in the context of advanced technologies like GAI and LLMs. The research has identified some key gaps including the need for trust mechanisms, data protection and privacy enhancement, emphasizing ethical considerations and frameworks. There is a necessity to implement strategic data management schemes and robust ethical frameworks. While it has been proved that GAI and LLMs have shown significant benefits such as enhancing knowledge transfer, creation and precision, improving work performance and operational efficiencies as well as real-time decision-making processes, their long-term impacts and implications on KM systems and practices are underexplored. Additionally, addressing issues like maintaining and establishing trust loyalty, reducing bias, and validation of knowledge outputs is essential to empowering knowledge exchange and maximizing the potential of reusing knowledge to create and validate new knowledge. Moreover, interdisciplinary research with diverse collaborations and participatory research approaches are critical for guaranteeing that these emerging technologies are aligned with organizational values and societal implications and expectations.

This study recognizes the limits of the publication inclusion procedure, which depended on a filter of supplied databases. As a result, the findings may be lacking in diversity among industries. Geographical concentrations in this study may limit the diversity of the findings, as one of the criteria is to rely on peer-reviewed publications to ensure the studies' reliability and quality. As a result, future research should address this issue, with the goal of balancing innovation with the challenges of integrating GAI and LLMs into knowledge management systems. Consequently, while there may be significant prospects for improving organizational performance and decision-making processes by including GAI and LLMs into KM processes, the integration of stakeholders as humans is critical. Collective intelligence and human commitment are expected to be considered when addressing ethical difficulties, scalability challenges, transdisciplinary approaches, and domain-specific adaptations. The efforts will not only ensure that GAI and LLMs are deployed appropriately but will also maximize the potential of these technologies to build long-term and intelligent knowledge management practices.

In responding to potential research directions, future research should concentrate on bridging the gaps in the identified papers through actionable frameworks and strategies. Future work should focus on navigating for future trust, including bridging the trust gaps. We should conduct longitudinal studies to investigate long-term strategies for building trust in digital AI systems, such as leadership roles, cross-cultural management, user engagement and feedback, and trust metrics. Secondly, ethical challenges should be addressed by deepening actionable ethical frameworks and tailoring industry-specific disciplines to illustrate biases, fairness, explainability, traceability, and transparency. Moreover, leveraging scalability and specific domain adaptation to improve the current capabilities of fine-tuning of LLMs for specified applications is currently critical and is heavily paid attention to. Reducing resource dependency will enhance efficiency. Securing and guaranteeing knowledge processes is to apply blockchain and federated learning to address data security issues, improving knowledge validation systems and mechanisms, developing data sensitive infrastructure. Finally, educational and professional training development, for example, interdisciplinary approaches, should be embedded into educational training programs to promote responsible adoption of AI-related technologies.

Conflict of Interest

The authors declare that there is no conflict of interest in this work.

Author Contributions

Lan T. K. Nguyen conducted research, performed data collection, and carried out the bibliometric analysis. Dr. James Connolly supervised the research design, guided the analytical approach, and assisted in structuring the findings. Professor Hoa N. Nguyen contributed to the methodological framework, data interpretation, and provided critical revisions to enhance the clarity of the manuscript. All authors collaboratively wrote and edited the manuscript and have approved the final version for submission.

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