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AI Agents for Organizational Knowledge Retrieval and Sharing: A Systematic Literature Review

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ABSTRACT

As data complexity and volume increase, traditional knowledge management systems struggle to keep up. Distributed teams have transformed how employees manage their knowledge within organizations. Artificial intelligence (AI), especially AI agents, is increasingly being used as a solution to these challenges, yet research on their capabilities and implications remains fragmented. This study evaluates recent research on AI agents for organizational knowledge retrieval and sharing. A PRISMA-based Systematic Literature Review (SLR) was carried out on English-language studies published between 2020 and 2025 across six databases: Scopus, IEEE Xplore, Science Direct, ProQuest, Sage Journals, and Taylor & Francis. Twenty-eight studies were analyzed to classify AI-agent capabilities, technologies, and key challenges across diverse domains. The results revealed five key capabilities: user-centered interaction, semantic knowledge extraction & retrieval, intelligent reasoning & decision support, automation & workflow management, and explainability & traceability. These capabilities were enabled by technologies, such as large language models, machine learning, natural language processing, knowledge graphs, ontologies, and other prominent technologies. Adoption challenges primarily included data quality & semantic alignment, system interoperability, trust & adoption issues, and ethical concerns. This review concludes that AI agents hold potential to improve knowledge processes, but it requires strategic integration, data governance, and human-centered design principles.

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1. INTRODUCTION

Knowledge is no longer just a supporting factor in organizations' survival. It is now one of the primary factors in deciding whether an organization will stay competitive for a long time [1], [2]. In a business environment filled with uncertainty, high complexity, and rapid change, organizations are required to have the ability to manage, distribute, and utilize knowledge effectively to adapt to the ever-changing business environment [3]. Failures in maintaining expertise or retaining key knowledge that's needed for the operation of the organization may result in a big financial loss, as experienced in a lot of Fortune 500 companies [4], [5]. This knowledge is especially important for

teams that work from different locations or operate remotely and must share information quickly to work together across time zones [6], [7]. The move to remote and hybrid work models was accelerated by the COVID-19 pandemic, and over the past two years, it has significantly increased. A study on job trends for 2025 indicates that hybrid roles have increased by 167% and fully remote roles have risen by 30% during this period [8]. This way of working, where the team are geographically dispersed, has increased dependency on asynchronous digital collaboration and communication.

For collaboration to remain effective across time and locations, knowledge must be able to be accessed, shared, and applied quickly [4], [6], [9]. According to a McKinsey report from 2012, the process of looking for the correct internal information usually takes up to 20% of employees' time [10]. This manual process can lead to lower productivity and efficiency at work. Therefore, a formal system and established methods are usually required to do these processes. This system will solve issues such as knowledge fragmentation, difficulty in locating information, and danger of loss when employees leave the organization [2]. However, traditional knowledge management systems are often not enough and have their own difficulties. Some systems can experience trouble in keeping up with the complexity and the growing amount of information as the organization grows larger [10], [12]. Solutions such as manual knowledge bases or static document repositories often cause disparities in access to knowledge resources, because they lack personalized features and adaptability. As mitigation, stakeholders must actively develop and distribute knowledge, which demands substantial motivation, effort, and leadership supervision [12], [13].

Artificial intelligence (AI) gives organizations innovative ways to handle their knowledge. Many businesses have increased the use of AI, especially when it comes to finding and sharing information in large and decentralized environments. According to a report by Dimension Market Research, the global market for AI-based knowledge management systems is expected to be worth USD 9.6 billion in 2025 and USD 251.2 billion in 2034, with exponential growth reaching 43.7 [14] A survey conducted by APQC (2025) found that 41% of KM experts think that combining AI and smart technologies is a top priority for KM right now. The same study also revealed that 44% of respondents hold the belief that generative AI is essential for creating new knowledge management artifacts and content, while 39% believe that AI is highly important for giving content or knowledge asset recommendations [15]. AI agents are one of the most major advances in AI-based knowledge management, an alternative for both traditional and full-scale AI-based KMS. It refers to autonomous systems that can do things by creating and executing workflows, which are sets of coordinated actions that utilize existing tools to achieve goals [16], [17]. These agents utilize natural language processing, machine learning, knowledge graph and reasoning techniques to facilitate the discovery, retrieval, and exchange of information [18], [19]. They do this by using interactive interfaces that have natural conversations with users, understand the context, process vast amounts of data, and give information that helps make decisions.

This potential has resulted in a growing body of research focused on AI agents that benefit organizations, particularly as these agents transition from traditional rule-based systems to generative model-based conversational agents using retrieval-augmented generation (RAG) architectures [20], [21]. Some previous research identifies how these agents make information retrieval more relevant, efficient, and long-lasting by solving challenges in how knowledge is identified, validated, and presented [20], [22]. It also assists people with new knowledge and ideas, organizes and shares them more quickly [23], [24]. Study from [25] also shows that intelligent agents help people share knowledge in three main ways: by acting as an external memory that stores and shares knowledge, by being active team members, and by becoming cognitive partners that help people do knowledge-based work better. Some studies also highlight challenges associated with achieving AI agents' full

potential in organizational contexts. Organizations often encounter significant impediments to adoption, including data quality issues, inadequate user trust, integration constraints, and ethical considerations [18], [26].

Despite the recent significant attention these subjects have received, the existing research remains dispersed. Most of the current research has only looked at generic KMS integration with AI technologies, high-level frameworks, or specific implementations or focuses more on technical development. Recent progress in generative AI, conversational agents, and retrieval-augmented architecture in knowledge management settings has not been sufficiently analyzed. This leads to gaps in awareness of the practical uses of AI agents for handling organizational knowledge and its challenges when implemented. Thus, a more comprehensive understanding is essential. This review helps organizations make informed decisions by investigating several research questions:

1. What are AI agents' main capabilities for enhancing knowledge retrieval and sharing?
2. What kinds of technology can enable these capabilities?
3. What are the challenges in adopting AI agents for knowledge retrieval and sharing?

This review aims to collect and analyze dispersed material produced between 2021 and 2025 to provide a more profound understanding of this topic. The analysis identifies the key capabilities of AI agents, explains how they operate, and highlights the challenges that must be addressed before they can be effectively implemented. The findings contribute to both theory and practice by offering structured insights and guidance for organizations, drawing on real-world examples, and addressing common issues that hinder efficient deployment.

2. RESEARCH METHOD

This research review was conducted using PRISMA 2020 guideline as the main references in organizaing the stages of a systematic review. This protocol includes several steps, such as defining eligibility criteria, selecting relevant articles, extracting data, assessing article quality to minimize bias, and synthesizing findings [27], [28]. This method ensured that the procedures and literature selection were clear and correct, while also making it easier to duplicate the review [29].

2.1. Eligibility Criteria & Search Strategy

The PICO (Population, Intervention, Comparison, and Outcome) model was used in this review to ensure a systematic and organized approach [28]. It helps in making a focused search plan for identifying useful material, such as explicit rules about what to include and what to leave out in the process, as outlined in Table 1.

Table 1. Structure of Research Using PICO Model

Element	Description
Population	All types of organizations that implement or aim to improve KM practices.
Intervention	Adoption or integration of AI agents that support knowledge sharing and retrieval within KM systems.
Control/Compare	N/A
Outcome	Identification of main capabilities of AI agents in KM; How they facilitate knowledge retrieval and sharing; and Challenges or barriers in their adoption.

The search was limited to the databases accessible through the authors' institution. Some commonly used databases could not be included due to the lack of institutional access, which may limit the knowledge base coverage. However, six available database sources and broad Boolean combinations were applied to mitigate this limitation. The research applied the systematic review search strategy described in Table 2.

Table 2. SLR Eligibility Criteria and Search Strategy

Database	Restriction	Filters	Query
Scopus	Metadata (Article title, Abstract, Keywords)	• Conference Paper, Article • 2020 – 2025 • English	TITLE-ABS-KEY (("AI agent*" OR "artificial intelligence agent*" OR "intelligent agent*" OR "conversational agent*" OR "generative agent*" OR "virtual assistant" OR "digital assistant") AND ("knowledge sharing" OR "knowledge retrieval" OR "knowledge exchange" OR "knowledge transfer" OR "knowledge management" OR "organizational learning") AND ("capabilities" OR "applications" OR "implementation" OR "use case*" OR "benefits" OR "challenge*" OR "barrier*" OR "adoption" OR "limitation*" OR "risk*"))
IEEE Xplore	Metadata (Article title, Abstract, Keywords)	• Conferences, Journals • 2020 – 2025	("AI agent*" OR "artificial intelligence agent*" OR "intelligent agent*" OR "conversational agent*" OR "generative agent*" OR "virtual assistant" OR "digital assistant") AND ("knowledge sharing" OR "knowledge retrieval" OR "knowledge exchange" OR "knowledge transfer" OR "knowledge management" OR "organizational learning") AND ("capabilities" OR "applications" OR "implementation" OR "use case*" OR "benefits" OR "challenge*" OR "barrier*" OR "adoption" OR "limitation*" OR "risk*")] Notes: the string query are same for these databases.
ProQuest	Anywhere (all)	• Conference Paper, Article • 2020 – 2025 • English	
Sage Journals	Anywhere (all content)	• Research Articles • 2020 – 2025	
Taylor & Francis	Anywhere (all)	• Article • 2020 – 2025	
Science-Direct	Anywhere (all)	• Research Articles • 2020 – 2025	("AI agent" OR "intelligent agent") AND ("knowledge sharing" OR "knowledge retrieval" OR "knowledge transfer") AND ("capabilities" OR "implementation") AND ("challenge" OR "limitation")

The default Boolean search string was executed in Scopus, IEEE Xplore, ProQuest, Sage Journals, and Taylor & Francis. Database Scopus and IEEE Xplore apply the query primarily to metadata fields (title, abstract, and keywords), while ProQuest, Sage Journals, ScienceDirect, and Taylor & Francis perform full-text indexing across the entire article's content and metadata. All databases execute the same string query, except for ScienceDirect, which has a limitation that only allows a maximum of 8 connectors. Therefore, simplified versions of the search string were used in these databases to ensure the search could be executed without errors.

Although the search string covered broad terms related to AI agents, knowledge retrieval, and knowledge sharing, the terminology used in this field is diverse and evolving. Alternative terms may not have been fully captured by the keyword set, resulting in some relevant studies using different vocabulary that may not have been retrieved. The study only includes English-language, peer-reviewed journal articles and conference proceedings, which may exclude relevant insights from non-English sources or grey literature. Using the keywords and criteria defined, 2457 records are identified through database searching. All articles retrieved were imported into CADIMA for further processing, which is to help in duplicate removal, screening, and article selection. The retrieved articles are then checked to determine if there are any duplicate articles that need to be removed. A total of 80 articles are removed due to duplication, and 2377 records are screened at the article selection level to check for any similarities with keywords and criteria.

2.2. Article Selections

The article selection process consisted of two stages: screening from the titles and abstracts, then reviewing from the full texts. The articles are selected based on the assessment of specific

inclusion and exclusion criteria defined to ensure that they meet the eligibility requirements identified. The list of inclusion and exclusion criteria (table 3) was developed based on the established PICO model and aligned with the scope of this review, which was used consistently while screening titles, abstracts, and full texts.

Table 3. Criteria Applied in Article Selection Process

Inclusion Criteria	Exclusion Criteria
The study involves AI agents within KM context	The study evaluates topics unrelated to AI agents in KM
It addresses knowledge sharing and/or knowledge retrieval within organization	It does not discuss organizational KM context, knowledge sharing or retrieval.
It focuses on capabilities, application, or challenges of using AI agents in organization.	It focuses solely on technical aspects of AI.
It provides empirical findings (primary or secondary data).	It is purely conceptual without empirical validation (only models or frameworks).
It is academic in nature (journal or conference).	It is a non-academic publication or a systematic review.

During screening, studies were included when they demonstrated AI agent involvement in knowledge-related tasks, evidence of knowledge retrieval or sharing, organizational relevance, empirical methodology, and publication in peer-reviewed academic venues. Studies were excluded when they lacked KM relevance, focused solely on technical AI development, were conceptual only without empirical validation, or were non-academic or non-English. These operational criteria definitions ensured a consistent process, while ambiguous cases were resolved through close examination of the study's objective, methods, and contributions at full-text review. At the title and abstract screening stage, a total of 2377 articles were screened, and after relevance assessment, the final selection was narrowed down to 340 articles. During the full-text review, each article was examined in detail to verify its suitability to criteria defined in table 3. Several articles were excluded because they didn't reach the criteria or because the full text of the paper could not be obtained (inaccessible). After completing this stage, a total of 34 articles remained for the next step.

2.3. Quality Assessment

After the article selection process was done, a quality assessment was conducted to ensure that the included studies are methodologically sound, transparently reported, and reliable for synthesis. The following criteria were used to make this assessment: (1) clarity of the research problem; (2) explicit research objectives; (3) adequate methodological explanation; (4) availability of empirical data; (5) transparent presentation of findings; (6) alignment between conclusions and research questions; and (7) relevance to organizational or theoretical contexts. Each criterion was scored on a scale of 0 to 1, with "Yes" receiving a score of 1, "Partially" receiving a score of 0.5, and "No" receiving a score of 0, producing a possible minimum score of 0 and a maximum of 7.

Some studies were relevant but received lower scores during quality assessment because they leaned more toward technical or purely conceptual discussions and less organizational integration. To select final studies for the review process, a full-score threshold (7 out of 7) was applied to ensure compliance with all quality criteria. The aim of the full score was to avoid including partially reported studies. This SLR focuses specifically on organizational knowledge retrieval and sharing, so partial compliance with multiple criteria would have introduced inconsistencies in the final synthesis. Therefore, studies with a total score of less than seven were eliminated from the final analysis, resulting in 28 articles for extraction and synthesis.

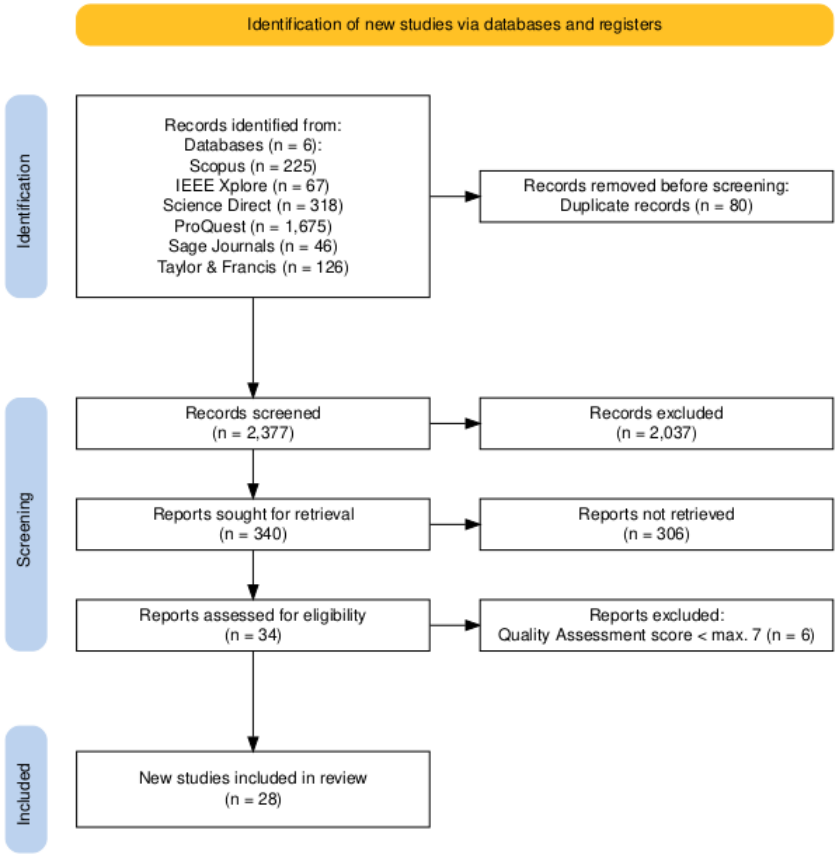


Figure 1. PRISMA Flow Diagram using Shiny app [27]

Study selection and initial quality assessment were conducted by a single reviewer (first author) and subsequently reviewed by the second and third authors. This approach was performed to minimize bias and ensure consistency in the selection process. However, due to time and resource constraints, a full dual-reviewer independent screening and a formal inter-rater reliability assessment (Cohen's Kappa or Fleiss' agreement coefficient) were not feasible to perform. As mitigation, the review used clearly defined inclusion and exclusion criteria, assessment guided by alignment with research questions, and repeated processes multiple times to reduce subjectivity. Any uncertainties or differing interpretations were discussed among the authors until a decision was reached.

2.4. Data Extraction and Synthesis

The data extraction process was conducted using a spreadsheet to systematically collect key information and details from each included study. Its objective was so that the results could be compared, analyzed, and combined, while ensuring the gathering process was consistent and transparent. The extraction process involved reviewing all included articles and recording key information, such as publication details (authors, publication year, article title, source or journal, publisher, country or region), organizationl or domain context, methodological details, type of AI agent, technology approach, reported capabilities, benefit, and challenge.

Following data extraction, the findings were synthesized using thematic analysis. In this method, data from the studies were coded and grouped into similar categories based on their relevance to the research questions [30]. These categories included the main capabilities associated with AI agents (RQ1), the technological approaches used to facilitate these capabilities (RQ2), and the difficulties encountered in practical application (RQ3). This approach enabled the identification of recurring patterns across studies and quantitative summaries of the findings across groups.

Both processes were conducted manually by the primary researcher, which included multiple iterations to ensure accuracy and consistency. These processes were executed with supervision and verification provided by other authors. Microsoft Excel was used to organize and track metadata for the data extraction process. No qualitative data analysis software (such as NVivo, ATLAS.ti, or MAXQDA) was used in this review, which the authors acknowledge may present a limitation and cause the risk of human error. However, this approach allowed for richer interpretation and traceability provided by the documentation and coding logic [30].

3. RESULTS AND DISCUSSION

The following section provides the results of data analysis, extraction, and synthesis in accordance with the research questions explained above. A bibliometric analysis was also performed using VOSviewer version 1.6.20 to examine co-occurrence of keywords, which can be seen from Figure 2 below. The analysis results show that there are 11338 keywords from 2331 records, and there are 98 keywords that appear more than 75 times. Among the keywords that appear the most frequently are artificial intelligence (841 occurrences), machine learning (391 occurrences), decision making (355 occurrences), algorithms (326), knowledge management (314), chatbots (217 occurrences), large language models (200 occurrences), intelligence agents (132 occurrences), and other related keywords.

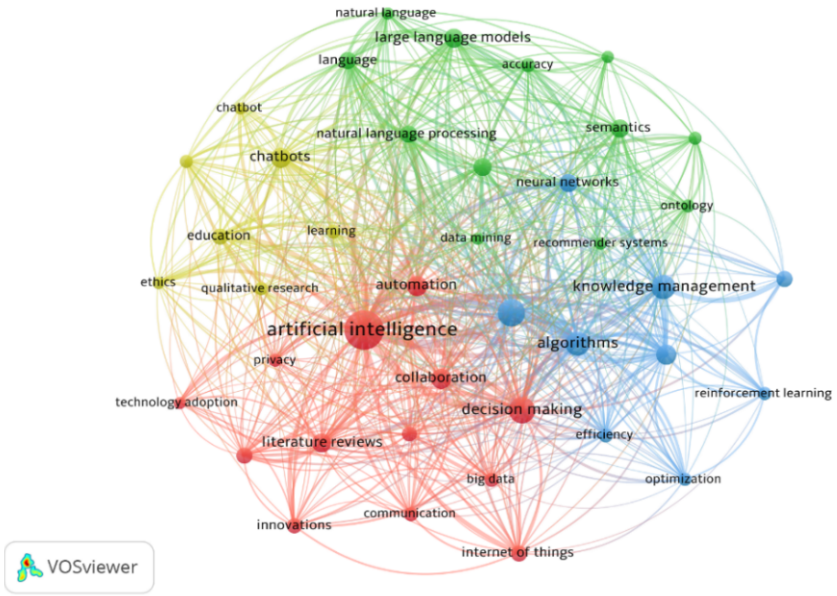
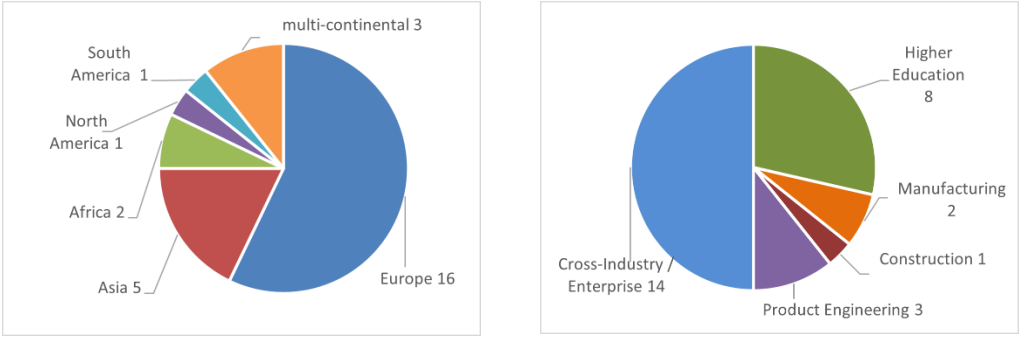


Figure 2. Co-occurence of keywords analysis

The SLR has produced 28 articles that focus on the use of AI agents for an organization's benefit, especially in knowledge retrieval and sharing. Based on the demographic distribution in the journal database sources, 5 studies come from Scopus, 3 from IEEE, 5 from ScienceDirect, 13 from ProQuest, and 2 from Sage Journals, published in 2020 (2 studies), 2021 (4 studies), 2022 (3 studies), 2023 (2 studies), 2024 (8 studies), and 2025 (9 studies). Figures below show the studies grouped by continent and industry.



(a) (b)

Figure 3. Group of Included Studies by: (a) Continent, (b) Industry

Based on literature review, various types of AI agents are employed by organizations all over the world to enhance knowledge practices. Numerous studies investigate the use of text or voice interaction by dialogue-based agents to facilitate knowledge search [24], [31], [32], [33]. Some studies examine multi-agent systems (MAS), collections of autonomous agents that work together to achieve common goals [34], [35], [36], [37]. Furthermore, there are also studies that discuss intelligent agents that are integrated into organizational systems (such as CRM or financial services) and perform AI functions for collective learning, automation, and decision support [38], [39], [40], [41], [42]. The classification of artificial intelligence (AI) agents used in the literature reviewed in this SLR is shown in the following table.

Table 4. Classification of AI Agent Types and Use Case

Category	Description
Conversational & Generative AI Agents	Dialogue-based and LLM-driven agent that facilitate information access, reasoning, and content generation through natural conversations. • In higher education, it's employed to facilitate learning, retrieval and reuse of knowledge for teaching and instutional KM process [25], [31], [33], [43], [44] • In academic-industry collaboration, it's deployed to facilitate knowledge retrieval, idea generation, employee training and innovation management [23], [24], [32], [45] • In enterprise cases, it's integrated across sales, decision-making, HR, and workplace systems to enhance organizational learning, decision support, and employee engagement [46], [47], [48], [49] • In the project management, it's employed to enable domain experts to access, interpret, and reuse project knowledge without deep technical expertise [26], [50]
Multi-Agent Systems (MAS)	A group of autonomous agents that collaborate or coordinate task to achieve a goal. • In higher education, it's deployed for systematic knowledge curation and explainable multi-agent collaboration in research contexts [35], [36] • In engineering and product design, it's used to enhance knowledge capitalization, distributed integration, and the construction of organizational memory [51]. • In manufacturing, these agents collaborate to support manufacturability analysis, design optimization, and engineering decision-making [37]. • It's used to orchestrate workflows in enabling domain experts to access, interpret, and reuse complex pipeline information without advanced DevOps expertise [34].
Intelligent / Domain-specific Agents	Knowledge-driven agents integrated in specific systems (CRM, HR, etc.) and perform reasoning, prediction, learning, and decision-making. • It's used across marketing in enterprises and in financial services, to transform business processes into intelligent, data-driven decision support, and collaborative ecosystems [38], [39], [40], [52].

Category	Description
	• In consulting settings and other sectors, it's used to bridge human expertise with organizational knowledge assets and helps in the tandem of tacit knowledge [42], [53]. • In higher education, it used to enhance personalization, collaboration, and academic integrity support [54].

3.1. Main Capabilities and Supporting Technologies

From the literature synthesis, several main capabilities were found that are generally possessed by AI agents to represent the necessary functions in supporting the search, process, and dissemination of knowledge in an organizational context. Based on findings from various studies, these capabilities can be grouped into several main categories that describe the role of AI agents in the knowledge management cycle. The main capabilities of AI agents within the KM context from reviewed studies are summarized in Table 5 below. The table reports each capability, its definition, the number of studies in which it appears or explained, and the key studies that focus on that capability.

Table 5. Main Capabilities of AI Agents in KM

Capability	Description
User-centered Interaction	Human-like dialogue using natural language interface; Personalization and tailored responses or feedback; Adaptive learning and support; Communication and real-time exchange. Key studies: [26], [42], [47], [48], [49], [54]
Semantic Knowledge Extraction & Retrieval	Extracts, annonates, and structure knowledge; Integration into repositories for reuse; enables context-aware, semantic, and vector-based retrieval. Key studies: [34], [35], [37], [40], [42], [44], [45], [50], [51], [53]
Intelligent Reasoning & Decision Support	Predictive analytics or insights; Explainable reasoning; Autonomous cognitive support and decision making. Key studies: [25], [36], [37], [38], [39], [41], [42]
Automation & Workflow Management	Task automation; Workflow orchestration and optimization; Integration with enterprise systems. Key studies: [37], [46], [53]
Explainability & Traceability	Transparency through explainable reasoning; Accountability by dialogue-based traces. Key studies: [26], [36], [38]

The synthesis of included studies reveals five dominant capabilities, as seen in the table. *User-centered Interaction* is the most dominant capability, appearing in 21 studies (75%), which reflects the heavy emphasis on conversational accessibility, personalization, and user engagement. Both *Intelligent Reasoning & Decision Support* and *Automation & Workflow Managemen*t appear in 19 studies (68%), while *Semantic Knowledge Extraction & Retrieval* appears in 15 studies (54%). This figure indicates that a large portion of existing research still focuses on enhancing cognitive processes and automating knowledge-intensive tasks, while functionality related to semantic enrichment, annotation, or context-aware retrieval is less frequently implemented and observed. Lastly, *Explainability & Traceability* is addressed in only 12 studies (43%), making it the least represented capability despite its importance for trust and transparency in AI-driven processes.



Figure 4. Frequency Comparison of Main Capabilities

Each of these capability categories is generally supported by technological approaches that serve to improve the agent's ability to understand context, interact naturally, and provide explainable recommendations. The combination of these capabilities and technological approaches demonstrates how AI agents can serve as intelligent facilitators in the process of sharing and utilizing organizational knowledge. The supporting technologies from reviewed studies are shown in table below.

Table 6. Key Technology Categories Supporting AI Agent

Category	Implementation
LLM & Generative AI	Use of ChatGPT, GPT-like, PaLM-2, and text-bison models for text generation, contextual reasoning, summarization, and adaptive conversational support. Key studies: [42], [44], [45], [46], [47], [50]
NLP & Dialogue Frameworks	Dialogflow, Rasa, NLTK, spaCy, Ivy.ai or other framework for entity recognition, intent detection, dialogue management, and conversational flow scontrol. Key studies: [23], [24], [31], [40], [42], [43]
Retrieval & Vector Databases	Use of RAG pipelines, LangChain, LlamaIndex, pgvector, or Pinecone for semantic document retrieval, embedding-based search, and context-aware grounding. Key studies: [34], [44], [45], [50], [53]
Ontology & Knowledge Graphs	Application of ontology-based semantic integration (RDF/SPARQL, WordNet) and knowledge graph construction tools (Naisc or Saffron) for knowledge extraction and linking. Key studies: [34], [35], [36], [40], [51]
Explainable & Multimodal AI	Integration of Explainable AI (XAI) frameworks and EDG dialogue protocols for transparent reasoning and traceability; Inclusion of multimodal systems combining text, image, and vision-based interfaces for knowledge representation. Key studies: [26], [36], [38], [39]
Machine Learning & Predictive Analytics	ML-based models used for pattern recognition, decision automation, forecasting, adaptive analytics, and supporting human-AI collaborative decision-making. Key studies: [25], [26], [34], [41], [42], [46], [49]
Multi-Agent Systems & Orchestration	Implementation of distributed reasoning and coordinated workflows using Chainlit, Kubeflow, LangChain agents, or other multi-agent orchestration for modular & scalable automation. Key studies: [34], [35], [36], [37], [39], [51]
Automation & Integration Stack	Embedding AI agents into enterprise environment via REST APIs, Slack integrations, AWS Lambda, Dockerized services, and CRM/ERP connectors to automated workflows. Key studies: [31], [34], [37], [46], [53]
Sentiment & Emotion Analytics	Use of sentiment and emotion-recognition models for organizational engagement; empathy-based dialogue and adaptive user feedback loops. Key studies: [47], [48]

The most frequently observed category of technologies across the included studies are *NLP & Dialogue Frameworks*, appearing in 19 studies (68%) and reflecting the reliance on conversational interfaces to enable natural interaction, summarization, and contextual responses. *Machine Learning & Predictive Analytics* appear in 15 studies (54%), while *Automation & Integration Stack* appear in 17 studies (60%), indicating that AI agents are increasingly embedded into enterprise systems to support prediction and task optimization. In comparison, the frequency of other approaches are all below half of the included studies, such as *LLMs & Generative AI* (11 studies, 40%), *Retrieval & Vector Search* (8 studies, 29%), and *Ontology & Knowledge Graphs* (6 studies, 22%), which demonstrates a growing interest in the subjects related to semantic grounding and structured representation but remains less commonly adopted. Similarly, *Explainable & multi-modal AI* (9 studies, 32%) and *multi-agent systems* (6 studies, 22%) also appear in a limited set of studies, reflecting a gap between their conceptual potential and practical deployment in organizational environments.

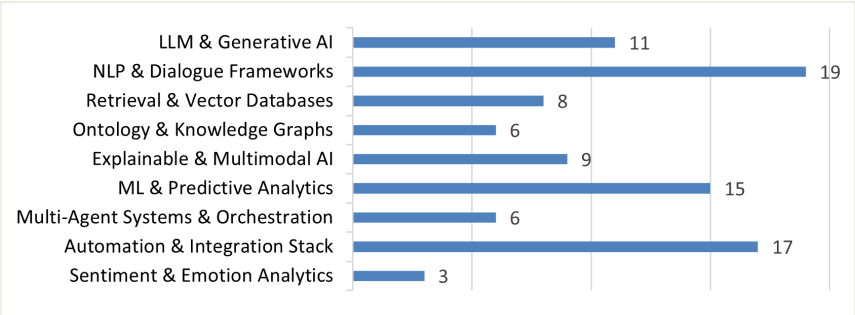


Figure 5. Frequency Comparison of Supporting Technologies

Across the studies, these technologies translate directly into the capabilities demonstrated by AI agents. Technologies such as NLP, LLMs, and machine learning enable user-centered interaction capabilities such as recognizing user intent, carrying out human-like conversational interaction, offering adaptive feedback, personalization, and giving sentiment-aware responses [23]. Semantic knowledge extraction & retrieval is supported by ontologies and knowledge graphs, which structure and integrate organizational knowledge [40], [51]. The addition of technologies such as RAG and vector DBs strengthens semantic search, especially to ensure context-aware retrieval [34], [50]. Organizations can also make informed decisions based on recommendations provided by intelligent reasoning, predictive analysis, and pattern recognition enabled by machine learning [26], [38], [53]. The implementation of explainable AI and sentiment analysis ensures that the output remains transparent, reliable, and trustworthy, while also providing empathy [36], [39], [48]. Some tools, such as AWS and Kubeflow, are also crucial for embedding AI agents because they provide orchestration and integrated components within enterprise workflows [31], [46].

3.2. Main Challenges of AI agents in KM context

Although the integration of AI agents promises significant enhancements in retrieval efficiency, contextual understanding, and collaborative sharing of knowledge within organization, the technological and organizational maturity of these systems is still at an early stage. The synthesis from the reviewed studies highlights various constraints found from the current implementation of AI agents, such as data issues, integration issues and human or organizational issues. The following table shows those challenges grouped into several categories.

Table 7. Main Challenges of AI Agent in KM

Category	Issues Identified
Data Quality and Semantic Knowledge Representation	Poor metadata management; inconsistent taxonomies and ontologies; complex data preprocessing; low knowledge graph precision; limited contextual grounding; immature repository structures. Key studies: [37], [40], [42], [44], [45], [51], [53]
Integration and Interoperability Complexity	Integration across distributed platforms; orchestration and runtime failures; limited scalability; lack of modular design; cross-system heterogeneity. Key studies: [34], [36], [37], [42], [45], [52]
Context Awareness, Adaptivity, and Domain Specificity	Lack of personalization and contextual awareness; absence of domain-specific datasets; difficulty handling structured or multi-step queries; lack of adaptive feedback loops. Key studies: [31], [37], [40], [42], [44]
User Adoption, Usability, and Cultural Resistance	Resistance to AI and automation; limited motivation and trust; usability and co-creation limits; cognitive fatigue in long interaction. Key studies: [31], [38], [42], [46], [48], [52], [53]

Category	Issues Identified
Explainability, Trust, and Human-AI Collaboration	Limited interpretability and transparency; explainability gaps; over-reliance on automated output; absence of feedback and continuous learning mechanisms. Key studies: [25], [36], [38], [41], [42], [50]
Ethical, Privacy, and Governance Concerns	Data privacy and copyright violations; liability issues; bias and fairness issues; transparency concerns; regulatory non-compliance; ethical and security vulnerabilities. Key studies: [26], [32], [39], [42], [46], [47], [53], [54]

The challenges identified across the included studies reflect a mix of technological and human-organizational issues, with several patterns related to the frequency analysis. Technological barriers, such as *Integration & Interoperability Complexity* and *Context Awareness, Adaptivity, and Domain Specificity* were the most frequently reported, appearing in 19 studies (68%). It highlights persistent difficulties in orchestrating AI agents across distributed platforms, handling heterogeneous and unstructured data sources, and generating outputs that are contextually relevant to diverse environments. *Data Quality and Semantic Knowledge Representation* are present in 14 studies (50%), with issues such as poor metadata management, inconsistent taxonomies, and inadequate integration between structured and unstructured sources causing the inaccuracy in retrieval and increased agent hallucination risks [34], [40], [44], [45]. On the human side, *User Adoption, Usability, and Cultural Resistance* also appear in 18 studies (64%), underscoring how emotional resistance to automation, low motivation, and usability constraints continue to limit the effective use of AI agents [31], [46], [48]. Challenges related to *Explainability, Trust, and Human-AI Collaboration* appear in 18 studies, showing that limited transparency, poor clarity, and lack of explainability of logic used can significantly weaken trust and hinder adoption [38], [41], [50]. Meanwhile, *Ethical, Privacy, and Governance Concerns* are less frequently reported (9 studies), yet they remain critical to address, involving issues regarding data privacy, copyright, security risk, and other regulatory compliance [26], [32], [39], [47], [54].

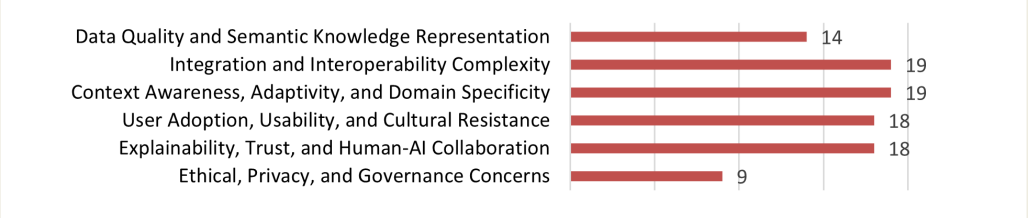


Figure 6. Frequency Comparison of Main Challenges

3.3. Limitation of Primary Studies

The review reveals several recurring limitations based on the primary studies included. One of the most prevalent problems is that, in more than 35% of the studies, evaluations only occur as one-time interactions (not longitudinal or long-term), which makes it impossible to track adoption, performance, or success over time [23], [39], [46], [49], [54]. Several of these studies are survey-based, which use self-reported perceptions instead of observed behavior [26], [32], [39], [43], [44], [54]. This raises the probability of common method bias. Several of these studies also use small sample sizes or very specific groups, which makes them less reliable and less relevant to other contexts [26], [47], [50], [54]. Some articles use case studies or pilot implementations, which offer insightful information but also constrain the ability to generalize across different industries [25], [41], [45], [53]. Some technical studies used simplified databases or early-stage AI approaches that may not reflect complex organizational knowledge processes [36], [37], [45], [51]. Furthermore, several studies do not include baseline comparisons with traditional search tools, making it ambiguous

whether the advantages stem from AI components or from overall enhancements in information management [24], [31], [34], [38], [45]. These limitations suggest that while the current body of work demonstrates the potential of AI agents, much of the evidence remains constrained by methodological boundaries.

4. CONCLUSION

This review analyzed the use of AI agents in organizational knowledge retrieval and sharing from articles published between 2020 and 2025 using PRISMA protocol. The findings from 28 articles confirm that AI agents can augment knowledge retrieval and sharing through five key capabilities: user-centered interaction, semantic knowledge extraction & retrieval, intelligent reasoning & decision support, automation & workflow management, and explainability & traceability. These capabilities are supported by technologies such as large language models, retrieval-augmented generation, knowledge graphs, machine learning, multi-agent or ontology-based frameworks. However, current implementations remain uneven and technically underdeveloped in several critical areas. While conversational NLP-based agent dominate recent development, categories such as generative models, semantic grounding, explainability mechanisms, and multi-agent orchestration remain underexplored. There are also a few challenges that require consideration so that AI-driven knowledge management can function effectively. This challenges include technological or organizational aspects, such as poor data quality and semantic inconsistencies, integration and interoperability barriers, limited context awareness and adaptivity, user adoption and cultural resistance, trust and transparency issues, and ethical or governance risks.

This review provides an evidence-based reference for organizations seeking to implement AI agents to enhance knowledge practices in organizations. However, this review also has several limitations, especially as most of the primary studies were short-term, exploratory, prototype-based, or reliant on self-reported perceptions. It provides limited insights into the long-term impact of the solution. Rapid technological advancement related to AI may also reduce the longevity of the results. Methodologically, the review relied on a single initial reviewer and lack a formal inter-rater reliability assessment, ntroducing some risk of subjective bias despite subsequent validation by co-authors. In addition, limited institutional access restricted the inclusion of certain databases, and a strict quality assessment threshold was applied, which may have influenced the breadth of the evidence base and excluded partially reported yet potentially useful studies. In accordance with this, future research should focus on developing understandable, trustworthy, and interoperable AI agents supported by strong data governance and human-in-the-loop design. Empirical and longitudinal studies are also needed to evaluate performance outcomes in a longer period of real-world adoption.

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