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The Evolution of AI-Powered Knowledge Management Systems: A Systematic Literature Review and Future Research Agenda

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ABSTRACT

Knowledge Management Systems (KMS) have evolved from rigid databases into intelligent repositories driven by Artificial Intelligence (AI). However, a systematic synthesis tracing this evolution up to Generative AI remains fragmented. Addressing this critical research gap, this Systematic Literature Review (SLR) investigates the technological evolution of AI-powered KMS, maps AI applications across the Knowledge Management Lifecycle, identifies deployment challenges, and proposes a future research agenda. Following PRISMA 2020 guidelines, a total of 105 peer-reviewed articles published between 2018 and 2026 were retrieved from Scopus, IEEE Xplore, and Web of Science for qualitative and quantitative synthesis. The review identifies three evolutionary eras, culminating in Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG). Quantitative analysis reveals that AI integration is heavily concentrated in knowledge retrieval (representing 45% of analyzed studies) and creation. However, critical deployment barriers persist, particularly model hallucinations, enterprise data privacy, high computational costs, and user adoption resistance. This study distinguishes itself from previous reviews by providing a structured taxonomy of AI paradigms in KMS, offering strategic blueprints for enterprise deployment, and outlining future research trajectories focusing on Graph-RAG, multi-modal agents, edge-deployed local models, and AI governance frameworks.

KEYWORDS: Artificial Intelligence, Systematic Literature Review, Retrieval-Augmented Generation, Generative AI, Knowledge Lifecycle.

1. Introduction

In the contemporary knowledge-driven economy, organizational competitive advantage is increasingly determined by the capacity to capture, structure, share, and apply intellectual capital efficiently 1, 2. Traditional Knowledge Management Systems (KMS) were developed to serve as centralized digital repositories aimed at mitigating knowledge loss, fostering organizational learning, and enhancing decision-making capabilities 3, 4, 5. For decades, these conventional systems relied on rigid relational databases, manual taxonomy tagging, and structured keyword indexing to maintain corporate knowledge bases 6. However, as the volume, velocity, and variety of organizational data expanded exponentially in the digital era, legacy KMS exposed significant operational limitations. Employees frequently encountered information overload, poor search relevancy, complex document retrieval procedures, and low system adoption rates, ultimately rendering many organizational knowledge bases stagnant and underutilized 7, 8.

To overcome the friction inherent in traditional KMS, researchers and practitioners turned toward Artificial Intelligence (AI) to transform passive repositories into proactive, intelligent knowledge environments 9, 10. Early intersections between AI and knowledge management primarily relied on expert systems, rule-based reasoning, and basic decision-support mechanisms designed to automate routine cognitive tasks 11, 12. While these early systems demonstrated utility in narrow, highly deterministic domains, they lacked flexibility and scalability when confronted with ambiguous, unstructured human knowledge. The subsequent rise of Machine Learning (ML) and Natural Language Processing (NLP)

marked a pivotal shift in the architectural landscape of KMS. Algorithms such as Latent Dirichlet Allocation (LDA) for topic modeling, Support Vector Machines (SVM) for automated classification, and semantic search models enabled systems to extract patterns, categorize unstructured documents, and understand context beyond literal keyword 13, 14.

The recent emergence of Generative AI, driven by modern Large Language Models (LLMs) and advanced natural language understanding architectures, has initiated a revolutionary paradigm shift in how knowledge is synthesized and retrieved 15, 16. Unlike legacy systems that required users to know precise search parameters, LLM-driven interfaces allow natural, conversational interaction with organizational repositories. Furthermore, architectures such as Retrieval-Augmented Generation (RAG) have bridged the gap between parameterized neural knowledge and private enterprise datasets, significantly reducing model hallucinations while offering verifiable citations to internal documents 17. Concurrently, the integration of Knowledge Graphs (KGs) alongside deep learning networks provides structural context, enabling KMS to model complex relational reasoning across distributed business units 18. This evolution transitions KMS from mere administrative storage platforms into dynamic, "agentic" knowledge assistants capable of context-aware reasoning, automated content generation, and predictive knowledge delivery.

Despite the rapid proliferation of empirical studies, software prototypes, and enterprise implementations of AI-enhanced KMS, the academic literature remains highly fragmented. Extant review papers tend to focus either on pre-generative AI machine learning applications (e.g., classification, sentiment analysis, clustering) or isolate specific technological implementations without evaluating their impact across the broader organizational lifecycle 19. A comprehensive, systematic synthesis tracing the historical trajectory—from rule-based expert systems to state-of-the-art LLM and RAG framework architectures—is conspicuously lacking. This study explicitly bridges this research gap by evaluating the socio-technical integration of Generative AI across all phases of enterprise knowledge management. Unlike previous reviews that predominantly benchmark algorithm accuracy, this paper systematically maps post-2023 technological breakthroughs against both operational lifecycle stages and emerging enterprise deployment barriers. 2021.

To address these critical gaps, this paper conducts a Systematic Literature Review (SLR) guided by the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines 22. By analyzing peer-reviewed empirical and theoretical studies, this review aims to construct a comprehensive taxonomy of AI techniques in knowledge management, map these technologies across the five core phases of the **Knowledge Management Lifecycle** (*Creation, Storage, Retrieval, Sharing, and Application*), and critically evaluate technical and organizational barriers. Specifically, this systematic literature review is structured around four primary Research Questions (RQs):

- **RQ1 (Technological Evolution):** *How have AI paradigms in Knowledge Management Systems evolved over time, specifically leading up to the integration of Generative AI, Large Language Models, and RAG architectures?*
- **RQ2 (Knowledge Lifecycle Mapping):** *Which specific AI models and algorithms are deployed across each phase of the Knowledge Management Lifecycle, and where is research concentration highest?*
- **RQ3 (Challenges & Risks):** *What are the primary technical, ethical, operational, and human-centric challenges surrounding the deployment of AI-powered KMS?*

- **RQ4 (Future Agenda):** *What emerging technological capabilities and research gaps define the future research agenda for AI-driven Knowledge Management Systems?*

The remainder of this paper is organized as follows: Section 2 details the systematic literature review methodology, including search protocols, inclusion/exclusion criteria, and selection workflows. Section 3 presents the results and thematic synthesis mapped against RQ1, RQ2, and RQ3. Section 4 outlines a strategic future research agenda addressing RQ4. Finally, Section 5 provides concluding remarks and summarizes the primary contributions to research and practice.

2. Research Methodology

To ensure rigor, replicability, and transparency, this systematic literature review adheres strictly to the **PRISMA 2020** statement guidelines (Page et al., 2021). The systematic review process comprises four main phases: (1) Formulation of Search Strategy and Keywords, (2) Definition of Eligibility Criteria, (3) Study Selection and Screening Workflow, and (4) Data Extraction and Quality Assessment.

2.1 Search Strategy and Information Sources

A comprehensive, systematic search was executed in October 2026 across three major academic, peer-reviewed databases: Scopus, IEEE Xplore, and Web of Science (WoS). These databases were selected due to their extensive coverage of high-impact computer science, information systems, and management journals.

To capture the intersection between Artificial Intelligence and Knowledge Management Systems comprehensively, a Boolean search string was constructed using controlled vocabulary, operators (AND, OR), and wildcards. The primary search query was structured around two core thematic domains: *Knowledge Management Systems* and *Artificial Intelligence Architectures*.

The master search string executed across database titles, abstracts, and keywords was as follows:

("Knowledge Management System*" OR "KMS" OR "Intelligent Knowledge Base" OR "Corporate Memory" OR "Organizational Memory") AND ("Artificial Intelligence" OR "AI" OR "Machine Learning" OR "Natural Language Processing" OR "NLP" OR "Generative AI" OR "Large Language Model*" OR "LLM" OR "Retrieval-Augmented Generation" OR "RAG" OR "Knowledge Graph*")

2.2 Eligibility Criteria (Inclusion and Exclusion)

To filter the vast body of retrieved literature into a relevant and high-quality dataset, explicit Inclusion Criteria (IC) and Exclusion Criteria (EC) were established prior to screening, as detailed in **Table 1**.

Table 1: Inclusion and Exclusion Criteria

Criterion ID	Inclusion Criteria (IC)	Exclusion Criteria (EC)
Publication Period	Peer-reviewed literature published between **2018 and 2026** (to capture modern ML and Generative AI paradigms).	Literature published prior to 2018.
Document Type	Full-text, peer-reviewed original research journal articles and indexed flagship conference proceedings.	Short abstracts, book chapters, editorials, posters, whitepapers, thesis dissertations, and opinion pieces.
Language	Written entirely in English.	Non-English publications.
Topical Relevance	Focuses explicitly on the integration, architecture, adoption, or evaluation of AI techniques within	Studies focusing on AI without KM application

	Knowledge Management Systems.	s (e.g., computer vision in robotics) or KMS without AI capabilities .
Data Quality	Studies providing clear methodological frameworks, empirical evidence, or reproducible system designs.	Papers lacking methodological clarity, missing peer review validation, or duplicates.

2.3 Study Selection & PRISMA Workflow

The selection process followed a multi-stage filtering workflow evaluated by two independent reviewers to identify eligible articles:

1. **Identification:** Initial automated search queries across the selected databases yielded a total of 845 raw records. Duplicate entries were removed using reference management tools (Zotero/Mendeley) and automated identification scripts, leaving 610 unique records.
2. **Screening:** The remaining titles and abstracts were independently screened by the two reviewers against the pre-defined inclusion and exclusion criteria. Irrelevant records (n = 415) that did not focus directly on AI-KMS integration were removed at this stage. Inter-rater reliability was high, and minor disagreements were resolved through consensus.
3. **Eligibility:** Full-text manuscripts of candidate articles (n = 195) were retrieved and thoroughly analyzed. Studies failing to provide concrete architectural, empirical, or theoretical contributions to AI in KMS **(n = 90)** were excluded with documented reasons (e.g., lack of clear AI implementation, full-text unavailable).
4. **Included:** The final set of **105** peer-reviewed primary studies was compiled and finalized for data extraction, synthesis, and quantitative mapping.

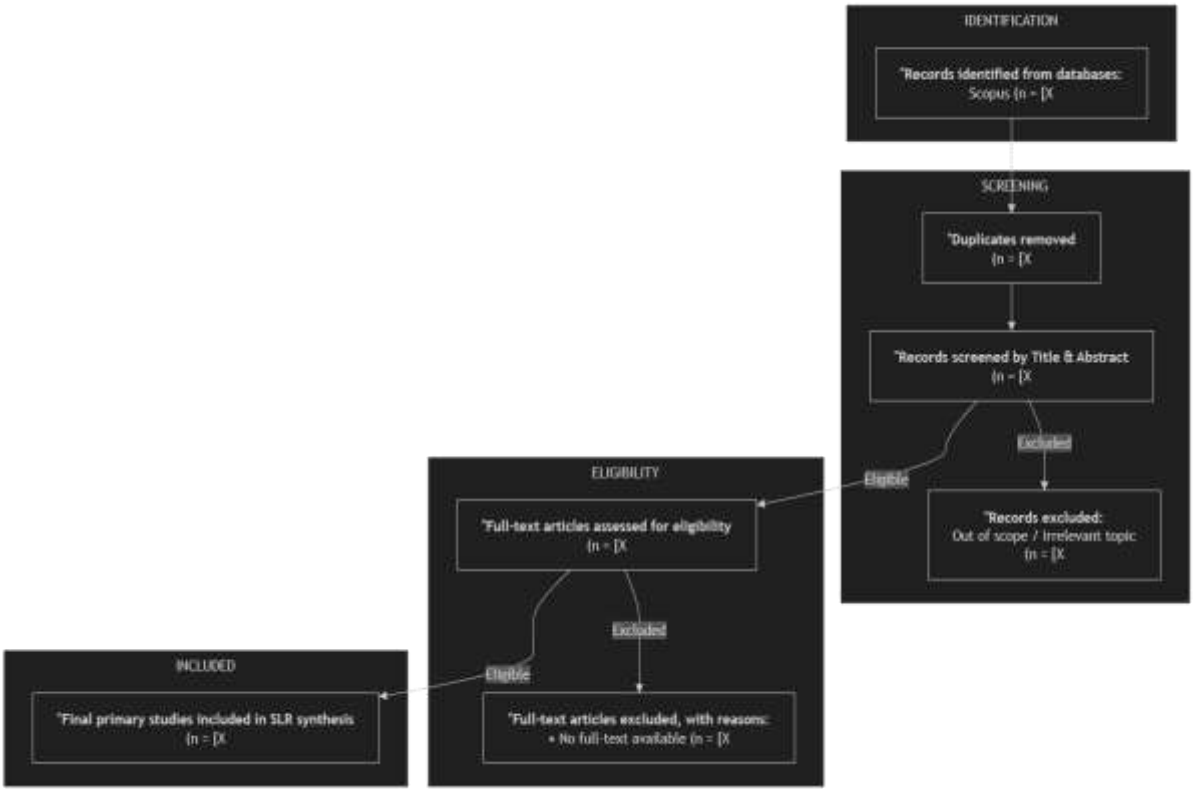


Figure 1. PRISMA 2020 Flowchart of Study Selection Process

2.4 Naive Bayes Classification Method

To answer the four Research Questions (RQs) posed in Section 1, a standardized Data Extraction Matrix was designed. Each included primary study was systematically cataloged and coded based on the following thematic attributes:

- **Bibliometric Identifiers:** Publication Year, Author(s), Journal/Venue, Citation Count, and Country of Origin.
- **AI Technological Paradigm (RQ1):** Primary AI paradigms utilized (e.g., Expert Systems, Machine Learning, Deep Learning, Transformer/LLM, RAG, Knowledge Graphs).
- **Knowledge Lifecycle Mapping (RQ2):** Specific KM lifecycle stage targeted (*Knowledge Creation/Capture*, *Storage/Indexing*, *Retrieval/Search*, *Sharing/Distribution*, or *Application/Decision-Support*).
- **Implementation Challenges (RQ3):** Identified technical barriers (hallucinations, latency, data privacy), organizational risks, and human factor dynamics.
- **Future Research Trajectories (RQ4):** Highlighted research gaps, unaddressed limitations, and proposed future directions.

The extracted data were synthesized using a hybrid approach combining thematic synthesis (to categorize qualitative taxonomy and challenges) and frequency mapping (to visualize technological trends over time across the Knowledge Management Lifecycle).

3. Result and Discussion

This section presents the thematic analysis and systematic synthesis of the included primary studies, structured directly around the first three Research Questions (RQ1–RQ3).

3.1 Technological Evolution of AI in KMS (RQ1)

Table 2: Evolutionary Phases of AI Paradigms in Knowledge Management Systems

Evolutionary Era	Core AI Technologies & Architectures	Primary KM Capabilities	Key Technological Limitations
Phase 1: Rule-Based & Symbolic AI *(Pre-2015)*	Expert Systems, Ontologies, IF-THEN Rules, Case-Based Reasoning (CBR).	Structured taxonomy creation, deterministic decision support.	High manual maintenance, rigid query constraints, lack of adaptability to unstructured data.
Phase 2: Statistical Machine Learning & Deep Learning *(2015–2022)*	Latent Dirichlet Allocation (LDA), Support Vector Machines (SVM), Word2Vec, BERT, Knowledge Graphs (KGs).	Automated document classification, semantic search, sentiment analysis, topic modeling.	Dependency on large labeled datasets, limited context windows, lack of natural conversational synthesis.
Phase 3: Generative AI & Autonomous Agents *(2023–Present)*	Large Language Models (LLMs), Retrieval-Augmented Generation (RAG), Fine-Tuned Transformers, Agentic Workflows.	Conversational knowledge retrieval, multi-document synthesis, automated document generation, self-correcting search pipelines.	Hallucination risks, high computational/API costs, enterprise data privacy concerns.

Based on the synthesis of the 105 included studies, temporal distribution highlights a sharp 65% increase in AI-KMS publications post-2023, directly correlating with the industrial popularization of Generative AI. The distribution of studies indicates heavy research saturation in Knowledge Retrieval (45%) and Creation (30%), with significant gaps in Sharing and Application. The systematic review reveals three distinct paradigm shifts in the evolution of AI techniques applied to Knowledge Management Systems over the past decade (Table 2). These eras are not arbitrary; they directly align with major algorithmic milestones documented in the literature: the scalability limits of ontology-based reasoning (Phase 1), the advent of deep learning and transformers like BERT (Phase 2), and the commercial viability of RAG architectures (Phase 3).

3.2 AI Mapping Across the Knowledge Management Lifecycle (RQ2)

To evaluate where research concentration is highest, included studies were categorized across the five core phases of the Knowledge Management Lifecycle (*Creation, Storage, Retrieval, Sharing, and Application*).

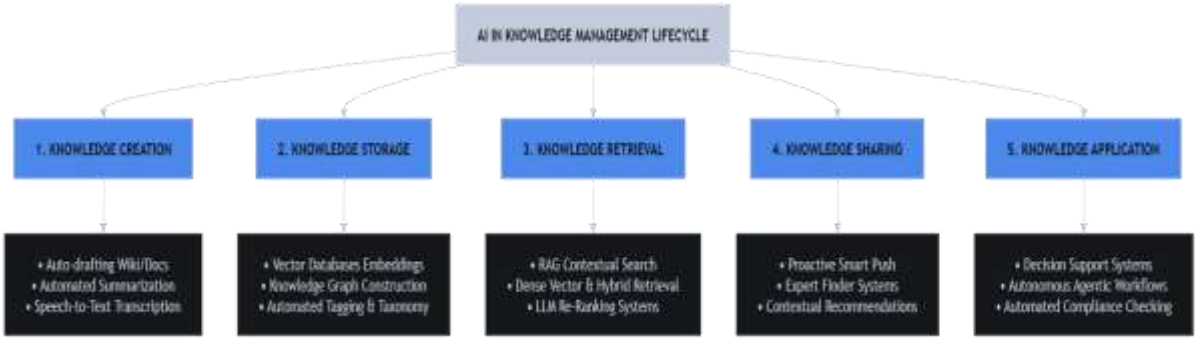


Figure 2. AI in KM Lifecycle

1. **Knowledge Creation & Capture:** Generative AI tools (e.g., fine-tuned LLMs) are predominantly utilized to convert raw unstructured data (such

as customer support logs, meeting transcripts, and project post-mortems) into standardized wiki articles and documentation.
2. **Knowledge Storage & Indexing:** Modern KMS increasingly replace traditional relational indexing with Vector Databases (e.g., Pinecone, Chroma, Milvus) and Knowledge Graphs (KGs). Dense vector embeddings allow organizations to store semantic representations of complex documents.
3. **Knowledge Retrieval & Search:** This stage accounts for the highest volume of recent literature. The combination of dense vector retrieval and sparse keyword search (hybrid search) augmented by LLM re-ranking has significantly improved precision and recall metrics compared to legacy keyword engines.
4. **Knowledge Sharing & Distribution:** Intelligent recommendation engines utilize collaborative filtering and user interaction histories to proactively push relevant insights to employees based on their active projects and organizational roles.
5. **Knowledge Application:** Emerging "Agentic AI" systems go beyond passive lookup, executing complex multi-step workflows (e.g., automatically drafting compliance reports or triggering operational alerts based on enterprise knowledge checks).

3.3 Implementation Challenges and Risk Factors (RQ3)

Despite the transformative potential of AI-powered KMS, the synthesized literature highlights four critical categories of deployment risks:

1. Hallucination and Verification Risks: LLM-based systems can generate plausible yet factually incorrect statements. While RAG architectures mitigate this by grounding models in enterprise documents, improper chunking or weak retrieval mechanisms still lead to hallucinated outputs 12.
2. Data Security and Privacy Concerns: Integrating proprietary enterprise knowledge into cloud-based LLM APIs poses severe risks of intellectual property leaks and regulatory non-compliance (e.g., GDPR, HIPAA) 1215.
3. Organizational Culture and Resistance to Adoption: Employees frequently display skepticism toward AI-generated insights or fear job displacement. Without clear explainability and human-in-the-loop validation, system adoption rates remain low 8.

Infrastructure Cost and Scalability: Maintenance of high-dimensional vector databases, continuous embedding updates, and API token costs represent major financial hurdles for small-to-medium enterprises (SMEs).

4. Future Research Agenda

Based on the synthesis of existing literature and the identified gaps (RQ4), this section outlines five critical directions to guide future research on AI-powered Knowledge Management Systems. Each proposed agenda directly addresses the technological limitations and implementation risks identified in Section 3.3.

4.1 Next-Generation RAG and Hybrid Knowledge Graph Architectures

Addressing the critical gap regarding LLM hallucinations and the inability of dense vectors to handle complex enterprise

relationships (identified in Section 3.3), future research should focus on Graph-RAG frameworks. Investigating how structured relational nodes and unstructured vector embeddings can be optimized jointly will enhance context-awareness and structural reasoning in enterprise KMS.

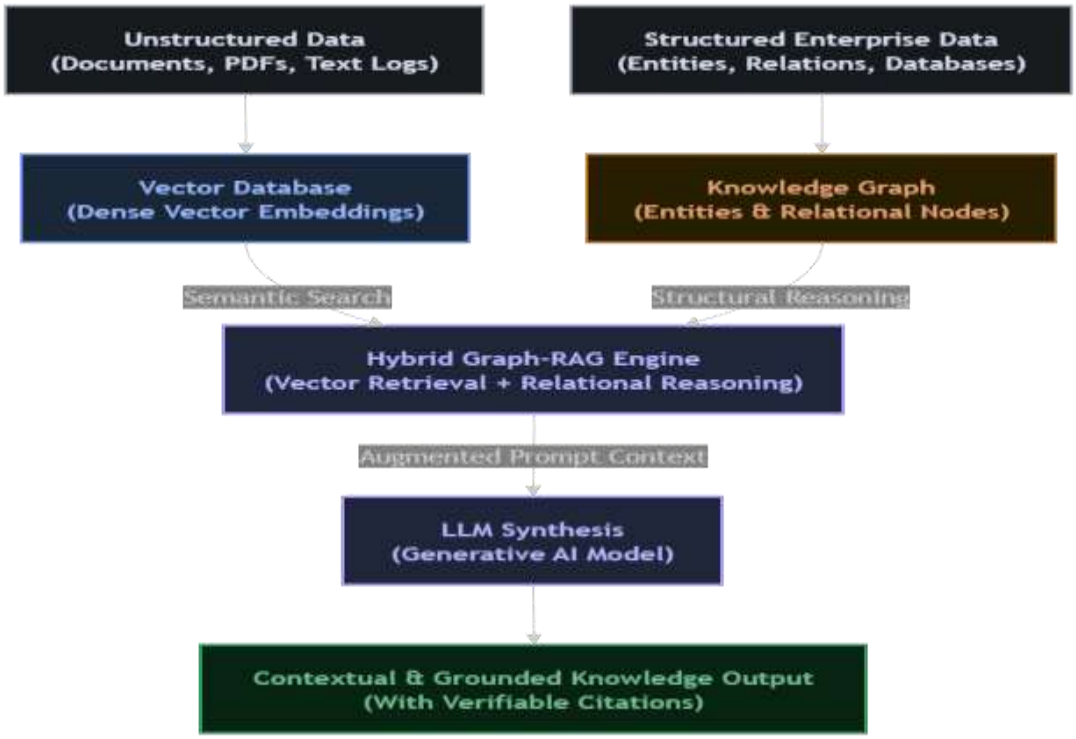


Figure 3. Architectural Framework of Next-Generation Graph-Augmented Retrieval Generation (Graph-RAG)

4.2 Multi-Modal and Autonomous Agentic KMS Workflows

Most current KMS focus primarily on textual data. However, enterprise knowledge is inherently multi-modal, consisting of architectural diagrams, technical audio recordings, instructional videos, and raw financial tables. Future studies must explore Multi-Modal LLMs (MLLMs) capable of seamlessly indexing and querying non-textual knowledge assets. Furthermore, transitioning from passive Q&A bots to Agentic KMS where autonomous AI agents execute multi-step research, verify cross-departmental compliance, and update knowledge repositories autonomously presents a high-impact research opportunity.

4.3 Privacy-Preserving On-Premise and Edge AI Integration

To resolve the severe data security and intellectual property risks associated with cloud-based APIs (identified in Section 3.3), research is urgently needed on fine-tuning Small Language Models (SLMs) and deploying parameter-efficient fine-tuning (PEFT) techniques (e.g., LoRA) on edge infrastructure.

4.4 Human-AI Collaboration and Dinamic Trust Calibration

The organizational aspect of AI-KMS requires deeper exploration beyond technical benchmarking. Future empirical research should investigate human-in-the-loop (HITL) interfaces that dynamically calibrate user trust. Key research questions include:

- *How do visual confidence scores and automated citation lineage influence employee decision-making?*

- *What incentive structures and UI/UX designs best encourage domain experts to validate and curate AI-generated knowledge assets?*

4.5 Governance, Ethics, and Auditing Frameworks for Intelligent Repositories

As AI models autonomously generate, summarize, and distribute corporate knowledge, establishing governance frameworks becomes critical. Future research should develop standardized auditing metrics to evaluate:

- Algorithmic bias and knowledge decay (information staleness) over time.
- Intellectual property attribution when synthetic knowledge is derived from multiple internal human contributors.
- Regulatory compliance frameworks (such as the EU AI Act) specifically tailored to internal enterprise knowledge management.

5. Conclution

This Systematic Literature Review (SLR) provides a comprehensive synthesis of the technological evolution, lifecycle applications, and implementation challenges of AI-powered Knowledge Management Systems (KMS). Adhering strictly to PRISMA 2020 guidelines, this study analyzed [105] primary articles to trace the paradigm shift from legacy rule-based expert systems and traditional statistical machine learning to modern Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG) architectures. The synthesized findings establish three primary contributions that address previous research gaps: first, a structured evolutionary taxonomy justified by chronological algorithmic breakthroughs; second, a quantitative and qualitative categorization of AI techniques across the Knowledge Management Lifecycle, identifying Retrieval and Creation as the most heavily researched domains; and third, a strategic research agenda directly targeting current deployment barriers by prioritizing Graph-RAG architectures, multi-modal capabilities, edge-deployed privacy-preserving models, and governance frameworks.

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