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Knowledge Documentation Practices in AI Initiatives: A Systematic Literature Review

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Abstract

Artificial intelligence (AI) has become an essential component of organizational strategy; however, the knowledge generated during AI projects, including design decisions, model behavior, development processes, and practitioner insights, is often insufficiently documented. This study aimed to examine how knowledge documentation is currently practiced in organizations implementing AI. Using a systematic literature review approach, this study analyzed twenty peer-reviewed studies published between 2020 and 2026. The articles were collected from five major academic databases, namely Scopus, ScienceDirect, ACM Digital Library, IEEE Xplore, and Emerald Insight, and were selected following the PRISMA 2020 guidelines. Based on five research questions structured using the PICOC framework, several key findings emerged. First, knowledge management in AI contexts has shifted from static repositories toward more dynamic and AI-supported systems, although this transition introduces challenges such as model drift, inconsistent documentation practices, and difficulties in capturing tacit knowledge. Second, the literature presents various knowledge documentation methods and frameworks, indicating that the field remains in development without a universally accepted standard. Third, structured documentation has been shown to positively influence organizational learning, knowledge reuse, and the overall effectiveness of AI initiatives. Fourth, despite these benefits, significant gaps remain, particularly regarding the absence of standardized AI/machine learning (ML) documentation practices and the limited integration of documentation throughout the AI lifecycle. In response to these challenges, this study proposed the Knowledge Documentation Framework for AI Initiatives (KDF-AI), consisting of twelve components organized into five phases and supported by different maturity levels. Overall, this review highlighted the increasing importance of knowledge documentation as a core capability in AI-driven organizations and provided a foundation for future research and practical implementation.

INTRODUCTION

The rapid development of artificial intelligence (AI) has fundamentally transformed the way modern organizations operate. Over the past decade, AI adoption has expanded across various industries, and more than half of organizations worldwide have implemented AI in at least one functional area (Mecca, 2025; Sipola et al., 2023). This growth reflects a broader shift in which organizations are moving beyond traditional digital transformation toward environments shaped by intelligent automation, predictive analytics, and AI-supported decision-making (Jacobides et al., 2021; Vudugula et al., 2023). In many cases, functions such as human resources, marketing, operations, and strategic management now rely on technologies including machine learning, deep learning, and natural language processing to improve efficiency and maintain competitiveness (Romeo & Lacko, 2026; Pramanik & Jana, 2023).

Nevertheless, the value generated by AI cannot be attributed to technology alone. The way knowledge is managed within organizations also plays a significant role. Knowledge management (KM) refers to organizational processes for identifying, capturing, sharing, and applying knowledge to achieve strategic objectives (Ha et al., 2016; Tseng & Lee, 2014). Extensive research has indicated that strong KM capabilities are associated with improved organizational performance, particularly when knowledge-sharing practices are effectively implemented. In rapidly changing environments, KM enables organizations to remain adaptive by positioning knowledge as a strategic asset rather than merely as supporting information (Alfawaire & Atan, 2021; Olan et al., 2022). This is particularly relevant in AI initiatives, where insights, decisions, and lessons generated throughout development processes need to be preserved and reused in future projects (Huang & Zhou, 2025; Nakash & Bolisani, 2025).

At the same time, AI is not only supported by KM but also influences how KM processes are conducted. Jarrahi et al. (2023), for example, demonstrated that AI can facilitate knowledge creation, storage, transfer, and application by automating aspects of documentation, recommending relevant information, and enabling analysis at a scale that would be difficult to achieve manually. In addition, Königstorfer and Thalmann (2022) emphasized that documentation plays an important role in linking AI system behavior with issues of accountability and transparency. Despite these advantages, knowledge documentation in many AI projects remains unsystematic and often relies on individual practices rather than established standards or organizational guidelines (Chang & Custis, 2022).

Within this context, knowledge documentation represents one of the primary mechanisms through which AI projects generate, preserve, and transfer knowledge. It involves recording and organizing knowledge produced throughout the AI lifecycle, including data sources, model design decisions, experimental results, and decision-making processes (Ding et al., 2014). Compared with conventional documentation, knowledge documentation in AI environments is broader in scope. It includes explicit artifacts, such as source code, model cards, and experiment logs, while also attempting to capture tacit knowledge from practitioners that is often difficult to formalize and may be lost when team members leave or change roles (Malgard, 2024; Navidi, 2017).

However, existing documentation practices in AI projects remain suboptimal. In many cases, these practices are fragmented, inconsistent, and lack standardized guidelines. Chang and (Custis, 2022), based on interviews with machine learning practitioners, found that documentation is frequently treated as a secondary activity and is largely influenced by individual preferences. Similarly, Hutchinson et al. (2021) identified limitations in dataset documentation that may create challenges related to reproducibility and accountability. Gelashvili-Luik et al. (2025) further highlighted the absence of unified theoretical frameworks and practical guidance for implementing KM practices within AI contexts. Consequently, organizations often experience difficulties in learning from previous AI projects, explaining model behavior, and preventing the recurrence of similar challenges.

Although the importance of knowledge documentation in AI initiatives has been increasingly recognized, a comprehensive systematic review specifically examining this topic remains limited. Existing studies generally discuss AI and KM from broader perspectives Al Mansoori et al., (2020); Pai et al., (2022) or focus on specific dimensions, such as business value Enholm et al., (2021) and innovation outcomes Haefner et al., (2021). This creates a research gap for a focused review that examines knowledge documentation practices throughout the AI project lifecycle and synthesizes existing findings into an integrated framework.

To address this gap, this study conducted a systematic literature review (SLR) of twenty peer-reviewed articles published between 2020 and 2026. This study made three main contributions. First, it provided a structured overview of knowledge documentation practices in organizations implementing AI. Second, it identified and categorized key challenges and gaps in existing documentation practices. Third, it proposed the Knowledge Documentation Framework for AI Initiatives (KDF-AI), consisting of twelve components across five phases and multiple maturity levels, developed based on insights from the reviewed literature. The remainder of this paper is organized as follows: Section II presents the theoretical background, Section III describes the research methodology, Section IV discusses the results and findings, and Section V concludes the paper by presenting key findings, implications, and directions for future research.

METHOD

This study adopted a Systematic Literature Review (SLR) approach guided by the PRISMA 2020 framework (Raisch & Krakowski, 2020). The review aimed to systematically identify, evaluate, and synthesize existing studies related to knowledge documentation practices in AI initiatives.

To define the scope of the review, the PICOC framework, consisting of Population, Intervention, Comparison, Outcome, and Context, was applied (Mucha, 2024; Santoro et al., 2026). In this study, PICOC served as a guiding framework to maintain focus and consistency throughout the literature selection process. The overview of each PICOC element is presented in Table 1.

Table 1. Picoc Framework

Dimension	Specification
Population	AI-driven and data-driven organizations implementing AI systems
Intervention	Knowledge documentation practices; KM practices; organizational memory
Comparison	Different KM approaches and documentation practices in AI projects
Outcome	AI initiative effectiveness; organizational learning; knowledge reuse
Context	Organizational AI implementation (2020-2026);

Based on this framework, five research questions (RQs) were formulated to guide the review:

1. RQ1: What are the current trends, contexts, and challenges in knowledge documentation practices within AI-driven organizations?
2. RQ2: What methods, frameworks, and knowledge management practices have been proposed or applied in AI initiatives?
3. RQ3: How does structured knowledge documentation influence organizational learning and AI initiative effectiveness?
4. RQ4: What gaps exist in current knowledge documentation practices in AI projects?

5. RQ5: What framework can be proposed to address the identified gaps in knowledge documentation for AI initiatives?

These questions are intended to explore current trends, identify commonly used methods and practices, examine their impact on organizational outcomes, and highlight gaps that could inform future research.

Search Strategy

The literature search was conducted across five major academic databases: Scopus, ScienceDirect, ACM Digital Library, IEEE Xplore, and Emerald Insight. These databases were selected to ensure coverage of both technical and management-oriented research.

Instead of relying on a single keyword, the search used combinations of terms from three main areas. The first relates to knowledge management (e.g., "knowledge management," "knowledge documentation," "organizational memory"), the second to artificial intelligence (e.g., "AI," "machine learning," "AI initiatives"), and the third to organizational context (e.g., "data-driven organization," "AI-driven organization," "digital transformation"). Boolean operators (AND/OR) were applied to connect these terms in a flexible way.

The search was carried out in March 2026, with a publication window limited to studies from 2020 to 2026. This time frame was chosen to capture more recent developments, especially given the rapid evolution of AI in organizational settings.

Inclusion and Exclusion Criteria

The article selection process was conducted in three stages, rather than filtering everything at once. In the first stage, titles and abstracts were reviewed to quickly remove studies that were clearly not relevant. At this point, only articles discussing AI or machine learning in an organizational context, and linked to knowledge management or documentation, were considered. Studies focusing purely on technical algorithms without organizational relevance were excluded.

In the second stage, full-text screening was performed. The main question here was whether the study actually discussed how knowledge is managed or documented within AI initiatives. Articles that only mentioned AI superficially, or whose full text could not be accessed, were excluded. The final stage involved quality evaluation. Only studies published in credible venues and offering clear contributions to the topic were retained. Papers with unclear methodology or duplicate records were removed to maintain consistency.

Quality Assessment

To ensure the reliability of the selected studies, a ten-item checklist (M1–M10) was applied. This checklist does not only assess general research quality, but also how relevant each study is to the topic of knowledge documentation in AI. On the general side, the checklist considers whether the study clearly defines its research problem, objectives, findings, and conclusions. On the more specific side, it looks at whether the study discusses knowledge management processes, AI implementation, and their relationship with organizational outcomes. Rather than being overly strict, a threshold was set: studies meeting at least seven of the ten criteria were included in the final analysis. This approach helps balance quality control with sufficient coverage of the literature.

Selection Results

The initial search resulted in 1,467 records. After removing 348 duplicates, 1,119 articles remained for the first screening stage. From this set, a large number of studies were excluded during title and abstract review, leaving 311 articles for full-text assessment. During the full-text stage, 204 articles were excluded due to limited relevance or insufficient discussion of knowledge documentation. The remaining 107 studies were then evaluated using the quality checklist. Of these, 27 met the minimum criteria, although 7 were later excluded due to insufficient data for synthesis. In the end, 20 studies were included in the final review. The overall process of identifying, screening, and selecting these articles is illustrated in Figure 1, following the PRISMA 2020 flow.

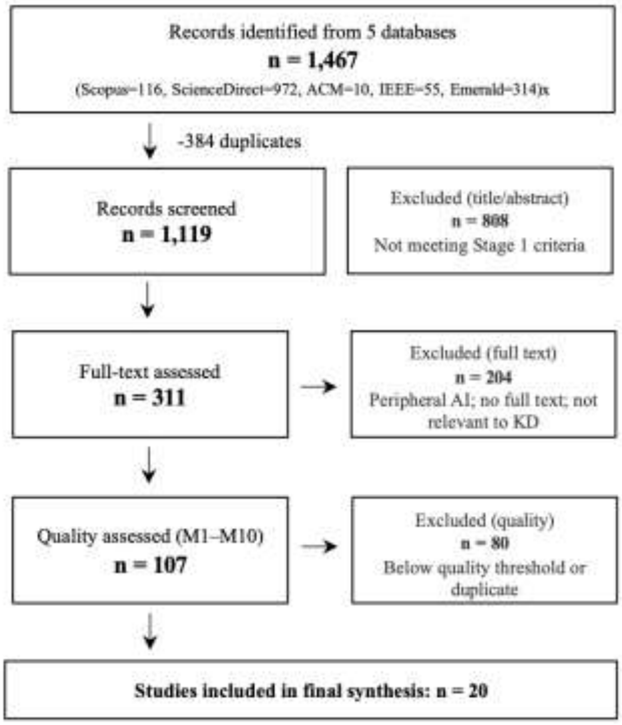

Figure 1. Prisma 2020 Flow Diagram: Article Selection Process

Data Extraction and Synthesis

Data extraction was carried outmanually for all selected studies using a structured format. The extracted information includes publication details (such as year and source), research focus, methodology, organizational context, and key findings related to knowledge documentation. For the analysis, this study combines thematic analysis with theory-driven interpretation. Patterns across studies were identified through a data-driven approach, while established frameworks such as the SECI model and the knowledge management process framework were used to interpret the findings in a more structured way. This combination allows the study to remain grounded in the data, while still being connected to existing theoretical perspectives.

RESULTS AND DISCUSSION

Characteristics of Included Studies

The twenty included studies span 2020–2026, reflecting accelerating scholarly attention to KD in AI (2020: 1; 2021: 3; 2022: 4; 2024: 4; 2025: 5; 2026: 3). Methodologically, the corpus is diverse: four empirical surveys (including two using fsQCA), four systematic/structured reviews, five conceptual or theory-building studies, four qualitative case/interview studies, and three using mixed, action research, or data-mining methods. By source database: Scopus (9), ScienceDirect (4), Emerald Insight (4), IEEE Xplore (2), ACM

(1). Two of the twenty studies are themselves systematic reviews (Yan et al., 2025); both are retained as they provide synthesized theoretical frameworks directly relevant to the RQs, with their status as secondary sources explicitly noted in the synthesis.

Tabel 2. Summary of Included Studies

No.	Reference	Year	Method	RQ Focus
1	Huang & Zhou	2025	Multi-case + Survey	1,2,3,5
2	Olan et al.	2022	Survey + fsQCA	2,3
3	Yan et al.†	2025	SLR (82 art.)	1,2,4
4	Gerlach & Lange	2026	Conceptual	1,4
5	Olan et al.	2024	Survey + fsQCA	2,3,5
6	Gelashvili-Luik†	2025	SLR (40 art.)	1,2,4
7	Nakash & Bolisani	2025	Survey (n=378)	1,2,5
8	Harfouche et al.	2022	Action Research	2,3
9	Leoni et al.	2024	Interviews	2,3
10	Colombari & Neirotti	2024	Mixed Methods	2,3
11	Chang & Custis	2022	Qual. Interviews	1,4,5
12	Georgiev et al.	2025	Conceptual	2,3,5
13	Mucha	2024	Multi-study	1,3,4
14	Raisch & Krakowski	2020	Review Essay	1,4
15	Enholm et al.	2021	Lit. Review	1,3,4
16	Haefner et al.	2021	Lit. Review	1,2
17	Hutchinson et al.	2021	Eng. Conceptual	1,4,5
18	Santoro et al.	2026	Case Study	2,3,5
19	He & Yang	2025	Conceptual	2,4,5
20	Latypova	2024	Data Mining	2,3,5

RQ1 — Trends, Contexts, and Challenges

The literature consistently evidences a fundamental transformation in organizational KM driven by AI adoption: the shift from static, document-centric repositories to dynamic, adaptive, real-time knowledge systems. On the opportunity side, AI enables organizations to automate routine knowledge capture, surface latent patterns in organizational data, and bridge information- processing limitations that constrain human-driven KM systems. Huang and Zhou (2025) emonstrate through a multi-case study and survey of 262 organizations that digital intelligence-driven KM systems contribute positively to innovation performance and sustainability outcomes. Nakash and Bolisani (2025) show that organizational openness to AI-augmented KM is conditioned heavily on user trust and perceived usefulness.

However, five structural challenges recur across the literature. First, model drift and knowledge loss: as AI models are retrained and updated, documentation validity degrades over time without deliberate intervention (Gerlach & Lange, 2026). Second, the automation–augmentation paradox: organizations face persistent governance uncertainty in deciding when to automate documentation versus requiring human oversight (He & Yang, 2025). Third, non-standardized ML documentation practices: practitioners document work in highly idiosyncratic, ad hoc ways with no shared vocabulary or governance expectation. Fourth, difficulties in scaling ML capabilities: knowledge required to scale ML across organizational units is deeply tacit and poorly transferred without structured KD (Georgiev et al., 2025). Fifth, heterogeneous contextual requirements: enabling conditions for AI, including KD practices, vary substantially by industry, organizational size, and digital maturity.

RQ2 — Methods, Frameworks, and KM Practices

A heterogeneous array of KD methods and frameworks is emerging, reflecting an exploratory phase of the field. Yan et al. (2025) synthesize the transformation of the SECI model in the AI era, proposing five propositions for how AI reconfigures each conversion mode. Harfouche et al. (2022) operationalize this through the Knowledge Augmentation Model (KAM), validated over a four- year action research project, in which iterative human-AI co-documentation creates progressively richer knowledge artifacts.

At the system level, three frameworks stand out. Santoro et al. (2024) present CESARE, a nine-phase GenAI integration model validated in ERP/CRM deployment, demonstrating measurable improvements in knowledge retrieval speed and decision quality. He and Yang (2024) propose a five- stage GenAI KM lifecycle incorporating a knowledge graph architecture as semantic backbone. Georgiev et al. (2024) develop an Automated Documentation Management System (ADMS) using ChatGPT for conversational document interaction.

Empirically, Olan et al. (2022) apply fuzzy-set Qualitative Comparative Analysis (fsQCA) across survey samples (n=262; n=300), demonstrating that specific combinations of AI capabilities and knowledge-sharing practices,not individual components,produce superior organizational performance (consistency ≥0.88). Latypova demonstrates association rule mining on documentation archives to surface decision patterns; Leoni et al. contribute a dual-mode decision framework with twenty critical KM decision factors.

RQ3 — Influence on Organizational Learning and Effectiveness

The evidence base for the positive impact of structured KD in AI initiatives is significant and multifaceted. Olan et al. (2022) provide the most robust empirical evidence: in two independent fsQCA studies involving 562 organizations, configurations combining AI-enabled knowledge sharing with suitable organizational conditions consistently produce superior performance (set-theoretic consistency ≥0.88). These findings confirm that investing in KD practices is not merely complementary to AI implementation but constitutive of it.

Santoro et al.'s (2024) case study documents tangible operational outcomes from CESARE: reduced search time for documented knowledge, elimination of redundant documentation, and increased decision- maker confidence. Harfouche et al. (2022) demonstrate compounding returns on organizational learning through recursive KAM documentation over time. Mucha (2025) shows that ML capability scaling is critically dependent on KD quality: teams without systematic KD processes consistently underperform in replicating and scaling ML initiatives. At the strategic level, both Enholm et al. [24] and Huang and Zhou (2025) confirm that KM integration is among the most consistently identified enabling conditions for realizing AI business value.

RQ4 — Gaps in Current KD Practices

Despite the progress discussed earlier, the literature also highlights several important gaps. A cross-study comparison identifies ten recurring gaps, which are summarized and categorized in Table III based on their severity and underlying issues.

Table 3 Taxonomy of KD Gaps for AI Initiatives

Gap	Description	Sev.
G1	No universal AI/ML documentation standard (model cards, data sheets, decision logs)	High
G2	Knowledge loss through model drift, no systematic repair protocol	High
G3	KD not integrated into AI project lifecycle, treated as afterthought	High
G4	Extended KM frameworks unvalidated empirically across diverse contexts	High
G5	Tacit practitioner knowledge rarely systematically captured	High
G6	No defined human-AI collaboration protocol in KD tasks	Med.
G7	Dataset documentation partial, bias, lineage, preprocessing often absent	Med.
G8	Weak governance and accountability for KD in AI projects	Med.
G9	KD practices do not scale from single-team to enterprise level	Med.
G10	Knowledge graph architectures lack practical implementation guidance	Med.

Among the most critical gaps are the absence of standardized documentation practices, the lack of integration between KD and AI project lifecycles, and the difficulty of capturing tacit knowledge from practitioners. Other gaps are related to governance, scalability, and the limited practical implementation of more advanced concepts such as knowledge graphs. These issues suggest that, while the importance of knowledge documentation is widely recognized, its implementation is still uneven and often incomplete.

RQ5 — The KDF-AI Framework

In response to the ten gaps, this review proposes the Knowledge Documentation Framework for AI Initiatives (KDF-AI): a twelve-component, five-phase framework organized around Capture, Organize, Share, Apply, and Evaluate phases, with components stratified across three maturity levels (Basic, Intermediate, Advanced).

Six design principles derived from the synthesis ground the framework: (1) lifecycle integration, KD embedded in every AI project phase rather than appended retrospectively (Latypova, 2024; Olan et al., 2024); (2) sociotechnical balance, explicit definition of human and AI roles in documentation (Gelashvili-Luik et al., 2025; He & Yang, 2025) (3) tacit-explicit integration, structured mechanisms for both knowledge types (Harfouche et al., 2022; Yan et al., 2025); (4) configurational implementation, components function as an integrated system (Colombari & Neirotti, 2024; Olan et al., 2022); (5) continuous drift monitoring, documentation validity actively maintained as AI evolves; (6) governance-first, accountability and policy defined before technical implementation.

Figure 2 KDF-AI FRAMEWORK

KDF-AI FRAMEWORK: 12 Components Across 5 Phases and 3 Maturity Levels The twelve components of KDF-AI are distributed progressively across the three maturity tiers to support scalable and incremental adoption. At the Basic tier, organizations establish foundational governance through C2 (AI/ML Documentation Protocol) and C10 (KD Governance and Accountability Framework), ensuring standardized documentation practices and policy alignment from the outset. At the Intermediate tier, four additional components, C1 (Knowledge Capture Layer), C4 (Knowledge Taxonomy and Ontology), C6 (Collaborative Sharing Platform), and C8 (Decision Support and Reuse Engine), enable systematic knowledge structuring and cross-team knowledge exchange. The Advanced tier introduces the remaining six components: C3 (Tacit Knowledge Elicitation), C5 (Knowledge Graph Architecture), C7 (Human-AI Collaboration Protocol), C9 (Real-time Integration Layer), C11 (Knowledge Drift Monitor), and C12 (Continuous Learning Loop), which together enable full-capability documentation that adapts dynamically as AI systems and organizational contexts evolve. Each component is explicitly mapped to one or more of the ten gaps (G1-G10) identified in the literature synthesis, ensuring that the framework is both theoretically grounded and practically traceable to known challenges in AI knowledge documentation.

The findings contribute to the literature in three substantive respects. First, they provide a systematic evidence base confirming that KD is not peripheral to AI initiative success but structurally constitutive of it. The empirical studies reviewed,particularly Olan et al. (2024) Santoro et al. (2026), and Harfouche et al.,demonstrate through diverse methodologies that organizations combining AI capability with structured KM consistently outperform those relying on AI alone. This aligns with the knowledge-based view of the firm while extending it to the specific dynamics of AI-mediated knowledge processes.

Second, the review reveals a critical and underappreciated challenge: the temporality of AI knowledge. Unlike conventional organizational knowledge, which depreciates gradually, the knowledge embedded in AI systems can depreciate abruptly and non-linearly as models are retrained, data distributions shift, and organizational contexts evolve. Gerlach and Lange's (2026) knowledge drift concept captures this dynamic and implies that KD frameworks must include continuous validity monitoring as a core, non-optional architectural component.

Third, the review highlights the governance dimension of AI knowledge accountability. As AI systems become increasingly consequential for organizational decision-making, the absence of structured KD creates accountability gaps extending beyond operational inefficiency to regulatory and ethical risk. Governance cannot be retrofitted onto AI systems post-deployment; it must be designed into the KD infrastructure from the outset.

CONCLUSION

This study aimed to synthesize and clarify how knowledge documentation (KD) is managed in organizations implementing AI. By reviewing twenty peer-reviewed studies published between 2020 and 2026 using the PRISMA 2020 approach, this study provided a comprehensive overview of the current state of the field. Regarding the first research question (RQ1), the findings indicated that knowledge management in AI contexts has moved beyond static repositories toward more dynamic and AI-supported knowledge ecosystems. However, this transition has introduced several challenges, including model drift, the balance between automation and human oversight, the lack of standardized documentation practices, difficulties in capturing tacit knowledge, and variations in documentation requirements across organizational contexts. These challenges demonstrate that although the direction of AI-supported knowledge management is becoming clearer, its implementation remains complex.

For RQ2, the findings revealed that no single dominant approach to KD in AI initiatives has yet been established. Instead, the literature presents various methods and frameworks, including adaptations of the SECI model, generative AI-supported KM lifecycles, and system-oriented approaches such as CESARE and ADMS. Some studies have also applied configurational methods, such as fuzzy-set Qualitative Comparative Analysis (fsQCA), to examine interactions among different influencing factors. This diversity reflects ongoing development within the field but also indicates that KD practices in AI initiatives remain fragmented and have not yet reached theoretical or methodological convergence.

Regarding RQ3, the findings consistently demonstrated that structured knowledge documentation contributes positively to AI initiative outcomes. Organizations that integrated AI capabilities with effective KD practices tended to achieve improved decision-making, enhanced knowledge reuse, and stronger overall performance. However, these benefits were not automatic and depended on the extent to which documentation practices were embedded into organizational workflows and actively utilized by practitioners.

For RQ4, this review identified ten major gaps that continue to limit the effectiveness of KD in AI initiatives. Several challenges emerged as particularly significant, including the absence of widely accepted documentation standards, knowledge drift over time, limited integration between KD practices and AI project lifecycles, and persistent difficulties in capturing tacit knowledge. These findings indicate that, despite increasing recognition of the importance of KD, implementation remains inconsistent and incomplete across organizations.

In addressing RQ5, this study proposed the Knowledge Documentation Framework for AI Initiatives (KDF-AI) as a structured approach to addressing these challenges. The framework consists of twelve components organized into five phases: Capture, Organize, Share, Apply, and Evaluate. It was designed with three maturity levels to allow adaptation according to organizational needs and capabilities. Rather than functioning as a rigid model, KDF-AI provides a practical foundation that organizations can customize based on their specific AI implementation contexts.

From a theoretical perspective, this study contributed in several ways. First, it provided systematic evidence that KD should be considered a strategic component of AI initiatives rather than a secondary documentation activity. Second, it highlighted the concept of knowledge temporality, emphasizing that knowledge embedded within AI systems evolves more rapidly and unpredictably compared with knowledge in traditional organizational contexts. Third, it introduced the KDF-AI framework as an evidence-informed approach integrating lifecycle perspectives, governance considerations, and practical implementation guidance. From a practical perspective, the findings suggested that organizations should treat KD as a strategic investment from the early stages of AI projects rather than as an additional activity implemented after development. Organizations should also establish foundational governance and documentation structures while recognizing that knowledge drift represents an inherent characteristic of AI environments rather than an exceptional occurrence.

This study also had several limitations. The review was limited to five academic databases and English-language publications published between 2020 and 2026. The quality assessment process involved a degree of researcher judgment, and two of the included studies were themselves systematic reviews. Furthermore, the proposed KDF-AI framework has not yet been empirically validated in organizational settings, meaning that its practical effectiveness requires further examination. Based on these limitations, future research should conduct longitudinal studies to evaluate KDF-AI implementation across different industries, develop more robust approaches for measuring KD maturity, establish standardized AI/machine learning (ML) documentation practices, investigate mechanisms of knowledge drift and its management, and explore deeper integration between KD frameworks, MLOps practices, and AI governance systems.

Overall, this review emphasized that knowledge documentation in AI initiatives is not merely a technical activity but a critical organizational capability that remains underdeveloped in many contexts. The proposed KDF-AI framework provides an initial foundation for organizations seeking to improve their KD practices and for researchers aiming to advance knowledge in this emerging field.

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