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A Framework for Implementing AI in KM †

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Abstract

This paper presents a framework for integrating Artificial Intelligence (AI) into Knowledge Management (KM), using the Jennex–Olfman KM Success Model as a foundation. Through a literature review and a thematic analysis of 400 practitioner comments from the global SIKM Leaders community, the study examines how AI is being applied in KM and the implications for practice. Findings highlight that AI expands KM across diverse sectors, enhances efficiency through automation and workflow integration, and supports human judgment in knowledge tasks. At the same time, risks concerning bias, accuracy, transparency, governance, and infrastructure remain central challenges. Mapping these insights to the KM Success Model shows that AI strengthens system and knowledge quality while requiring leadership and governance to safeguard service quality. The analysis extends the model by extending construct definitions with AI and moderating all constructs with AI. Overall, the study concludes that AI can and should be integrated into KM. Successful AI integration is best understood not as isolated technical interventions, but as extensions of KM success theory.

Keywords: artificial intelligence (AI); knowledge management (KM); knowledge management success

1. Introduction

With the advent of generative Artificial Intelligence (AI), Large Language Models, (LLM) and Agentic AI are considered the greatest new things in the digital world and they can possibly change the world [1]. Generative AI can also create new text/images mimicking human writers/artists and will possibly replace 300 million knowledge workers [2]. Generative AI could be the fourth industrial revolution [3]. One thought is that generative AI/LLMs could replace knowledge management, KM, as the technology/process for managing organizational knowledge. Another thought is that generative AI/LLMs will augment KM. This paper agrees with those who suggest AI and generative AI/LLMs will augment KM and knowledge managers. This paper examines how AI/generative AI/LLMs, henceforth referred to simply as AI, fit into KM through the lens of KM success and then explore how KM practitioners view the issues of implementing AI in KM. This is important for two reasons: the first is that the literature on AI in KM has focused on how AI impacts various KM processes but not on overall KM success. However, there are risks in how organizations will change in how their knowledge is used [4] and the KM success lens helps to focus on issues like this. The second reason is that practitioners may have

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a different viewpoint on how successful implementation of AI into KM will be and these viewpoints need to be recognized for AI integration into KM to succeed.

The rest of this paper proceeds as follows. First will be a discussion on KM success and a review of research literature to support integrating AI into KM. This is followed by a discussion on the methodology used to identify KM practitioner AI implementation concerns followed by the results of that analysis. The paper concludes with a discussion on how to address practitioner issues and the overall conclusions of the paper.

2. KM Success

Jennex and Olfman [5] present a KM success model based on the DeLone and McLean IS success model and its ten-year update [6,7]. This model was updated based on further KM research and technology developments and is shown in Figure 1 [8]. It is hypothesized that the three foundational dimensions of the model, system quality, knowledge quality, and service quality, are where AI can be implemented directly to support KM. The intent to use/perceived benefit extrinsic motivation and user satisfaction dimensions reflect the use of KM and will reflect the impact of AI on users. The final dimension, net benefits, reflects outcomes of using KM and will include the impact of AI on the measures of leadership, KM strategy, KM content, and process performance.

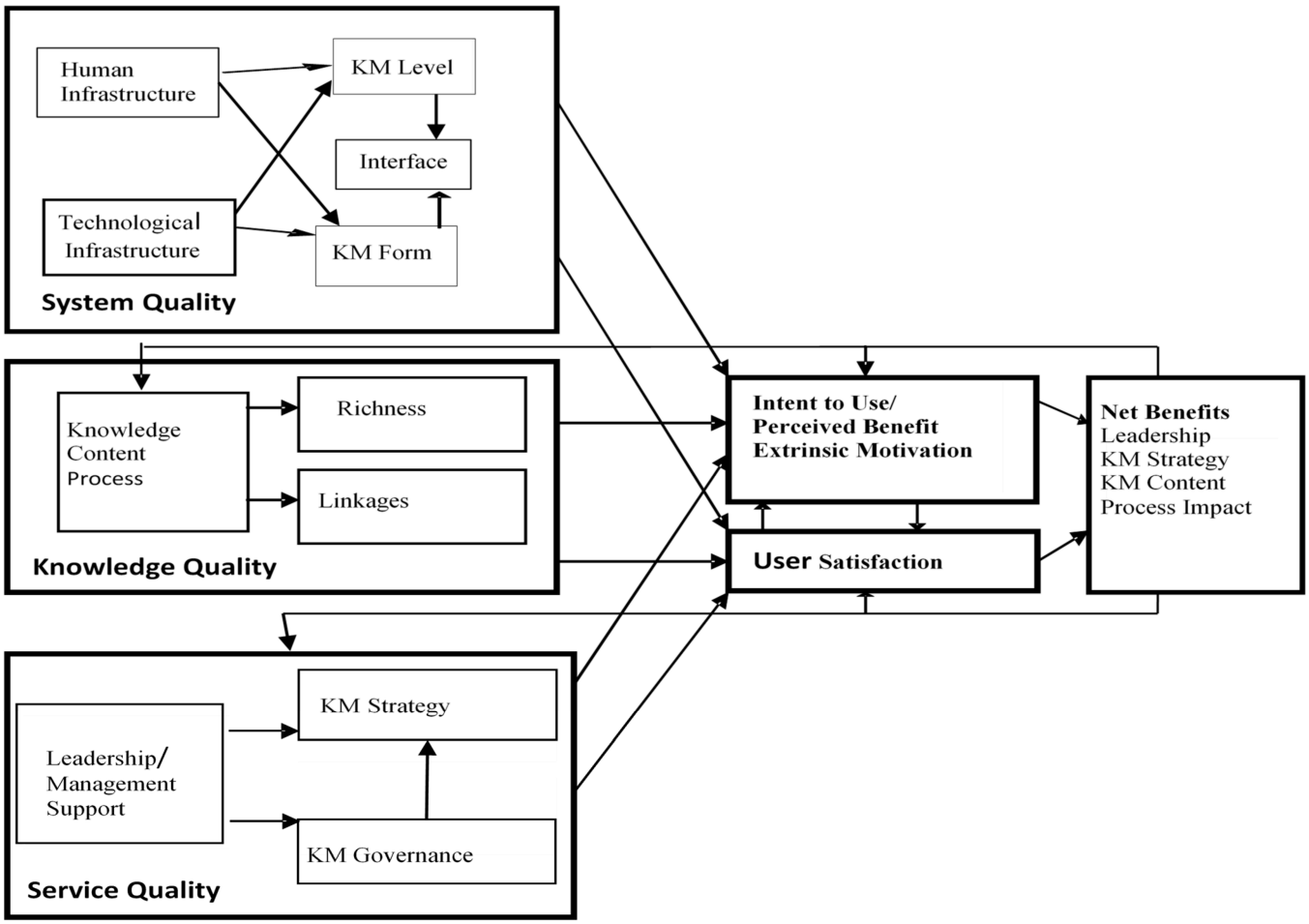


Figure 1. Revised KM success model [8].

The system quality dimension reflects how well KM assists users in capturing, finding, retrieving, manipulating, and using knowledge. The dimension consists of five constructs: technical infrastructure, human infrastructure, KM form, KM level, and interface. Technical infrastructure defines the technical capabilities of an organization to develop, operate, and

maintain KM infrastructure and systems. These include all technologies used in KM, including AI. Human infrastructure reflects the perspective of this paper that KM systems follow a Churchman [9] philosophy that includes users and tech support as part of the system. Human infrastructure identifies the skills and capabilities needed to integrate, operate, secure, and maintain the technologies used in KM, including AI skills. Technological infrastructure enables the KM form and KM level constructs while human infrastructure ensures the skills and capabilities exist to utilize the KM form and level. KM form refers to the extent to which the knowledge and KM processes are computerized and integrated. This includes how much of the accessible knowledge is online and available through a single interface and how integrated the processes of knowledge creation, storage/retrieval, transfer, and application are automated and integrated into the routine organizational processes. It is expected that AI enhances KM form. This construct, along with the technological infrastructure and human infrastructure constructs, influence the KM level construct. KM level refers to the ability to bring knowledge to bear upon current activities. AI can improve and simplify KM mnemonic functions such as search, retrieval, manipulation, and abstraction. Interface is how the users interact with the KM system through the constructs of KM level and KM form. The Interface construct reflects how users interact with KM and can be enhanced with AI, specifically generative and agentic AI. This construct interacts with the use dimension and reflects how users implement, request, and obtain results from the KM system.

The Knowledge Quality dimension is about the usefulness and accuracy of the content and its ability to assist users in performing their duties. There are three constructs: knowledge content process, richness, and linkages. The knowledge content process construct looks at the organizational processes for identifying knowledge sources and users, knowledge storage formats, and knowledge capture processes. AI can support this construct by finding and using data/information/knowledge that is not necessarily in a set format and can map knowledge locations. Richness reflects the accuracy and timeliness of the stored knowledge as well as having sufficient knowledge context and cultural context to make the knowledge useful. Linkages reflect the knowledge and topic maps and/or listings of expertise available to identify sources of knowledge to users in the organization. AI can assist these constructs by providing summarized knowledge and assist with mapping. AI hallucinations are a concern for this use.

The service quality dimension is about the organization's ability to support KM and to ensure it provides the benefits expected from knowledge use. It consists of three constructs: leadership/management support, KM governance, and KM strategy. Leadership/management support refers to the direction and support an organization needs to ensure that adequate resources are allocated for the creation and maintenance of KM: a knowledge sharing and using organizational culture is developed; encouragement, incentives, and direction are provided to the work force to encourage KM use, knowledge reuse, and knowledge sharing; and sufficient control structures are created in the organization to monitor knowledge and KM use. Leadership/management support enables the other two constructs. KM governance is a construct enabled by leadership/management support and is responsible for providing oversight to ensure that knowledge use/KMS benefits identified by KM strategy are realized while also ensuring that risk is monitored and controlled. KM strategy is enabled by leadership/management support construct and overseen by the KM governance construct. The KM strategy construct identifies KM goals, alignment, metrics, and knowledge sharing/use incentives. AI is not directly implemented in this dimension; rather, this dimension provides the leadership and support for implementing AI in KM.

The User Satisfaction dimension is used to measure how satisfied users are with using KM and knowledge. The intent to use dimension is needed to assist in determining if the KMS is sufficient to ensure that users will use the KMS when appropriate. AI is not directly implemented in this dimension but can impact user satisfaction. Generative AI and agentic AI can improve user satisfaction by facilitating KM use; it can also create user frustration over difficulties with AI use or the generation of AI hallucinations.

The net benefits dimension measures the actual benefits derived from using knowledge/KM. Benefits are looked for in four areas: impacts on business processes, impacts on KM strategy, impacts on knowledge content, and leadership/management support. For AI implementation into or automation of KM to be successful, it needs to result in improvements in the previous areas. Metrics for KM success need to be modified to include AI use.

3. Literature Support for Implementing AI in KM

This section summarizes the literature related to implementing AI in KM. This section also maps the AI recommendations to the KM success model. The literature for this section was initially identified for the early version of this paper using a Google Scholar search for 2023 and 2024 papers and searching for AI in KM. This section was expanded for this version of the paper using Google Scholar and searching for AI in KM for papers from 2024 and 2025. Papers from 2024 and 2025 were selected for their focus on generative AI over earlier AI approaches. It is recognized that there is earlier literature that addresses AI in KM but the selected literature is considered appropriate as it reflects research incorporating more mature AI technologies into KM and the purpose of this section is not to be exhaustive, but to show that there is support for AI in KM. The below literature is considered to be a representative sample of the large amount of research that has been done on using AI in KM. This search was done in early April of 2026.

Al-Qaysi et al. [10] used a survey on university students in Malaysia who use generative AI to determine the impact of KM factors and generative AI attributes on generative AI use. The findings show that KM factors of knowledge acquisition, knowledge sharing, and knowledge application support AI use, mapping to the intent to use construct of the use dimension.

Chin et al. [11] address how AI–human interactions can be interpreted as a knowledge creation system for cross cultural systems dealing with humanitarian logistics. This maps to the interface construct in the system quality dimension.

Deng et al. [12] investigates the use of digital technologies in facilitating KM only concerning decision making and the knowledge-sharing process and found support for AI as a digital technology. This maps to the technical resources, KM level, KM form, and interface constructs of the system quality dimension. This also maps to the knowledge content process and richness constructs of the knowledge quality dimension. Finally, it also addresses the net benefits dimension.

Garfield [13] demonstrates that cognitive computing and AI can be used to support decision making, deliver highly relevant information, and optimize the available attention to avoid missing key developments. This maps to the process impact construct of the net benefits dimension.

Gelashvill-Luik et al. [14] did a focused literature review of 40 articles focused on the integration of AI into KM. They found that AI enhances knowledge identification, generation, capture, and sharing; data analysis and decision making; and scaling and automation. They also found an association with risk and governance. These findings map to the technical resources, KM level, KM form, and interface constructs of the system quality dimension. This also maps to the knowledge content process and richness constructs

of the knowledge quality dimension. Thie also maps to the service quality dimension, specifically knowledge strategy and governance constructs. Finally, it also addresses the net benefits dimension.

Guan et al. [15] applied stress coping theory to understand how service robot utilization affects employee knowledge behaviors in the tourism and hospitality industry. They found that service robot utilization led to job insecurity tensions, prompting employees to upgrade their skills and engage in KM. These tensions map to the human resources construct of the system quality dimension, all the constructs of the service quality dimension, and the intent to use construct of the use dimension.

Husayn et al. [16] used a survey of 210 university faculty members in Libya to explore how AI influences KM in higher education. Over 50% of the respondents found that AI supported all dimensions and constructs of the KM success model. Additionally, the survey found that awareness of AI was a significant issue supporting the human resources construct of the system quality dimension.

Jarrahi et al. [17] sees AI assisting KM in areas such as knowledge creation and knowledge search and retrieval. AI pattern identification is used in knowledge creation to find rules and chatbots assist users in searching and retrieving knowledge. We suggest personnel intelligent agents and chatbots will augment humans in undertaking KM processes. This maps to the technical resources, KM level, KM form, and interface constructs of the system quality dimension. This also maps to the knowledge content process and richness constructs of the knowledge quality dimension and to the intent to use/perceived benefit dimension.

Kaczorowska-Spychalska et al. [3] proposed that AI can transform KM by generating new knowledge to improve organizational performance by examining vast datasets to find patterns and links that may not be immediately obvious. Moreover, AI can automate the production of fresh content, saving employees' time and allowing them to concentrate on more imaginative and strategic activities. It can also provide personalized and context-aware recommendations. AI has potential to transform KM by automating repetitive operations and producing fresh and inventive goods and services. Also, AI in KM can improve the quality of data, the requirement for human oversight, and ethical issues. Businesses need to analyze these issues and create plans that maximize the advantages of AI while lowering the hazards. AI can potentially be a potent tool for enhancing organizational performance and establishing a competitive edge in a market undergoing fast change. This maps to the technical resources, KM level, KM form, and interface constructs of the system quality dimension. This also maps to the knowledge content process and richness constructs of the knowledge quality dimension. It also maps to the constructs of the service quality and the net benefits dimensions.

Kumar [18] used semi-structured interviews and a literature review to generate a model of AI augmented KM. This model was then tested using a survey of health-care professionals in India. They found a significant positive relationship between AI integrated into KM and clinical performance, mediated by improved knowledge access and analysis. This maps to the technical resources, KM level, KM form, and interface constructs of the system quality dimension. This also maps to the knowledge content process and richness constructs of the knowledge quality dimension. Finally, it also addresses the net benefits dimension.

Leoni et al. [19] conducted 52 interviews with KM and AI leaders from 52 organizations. They found that all the different interviewees confirmed the crucial role that AI is currently playing in KM processes within their organizations. They state that AI is indispensable to carry out KM processes for three main reasons: the number of collectable data and information has increased in a potentially infinite way; it is unthinkable that

humans can perform the analysis, integration, dissemination and storage of this infinite variety effectively and efficiently in space and time; and the organization's overall performance is ameliorated thanks to the possibility to make better decisions through the application of AI-enhanced knowledge. AI pervades all KM processes, playing a crucial role in organizational decision making. Finally, future research must delve deeper into understanding how the human–AI interplay influences decision outcomes. Understanding these nuances is essential for designing effective decision support systems and optimizing human–AI collaboration. This maps to the technical resources, KM level, KM form, and interface constructs of the system quality dimension. This also maps to the knowledge content process and richness constructs of the knowledge quality dimension. This also maps to the intent to use/perceived benefit dimension. Finally, it also addresses the net benefits dimension.

Leoni et al. [20] investigated the role of KM processes on using AI in a manufacturing organization and, in particular, demonstrated that KM processes act as a mediator through which AI benefits Supply Chain Resilience and Manufacturing Firm Performance; thus, they play a crucial role in manufacturing firms interested in properly applying AI tools to ameliorate their performance and resilience. This maps to the technical resources, KM level, KM form, and interface constructs of the system quality dimension. This also maps to the knowledge content process and richness constructs of the knowledge quality dimension. Finally, it also addresses the net benefits dimension.

Mahmoud et al. [21] used a survey of 372 technical staff and administrators in the Egyptian pharmaceutical industry to explore how integrating smart technologies, including AI, into KM can improve organizational performance. Additionally, it was found that leadership plays a moderating role in improving organizational performance. These findings specifically support all the constructs of the service quality dimension and the net benefits dimension. Additionally, the findings map to the technical resources, KM level, KM form, and interface constructs of the system quality dimension. This also maps to the knowledge content process and richness constructs of the knowledge quality dimension.

Marvi et al. [22] used content analysis of a systematic literature review to identify areas where AI and KM can support marketing. They suggest that integrating AI into KM can support knowledge sharing and data analysis for knowledge discovery and generation and enhance decision making and strategic planning. This maps to the technical resources, KM level, KM form, and interface constructs of the system quality dimension. This also maps to the knowledge content process and richness constructs of the knowledge quality dimension. Finally, it also addresses the net benefits dimension.

Nakesh and Bolisani [23] used a survey of 378 employees and managers to look at the perceived usefulness of AI in KM. They found significant support for the use of AI in the KM processes of knowledge acquisition, documentation, sharing, and application. The strongest support was in the areas of knowledge creation and documentation processes. This maps to the knowledge content process and richness constructs of the knowledge quality dimension and to the technical resources, KM level, and KM form constructs of the system quality dimension.

Nakesh and Bolisani [24] used semi-structured interviews of 28 Chief Knowledge Officers, CKOs, to suggest that KM processes should be integrated into the organization. They proposed the use of AI to identify knowledge needs and push that knowledge to the targeted users. This maps to the knowledge content process and richness constructs of the knowledge quality dimension; to the technical resources, KM level, and KM form constructs of the system quality dimension; and the user satisfaction construct of the intent to use/perceived benefit dimension.

Rezaei [25] used a Delphi panel to identify and address the challenges of implementing Ai into KM. Three types of challenges were identified: technical, organizational, and ethical. These challenges reflect areas where AI is being implemented into KM. They map to all dimensions and constructs of the KM Success Model.

Rezaei. et al. [26] used a survey of 198 respondents to determine ethical challenges with using AI in knowledge sharing and decision making. Ethical challenges focused on accountability, societal impact, privacy, trust, impact on employees, etc., reflected issues upon which management needs to focus. These challenges map to all the constructs of the service quality dimension.

Storey [4] proposed a framework that integrated AI into all KM processes and technical infrastructure. Uniquely, this paper also addresses issues of risk and knowledge shifting between novices and experts. This framework maps to all constructs in the model, including those in the service quality, intent to use, and user satisfaction dimensions.

Zauoui Seghroucheni et al. [27] did a comparative evaluation of Natural Language Processing, NLP, algorithms for determining AI/NLP support for tacit knowledge conversion in KM systems. This maps to the technical resources, KM level, KM form, and interface constructs of the system quality dimension. This also maps to the knowledge content process and richness constructs of the knowledge quality dimension.

Zhang et al. [28] used a literature review to assist in the generation of an AI-based SECI (socialization, externalization, combination, and internalization) model and AI-based model. These models focus on knowledge generation, capture, sharing, and transfer. This maps to the technical resources, KM level, KM form, and interface constructs of the system quality dimension. This also maps to the knowledge content process and richness constructs of the knowledge quality dimension.

Collectively, the literature demonstrates broad and consistent support for the integration of AI into knowledge management processes, particularly in enhancing knowledge creation, retrieval, sharing, and application across diverse contexts. Across studies, AI is shown to strengthen key dimensions of the KM Success Model, especially system quality through improved technical infrastructure and automation, and knowledge quality through enhanced content generation, analysis, and linkage capabilities.

Additionally, several works highlight AI's contribution to net benefits, including improved decision making, operational efficiency, and organizational performance [29–32]. However, recent research has also highlighted the potential negative consequences of AI integration in workspace. They include reduced autonomy, uncertainty, cognitive conflicts, and AI-induced stress, which may affect employee's adaptation and creativity [33,34]. At the same time, the literature also recognizes the growing importance of service quality, particularly in relation to governance, leadership, and ethical oversight, as organizations navigate the risks associated with AI adoption.

Despite this strong foundation, the literature remains fragmented in several important ways. First, most studies examine AI within isolated KM processes or specific contexts, rather than evaluating its role across the full KM Success Model. While many works implicitly map to individual dimensions, few explicitly assess how AI integration influences overall KM success in a holistic and theoretically grounded manner. Second, although risks related to bias, transparency, and governance are acknowledged, they are often treated as secondary considerations rather than systematically integrated into KM frameworks. Third, there is limited incorporation of practitioner perspectives, with much of the existing research relying on surveys or conceptual models, rather than capturing how KM professionals experience and interpret AI implementation in real-world settings.

This study addresses these gaps by explicitly examining AI through the lens of the revised KM Success Model [8], providing a structured and comprehensive view of how

AI impacts all dimensions of KM success. By combining the literature insights with a thematic analysis of practitioner experiences, the paper bridges the divide between theory and practice, offering a more grounded understanding of AI-enabled KM. In doing so, it extends the KM Success Model by emphasizing the critical roles of explainability, transparency, and human oversight, and positions AI not as a replacement for KM, but as an augmentation that must be carefully aligned with organizational strategy, governance, and human expertise.

4. Materials and Methods

To examine practitioner perspectives on the implementation of AI in KM, a thematic analysis was conducted on approximately 400 comments drawn from the SIKM Leaders discussion group under the hashtag AI. The SIKM Leaders community was selected because it consists of a globally active network of KM scholars and practitioners. The group regularly engages in discussions on real world KM implementation. Many KM topics are discussed and because of the application of AI to business organizations, the topic of how AI can be implemented in KM was raised. The SIKM group is not an AI-focused group but it does have a focus on analyzing and applying technology to support KM as well as other focuses on KM organizational issues. Many of the group have many years of experience in KM and have seen technology fads come and go and have developed a healthy skepticism of technology claims, suggesting this group is not biased for or against AI. Additionally, discussion threads are curated using hashtags describing the discussion topic, making it easy to find relevant comments. This online discussion group was selected for analysis because it represented the KM practitioner community and it had an accessible repository of discussion threads. Also, as the focus of this paper is on integrating AI into KM, it is expected that many members of this group are leading this effort and their postings reflect experience gained in implementing AI into KM.

The analysis followed an inductive approach, allowing themes to emerge from the data, while subsequent interpretation involved mapping these themes to the Jennex–Olfman KM Success Model. Prior to the analysis, the comments were cleaned of extraneous data (headings, formatting, etc.) and names. Comments under the hashtag AI were curated to those focused on the topic of AI in KM. To maintain neutrality, we used gender neutral names like Taylor, Alex, Jesse, Jackie, Jamie, Kim, Robin, Parker, River, Rory, Blake, and Basil.

The dataset comprised practitioner-generated discussion threads explicitly focused on AI in KM. Comments were screened for relevance by the research team and reviewed by the senior author to ensure alignment with the study's scope. Prior to analysis, all data were cleaned to remove formatting artifacts and identifying information. Coding was conducted using Atlas.ti and followed an iterative, multi-stage process. Two researchers independently coded an initial subset of the data (approximately 10–15 pages) to generate preliminary codes. These were compared and consolidated into a shared codebook through discussion. The refined codebook was then applied to the same subset to assess internal consistency. To further establish coding alignment, both researchers independently coded an additional subset (approximately 5 pages), after which discrepancies were resolved through consensus, resulting in a stable coding framework.

Following codebook stabilization, the remaining dataset was coded using the agreed framework. Coding was continuously synchronized within Atlas.ti to facilitate collaboration and maintain a transparent record of code development and application. Disagreements were resolved through discussion, with decisions grounded in both the data and the relevant theoretical and empirical literature. Methodological rigor was strengthened through iterative coding, systematic codebook refinement, and consensus-based validation.

An audit trail was maintained through documented coding iterations and versioning within Atlas.ti, enabling transparency in analytical decisions. In addition, senior author review of data selection and thematic development served as a form of peer debriefing, providing an additional layer of analytical validation. This approach ensured that the findings are both empirically grounded and theoretically informed.

5. Results

Thematic analysis revealed several recurring patterns in how AI is being understood and applied within knowledge management contexts. Table 1 provides a summary of the key themes that emerged, along with selected quotes to illustrate how experts described their experiences. These themes offer insight into both the practical opportunities and ongoing challenges associated with implementing AI in KM.

Table 1. Thematic analysis.

Theme	Description	Illustrative Quotes (Paraphrased)
1. AI used in different fields	AI is widely used across sectors such as commercial, education, healthcare, and HR, demonstrating its widespread relevance.	Taylor said her last two jobs in payments heavily used AI and automation. Alex noted that AI is the future and every company will adopt it. Jesse shared that in healthcare, AI supports diagnostics and offers insights for treatments.
2. AI as a support tool in KM	Experts view AI as a partner, not a replacement, supporting knowledge tasks while preserving human judgment.	Jackie emphasized that AI should help people use their knowledge rather than take over databases. Jamie shared that their programs focus more on personal productivity AI than technical skills. Kim described using Hybrid AI, where people guide the structure and AI executes tasks.
3. AI enhances KM efficiency and productivity	AI improves KM efficiency and productivity through automation, workflow support, and reduced manual effort.	Robin shared that AI reduced story capture time and automated tagging and summarization tasks. Alex noted that AI can automate workflows and support strategic work. Basil explained that AI reduces manual effort and increases time for analysis, while Blake described improvements in collaboration and knowledge visibility through AI-enabled KM platforms.
4. Concerns and challenges of AI in KM	AI implementation in KM raises concerns related to accuracy, data quality, ethics, transparency, bias, governance, infrastructure, and system integration.	Jesse noted that AI provides the “what” but not the “why,” while River and Rory emphasized concerns related to governance, misinformation, and ethical risks. Basil reported that inconsistent document tagging reduced AI effectiveness, and Robin highlighted challenges with system integration and deployment readiness.
5. AI embedded in KM tools	AI is increasingly integrated into platforms like SharePoint, Microsoft 365, and custom KM tools.	River explained that they are shaping the Copilot layer on Microsoft products. Susan shared that their content is automatically tagged and indexed using machine learning. Blake noted their system recommends knowledge in real time based on user behavior.

5.1. Theme 1: AI Used in Different Fields

Practitioners consistently framed AI as becoming embedded within core organizational workflows rather than remaining an experimental or technology-specific innovation. Across finance, healthcare, education, customer service, and enterprise KM environments, AI was described as increasingly influencing how organizations capture, process, apply, and distribute knowledge. These discussions suggest that AI is being viewed not simply as

a support tool, but as an emerging infrastructure for organizational knowledge processing, decision support, and learning.

Professionals working in finance and enterprise settings highlighted how AI is already integrated into operational knowledge activities. Taylor noted that her previous "roles in the payments industry heavily relied on AI and automation for operational efficiency and knowledge documentation", while Alex described AI as "the future" and argued that AI literacy will soon become a necessary professional competency. Jesse further explained that organizations are developing AI-driven systems capable of identifying patterns and surfacing insights from unstructured knowledge sources. These examples indicate that experts increasingly perceive AI as central to organizational competitiveness and knowledge-driven work.

Experts also emphasized that AI is expanding beyond automation into more adaptive and context-sensitive KM functions. In healthcare contexts, professionals described AI applications in drug discovery, medical imaging analysis, clinical decision support, and robotic surgical assistance, illustrating AI's growing role in high stakes knowledge environments. Bob discussed the possibility of AI generating individualized knowledge assignments using organizational profiles, suggesting that AI may support personalized learning and task design within enterprises. Similarly, Rory described "AI tools that analyze student interactions and support curriculum development", while Grey highlighted "AI systems designed to capture tacit knowledge during employee exits". Robin additionally noted that "AI integration within customer support systems and digital assistants has become increasingly normalized, shaping expectations regarding responsiveness and knowledge accessibility within KM systems". Findings suggest that AI is reshaping both the operational and strategic dimensions of KM across industries. Rather than being confined to isolated use cases, AI is increasingly conceptualized as a cross-sector mechanism for improving organizational learning, knowledge accessibility, and knowledge-driven decision making.

5.2. Theme 2: AI as a Support Tool in KM

A dominant theme across the discussions positioned AI as an augmentation mechanism rather than a replacement for human knowledge work. Practitioners consistently described AI as most valuable when used to support, streamline, and enhance KM activities while preserving human judgment, contextual reasoning, and strategic oversight. These discussions reflect a broader perception that effective AI-enabled KM depends on maintaining a balance between automation and human expertise.

Several experts emphasized that AI should function as an assistant rather than an autonomous decision maker. Jackie explained that her goal was to build systems that "help people activate their knowledge without turning over organizational knowledge entirely to large language models, reflecting concerns about preserving human control over knowledge interpretation and application". Similarly, Jamie noted that KMI's AI initiatives focused more on personal productivity than technical replacement, reinforcing the idea that AI tools are intended to empower users rather than substitute them. The examples suggest that professionals view AI as a mechanism for extending human capability rather than replacing human knowledge processes.

Professionals also described how AI can reduce repetitive and time-intensive KM tasks while still requiring human oversight. Robin highlighted the value of automating tagging processes to reduce the manual workload, while Morgan stressed that AI-generated outputs for client-facing work should always involve careful human verification. Kim described a "hybrid AI" approach in which people provide structure, expertise, and contextual direction while AI executes and accelerates elements of the workflow. Similarly, Sam

observed that machine learning is becoming increasingly embedded within organizational processes, making automated knowledge generation more visible across knowledge flows. These discussions collectively point toward a collaborative human AI partnership model in which AI supports operational efficiency but remains guided by human expertise and organizational context.

5.3. Theme 3: AI Enhances KM Efficiency and Productivity

KM experts consistently described AI as improving KM efficiency by reducing manual effort, streamlining workflows, and accelerating knowledge-related tasks across organizational settings. Rather than replacing employees, AI was framed as a mechanism for improving productivity and enabling professionals to focus more on strategic and analytical work. Alex noted that AI would help "remove duplication, automate workflows, and focus people on strategic tasks," while Basil stated that AI reduces "grunt work" and allows professionals to spend more time on analysis and strategic recommendations.

Professionals also emphasized that effective AI integration still depends on governance and oversight. Barry explained that his KM team was actively working to ensure the "quality, validity and authenticity of Copilot responses" through governance and lifecycle management practices. Experts shared multiple examples of AI improving the speed, consistency, and scalability of KM activities. Grey described using generative AI tools to support search, generate summaries, and automate KM workflows, including a bot that reduced story drafting time from fifteen minutes to one minute. Robin noted that his team was experimenting with AI-assisted "auto tag and summarize" functions to improve knowledge retrieval and reuse, while Basil highlighted how AI accelerated document tagging and organization.

The discussions also highlighted AI's role in improving organizational learning, collaboration, and knowledge accessibility. Blake described how "one institution using an AI enabled KM platform experienced a 25% increase in search productivity," while Morgan noted that "AI systems can reduce barriers between organizational silos by surfacing relevant knowledge assets proactively rather than relying solely on manual search". Rory similarly emphasized "AI's role in supporting communities of practice, contextual learning, and real time knowledge exchange".

AI was also framed as supporting broader organizational scalability and KM maturity. Taylor argued that AI could "make KM more scalable" in documentation-intensive environments, while Harley suggested that AI could help "build KM maturity faster" by systematizing knowledge capture practices that often rely on individual initiative. Thus, the findings show that experts overwhelmingly view AI as a mechanism for enhancing KM efficiency, productivity, and organizational knowledge accessibility across sectors and organizational contexts.

5.4. Theme 4: Concerns and Challenges of AI in KM

Although experts were generally optimistic about AI's potential in KM, many also raised concerns related to accuracy, data quality, ethics, governance, infrastructure, and implementation readiness. Across the discussions, KM leaders emphasized that AI adoption in KM requires careful oversight to avoid misinformation, biased outputs, weak knowledge quality, and operational risks.

Experts also highlighted concerns regarding governance, transparency, and overreliance on AI-generated outputs. Morgan noted that AI provides the "what but not the why," reflecting concerns about the interpretability and reliability of AI-assisted knowledge processes. Barry similarly emphasized the need for "high governance and lifecycle management" to maintain quality and avoid reputational damage caused by misinformation or

poorly validated outputs. Basil explained that her organization was actively evaluating "what is appropriate to automate versus what still needs human touch," while Taylor cautioned that organizations may adopt AI too quickly "just because it is new" without fully understanding its limitations. Rory additionally warned about "ethical risks and unintended consequences," arguing that KM systems require safeguards to prevent bias and misinformation.

Experts also discussed challenges related to knowledge quality, auditing, and organizational trust in AI systems. Grey noted that "automation can sometimes produce generic or diluted content that weakens organizational knowledge over time", while Susan highlighted the difficulty of auditing decisions made through black box AI models. Bart further raised concerns regarding intellectual property and data security when organizational knowledge is entered into public AI systems.

In addition to governance and ethical concerns, professionals described several technical and infrastructure-related barriers that complicated AI implementation in KM environments. Basil explained that inconsistent tagging and legacy systems limited the effectiveness of AI tools because many organizational documents were not digitized or structured consistently. Robin similarly noted that integrating AI into existing collaboration platforms was "not as plug and play as people think." Grey highlighted difficulties maintaining consistent data quality across departments, while Barry explained that "deploying Copilot required substantial preparation related to governance, permissions, and security". Susan additionally noted that limited computing resources restricted experimentation opportunities, and Morgan pointed out that enterprise systems are often dependent on slow vendor and IT update cycles.

These conversations reflect a broader understanding that successful AI implementation in KM depends not only on technological capability, but also on governance, infrastructure readiness, knowledge quality, and responsible organizational adoption practices.

5.5. Theme 5: AI Embedded in KM Tools

Experts consistently described AI as becoming increasingly integrated within existing KM platforms and workflows, reflecting a shift from experimental adoption toward operational implementation. Rather than functioning as a separate innovation layer, AI was described as being embedded directly into everyday KM tools to support knowledge retrieval automation, personalization, and workflow efficiency.

Several professionals highlighted how AI features were being incorporated into enterprise collaboration and knowledge systems. Barry explained that his KM team was actively shaping the "Copilot layer" within Microsoft products to automate tasks while maintaining governance and quality controls. Similarly, Grey described integrating AI assistants into story capture workflows using Power Automate and adaptive cards, reducing the process from fifteen minutes to one minute. Basil noted that AI tools integrated with SharePoint and collaboration systems were automatically tagging documents and recommending related content, while Susan described machine learning systems that automatically tagged and indexed organizational content to support adaptive learning pathways.

Experts also emphasized the growing use of AI-driven recommendation and personalization systems within KM environments. Morgan described "knowledge recommendation engines" that surface relevant documents based on user activity, while Blake explained that their KM platform proactively "pushes" relevant knowledge to users in real time rather than relying solely on manual searches. Bart similarly noted that AI was being used within taxonomy building systems to suggest metadata labels and categories based on user interactions with content. Grey additionally described embedding generative

AI directly into onboarding and knowledge capture workflows to reduce friction during employee transitions.

These discussions suggest that AI is increasingly being embedded within the foundational infrastructure of KM systems rather than operating as an external add on. Across organizational contexts, professionals described AI-enabled KM environments that support more automated, adaptive, and responsive knowledge processes.

6. Discussion

The findings from both the literature and practitioner analysis highlight that AI is rapidly reshaping KM practices across diverse sectors. Practitioners express optimism about AI's capacity to increase efficiency, automate routine tasks, and improve knowledge accessibility. However, these benefits are not without significant caveats.

6.1. The Human–AI Partnership: Promise and Limitation

As observed in Themes 2 and 5, experts overwhelmingly perceive AI as an augmentation of human knowledge work, rather than a replacement. Specifically, in Theme 2, scholars described AI as a supportive tool or "assistant" that automates repetitive KM tasks but leaves strategic thinking, ethical judgment, and nuanced decision making within the human domain. This direct practitioner feedback reinforces the literature findings [3,13,14,17–19,26] and underlines the emergence of hybrid intelligence models in KM. This consensus points toward an emerging model of hybrid intelligence, where human expertise and AI capabilities complement one another. However, this partnership introduces new forms of dependency that carry important implications. As organizations increasingly rely on AI-generated outputs, there is a risk that critical human skills, such as deep reasoning, creative problem-solving, and nuanced decision making, could erode over time. If AI becomes the default mechanism for knowledge retrieval and curation, the culture of active knowledge engagement could shift toward more passive consumption, potentially undermining the very purpose of KM systems.

These developments suggest that organizations must thoughtfully design KM processes that maintain a balance between automation and human oversight (Theme 3). Fostering a culture of critical engagement with AI outputs, rather than uncritical acceptance, will help preserve and even enhance human expertise. For KM professionals, the evolving landscape points to a shift in roles, with greater emphasis on strategic, advisory, and evaluative functions. This requires not only technical AI literacy, but also strong critical thinking skills and the confidence to challenge and contextualize AI outputs when necessary. For those designing AI systems, there is a responsibility to prioritize transparency, explainability, and user-centered design, ensuring that technology supports, rather than substitutes, human judgment. Human in the loop features, such as transparent AI recommendations and adjustable automation, can help preserve human expertise in KM. Although AI offers strong potential for KM, overreliance on automation may weaken human judgment and knowledge sharing [33,34]. This highlights the need for continued research on maintaining strong knowledge cultures in AI-enabled environments.

6.2. Technical and Organizational Barriers

Our thematic analysis, particularly Themes 1, 3 and 5, highlights that while enthusiasm for AI in KM is high, implementation is fraught with technical and organizational challenges across disciplines (Theme 4). Practitioners cited difficulties with legacy systems, inconsistent data, and integration bottlenecks, echoing concerns seen in the literature. These grounded insights from practitioners illustrate that successful AI adoption is as much about organizational transformation as it is about technical innovation. Practitioner experiences

and the literature both reveal that integrating AI into existing organizational infrastructure is often more complex than anticipated. These obstacles underscore that introducing AI into KM is not a one-time technical upgrade, but an ongoing process requiring sustained investment in data curation, IT support, and system governance [3,4,25,33,34].

The implications of these technical barriers suggest that the success of AI in KM is as dependent on organizational readiness and resource allocation as it is on technology. For organizations, this means that realizing the benefits of AI-enhanced KM will require a willingness to invest in upgrades and ongoing support, not just the procurement of new tools. Moreover, as KM practitioners navigate these constraints, their roles increasingly encompass responsibilities such as data stewardship, change management, and cross-departmental collaboration to ensure that AI tools are not only deployed, but also integrated in ways that add real value.

From an organizational perspective, these challenges point to the necessity of strategic planning, with close attention to existing content, workflow, and cultural barriers. Failure to address these issues risk not only under-utilizing AI capabilities but also creating new silos or inefficiencies, ultimately limiting the impact of KM initiatives. Additionally, organizations must recognize that technical hurdles can exacerbate disparities in KM effectiveness, with resource-rich organizations being able to move faster and derive greater benefit, while others struggle to keep pace. Ultimately, these barriers highlight that the journey toward effective AI-enabled KM is as much about organizational transformation as it is about technological innovation. Success will depend on the willingness and ability of organizations to address legacy issues, invest in necessary infrastructure, and foster a culture that is adaptive to both technological and process change.

6.3. Risk, Ethics, and Governance

Theme 4 of our analysis also highlighted some critical concerns and risks of AI in KM, specifically around accuracy, bias, transparency, and data security. KM leaders recounted real-world scenarios in which unchecked automation could lead to misinformation or reputational harm. These practitioner perspectives not only mirror but deepen the ethical considerations discussed in the literature, emphasizing the need for robust governance and human oversight. While the literature frequently acknowledges these challenges, real-world accounts show that many organizations are still grappling with how to implement effective governance and oversight.

The implications of these risks are far-reaching. For organizations, the rapid adoption of AI in KM without robust governance frameworks can expose them to reputational, legal, and operational harms [3,14,22,24]. This reality demands that leadership prioritize the development of policies, guidelines, and review processes that ensure AI-generated knowledge is reliable, explainable, and aligned with organizational values. For KM practitioners, the heightened emphasis on ethics and governance elevates their roles from mere implementers to stewards of organizational knowledge integrity. They should develop expertise to identify when human intervention is required, how to interpret AI-driven recommendations, and how to advocate responsible use of technology within their teams. The need for continuous training and the establishment of clear escalation protocols when errors or ethical dilemmas arise becomes increasingly important as AI becomes more embedded in daily workflows.

From a system design perspective, these risks imply that AI tools must be built with transparency and human oversight in mind. Features such as clear documentation, traceability of decision-making processes, and customizable controls for users are essential for enabling responsible AI integration in KM. Without these safeguards, organizations risk undermining both the effectiveness and the credibility of their KM efforts. While AI

holds significant promise for improving knowledge management, these advances cannot come at the expense of ethical responsibility or trust. Addressing the risks associated with AI in KM is not a one-time challenge, but an ongoing organizational commitment: one that will ultimately determine whether AI strengthens or weakens the foundations of knowledge work.

7. Conclusions

The conclusion of this paper is that AI can and should be integrated into KM. Theme 1 found that AI is being used in many industry sectors to support KM. However, successful AI integration is best understood not as isolated technical interventions, but as extensions of KM success theory, where the system, knowledge, and service quality must evolve together. The themes identified in our practitioner analysis map closely onto the core dimensions of the Jennex–Olfman KM Success Model. The technical and organizational challenges discussed in Theme 4 relate directly to the model's system quality dimension and organizations should address it. Theme 3 affects the net impacts of KM by emphasizing KM effectiveness. Theme 2 supports the intent to use dimension by focusing on AI in KM being used to a support tool rather than replace them. By grounding our theoretical reflections in empirical practitioner themes, we extend and enrich the Jennex–Olfman [5] framework for the AI era. This research extends the Jennex–Olfman [5] framework by extending and moderating the existing constructs with AI:

- System quality: Technical infrastructure is extended with AI infrastructure requirements, including computing power, data storage, and high-speed networks, and moderated by including AI transparency in the generation of these requirements. Human infrastructure is extended by incorporating AI skills into the human skills needed for KM. The interface construct is extended by AI adaptive user interfaces and AI agents. KM form may not be impacted by AI but AI will encourage organizations to make more data available to AI. KM Level is moderated by AI, as AI will improve mnemonic functions.
- Knowledge quality: This is moderated by AI. Knowledge content processes are moderated by incorporating AI processes into content processes. Richness is moderated by AI's ability to generate, summarize, and link information, incorporating explainability, and by new risks of AI's potential to introduce errors, bias, or "hallucinations." Linkages are moderated by AI's ability to find, map, and create links to knowledge and incorporate explainability.
- Service quality: Leadership/management support is expanded and moderated to include supporting AI use in KM. KM strategy is expanded to include the use of AI in knowledge identification, generation, and use. KM governance is expanded to include human oversight of AI and including the creation of management practices, policies, and cultures that prioritize responsible and strategic use of AI, including risk management, who is responsible when AI takes action, explainability of AI, and ethical use of AI.
- Intent to use/perceived benefit is moderated through use of AI interactive interfaces and AI agents.
- Net benefits is moderated by AI in KM by through the four identified success measures. Additionally, AI in KM may lead to the identification of another success measure. Future research will be needed to determine if there is a new measure.

Additionally, the literature supports integrating AI into KM using the KM Success Model. Table 2 summarizes the literature support for integrating AI into the dimensions of the KM Success Model.

Table 2. Literature support for the dimensions of the KM Success Model.

KM Success Model Dimension	Sources Mapped to the Dimension
System Quality	[3,4,11,12,14–25,27,28]
Knowledge Quality	[3,4,12,14,16–25,27,28]
Service Quality	[3,4,14–16,21,25,26]
Intent to Use/Perceived Benefit	[4,10,14,16,17,19,23,25]
Net Benefits	[3,4,12–14,18–20,22,25]

Finally, the KM Success Model was applied to modifying the Knowledge Pyramid from being a taxonomy to being a taxonomic process model [32]. This model, shown in Figure 2, shows that between each level of knowing, there is a strong filter. This filter provides the transformation process from the lower level to the higher level. The model shows that the strong filters at the lowest levels, Internet of Things, IoT, and Big Data, are machine networks, and automated analysis tools and systems. In 2017, machine networks/automated analysis tools were traditional AI tools. These tools were necessary, as the velocity and quantity of data in IoT and Big Data are greater than what humans can handle. Higher levels of knowing transformation used strong filters based on analysis tools and the application of the knowledge content process from the knowledge quality dimension. The sources listed in Table 2 under the knowledge quality dimension describe how newer AI, generative and agentic, can be used for knowledge discovery, generation, and capture, and suggest that AI can also be applied to the strong filters used to transform higher levels of knowing.

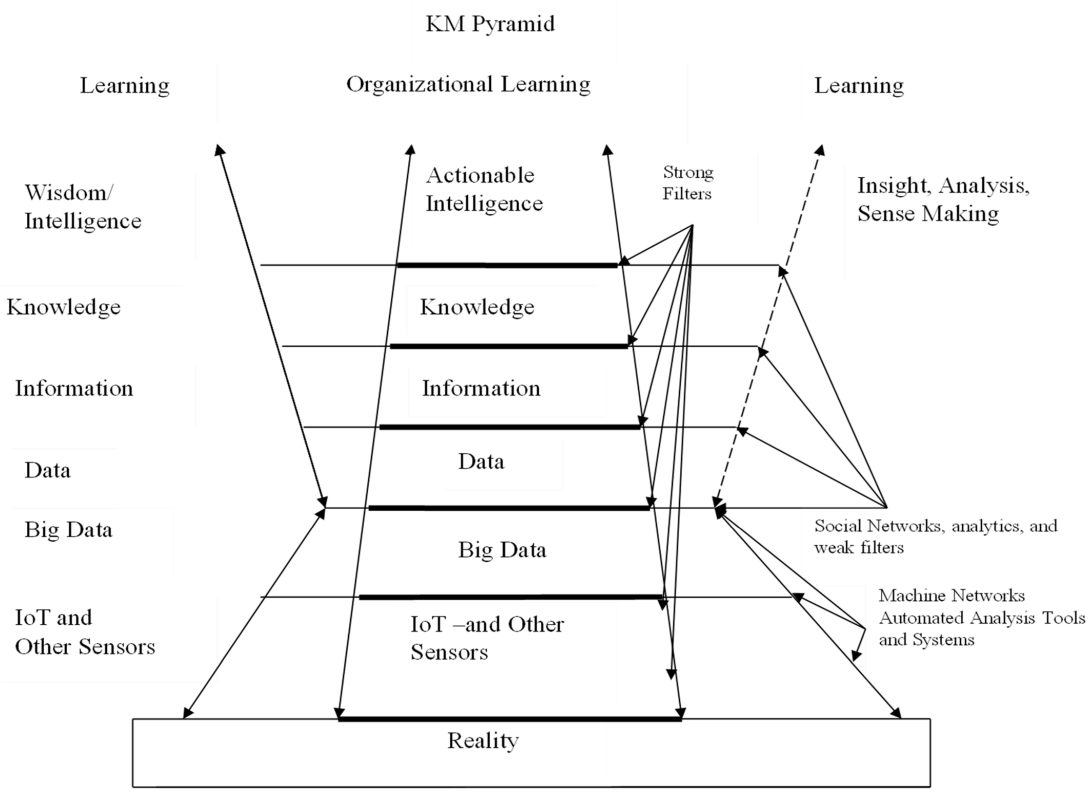


Figure 2. Revised knowledge pyramid [32].

To summarize, both the practitioner thematic analysis and the academic literature review support the integration of AI into the Jennex–Olfman KM Success Model. Figure 3

annotates the KM Success Model with how AI impacts the various constructs and dimensions. However, this study underscores the importance of user satisfaction and intent to use as dynamic constructs in the context of AI adoption. The introduction of AI tools can dramatically reshape user expectations and experiences, sometimes improving satisfaction and perceived benefit, but at other times causing frustration or distrust if the tools are poorly implemented or inadequately explained. Collectively, these implications suggest that the Jennex–Olfman model [8] remains highly applicable, but organizations may need to revisit and adapt its constructs to address the new realities of AI-driven KM. Future theoretical work should explore how measures of KM success evolve as the boundaries between human and machine intelligence become increasingly blurred, and how the interplay of these dimensions influences long-term organizational outcomes.

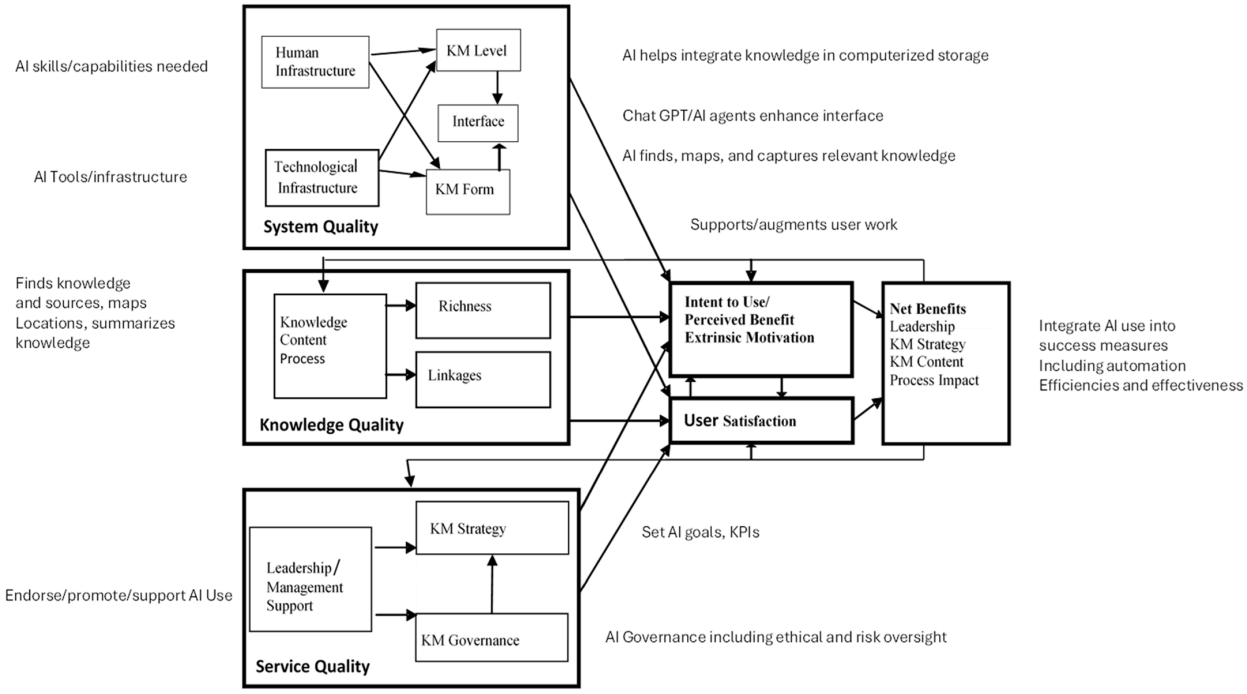


Figure 3. Jennex–Olfman KM Success Model annotated with AI.

7.1. Practical Implications: Navigating AI Integration in KM

Drawing on the practical insights shared across Themes 5 and 6, several actionable guidelines for AI integration in KM emerge. These lived experiences form the foundation for the following recommendations. First, organizations should approach AI integration with a KM strategy that emphasizes balance and complementarity. Rather than aiming for full automation, leaders should focus on building systems where AI supports human expertise and vice versa. This includes designing workflows that require human oversight for high-stakes or ambiguous decisions and promoting a culture of critical engagement with AI outputs. Regular reflection on the boundary between tasks suited for automation versus those requiring judgment is essential for preserving human strengths.

Second, invest in technical infrastructure. AI-enhanced KM depends on high-quality, well-organized data, robust IT systems, and cross-functional collaboration. Organizations should prioritize efforts to digitize legacy knowledge, standardize tagging and metadata practices, and ensure interoperability between KM platforms and new AI tools. Phased, well-governed implementation, rather than rapid, wholesale adoption can help manage risk and build organizational confidence.

Third, establish robust KM governance and ethical frameworks. Organizations should proactively develop policies and procedures for monitoring AI behavior, auditing out-

puts, and responding to errors or ethical concerns. Clear lines of accountability, regular training for KM professionals, and transparent communication about AI's capabilities and limitations support building trust and safeguarding organizational integrity.

Fourth, support continuous human infrastructure development. Upskilling in AI literacy, data management, and critical evaluation techniques ensures that staff can effectively interpret, contextualize, and, when necessary, challenge AI-generated knowledge. Cultivating these capabilities at all levels empowers organizations to get the best out of human and artificial intelligence.

7.2. Gaps and Future Directions

The thematic analysis reveals generally positive practitioner sentiment about AI's role in KM (Themes 1, 2, 5), but it also exposes important gaps and limitations. Notably, there is a scarcity of discussion around failed implementations, unintended negative consequences, or outright resistance to AI adoption. This absence may be due to the optimism bias among early adopters or a reluctance to share negative experiences in professional forums. Our analysis suggests that many organizations are still in the early stages of AI experimentation (Theme 3), with few having established mature, organization-wide governance or evaluation processes. As a result, there is limited longitudinal evidence on the sustained impact of AI on knowledge quality, organizational learning, or KM culture, particularly in terms of maintaining human expertise and managing ethical risks (Theme 4). This suggests a need to explore cases where AI adoption has fallen short or led to unintended drawbacks such as loss of tacit knowledge, skill atrophy, or increased organizational silos. Longitudinal studies that track the real-world evolution of KM practices over time, as well as comparative studies across sectors and organizational sizes, would provide valuable insight.

Also, while we conclude that integrating AI into KM extends the definitions of the constructs in the KM Success Model and that AI acts as a moderating variable in predicting KM success, there is a need for future research to identify measures for these constructs that include AI. This research could be done as part of an effort to validate an AI-enhanced KM Success Model.

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