Duality of AI in Knowledge Management: Correlating Utility Perceptions with Implementation Challenges

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Abstract: This study investigates how organizational members concurrently perceive the benefits of artificial intelligence (AI) for knowledge management processes (KMPs) and the challenges involved in implementing AI within knowledge management systems (KMSs). Based on survey data from 378 respondents across diverse sectors and roles, the research employs validated instruments measuring perceptions of AI's contribution to knowledge acquisition, documentation, sharing, and application, as well as perceived human, technological, financial, and ethical-regulatory barriers. The results show a consistent positive relationship between perceived AI usefulness and perceived implementation barriers: individuals who attribute greater value to AI-enhanced knowledge processes also express heightened awareness of the complexities required to integrate AI into organizational systems. Knowledge documentation presents the strongest associations with all barrier categories, while knowledge sharing exhibits the weakest. Human-related barriers emerge as the most pervasive across all processes, indicating the central role of employee readiness and organizational culture in shaping AI-enabled KM. These findings reveal a dual perception in which optimism regarding AI's potential coexists with recognition of the organizational adjustments it demands. The study contributes to a more integrated understanding of AI adoption in KM, emphasizing that effective implementation requires aligning technological capabilities with human, cultural, and governance considerations.

Keywords: Artificial intelligence, Knowledge management processes, Artificial knowledge, Knowledge management systems, AI-KMS integration, Organizational change

1. Introduction

Knowledge management (KM) focuses on the systematic processes through which organizations create, capture, organize, share, and apply knowledge in order to support learning, innovation, and decision-making (Davenport and Prusak, 1998). These activities are commonly conceptualized as knowledge management processes (KMPs), including knowledge acquisition, documentation, sharing, and application (Jarrahi et al. 2023; Scarso and Bolisani, 2023). Knowledge management systems (KMSs) have traditionally been developed to support these processes by enabling the storage, organization, and dissemination of organizational knowledge (Alavi and Leidner, 2001). In the literature, KMSs are often understood more broadly as socio-technical systems that extend beyond technology to include organizational structures and practices (Hislop et al. 2018).

Recent advances in artificial intelligence (AI) are expanding the capabilities of KMSs. Technologies such as machine learning, natural language processing (NLP), and generative AI enable organizations to analyze large datasets, identify patterns, and generate insights that support knowledge-intensive activities (Abbasi et al. 2025; De Pretto et al. 2025; Kirchner et al. 2024). As a result, AI increasingly participates not only in the storage and retrieval of knowledge but also in the generation of "artificial knowledge" – knowledge inferred, structured, or generated by AI applications through algorithmic analysis of data (Bolisani et al. 2026; Bratianu and Bejinaru, 2026). Consequently, AI-enabled KMSs are gradually evolving into hybrid knowledge environments in which knowledge is co-produced by human expertise and intelligent systems (Benbya et al. 2020; Dwivedi et al. 2021).

While AI technologies offer significant opportunities for enhancing knowledge processes (Alavi et al. 2024; Alghanemi and Al Mubarak, 2022; Böhm and Durst, 2026; Jarrahi et al. 2023; Kirchner et al. 2024), their integration into KMSs also introduces organizational challenges. Prior studies highlight barriers related to human capabilities, technological infrastructures, financial resources, and ethical or regulatory considerations (Campion et al. 2022; Dwivedi et al. 2021; Kurup and Gupta, 2022; Romeo and Lacko, 2026). However, existing research often examines either the potential benefits of AI for knowledge processes or the barriers associated with its implementation. Less attention has been devoted to understanding how these two dimensions relate to one another. Addressing this gap, the study examines the following research question: How is the perceived usefulness of AI for enhancing KMPs related to organizational perceptions of barriers to implementing AI in KMSs?

2. Related Works

The relationship between KM and AI has increasingly attracted scholarly attention, reflecting a broader shift toward data-driven and algorithmic forms of organizational knowledge work (Alghanemi and Al Mubarak, 2022; Böhm and Durst, 2026; Jallow et al. 2020; Jarrahi et al. 2023; Kirchner et al. 2025; Taherdoost and Madanchian, 2023). Much of the literature at this intersection remains conceptual, seeking to theorize how algorithmic capabilities may reshape traditional KM assumptions, knowledge processes, and organizational epistemologies. While research has developed rich theoretical perspectives on AI's potential to augment or transform KM (Nakash and Bolisani, 2024a), empirical studies exploring how organizational members perceive these transformations in practice are still relatively limited (Nakash and Bolisani, 2025).

Within KM scholarship, core knowledge processes – acquisition, documentation, sharing, and application – provide a useful conceptual lens for examining the influence of AI technologies. These processes describe how organizations identify new knowledge, structure and store it, disseminate it across units, and apply it to decisions and actions (Jarrahi et al. 2023; Taherdoost and Madanchian, 2023). Recent works suggest that AI can act as a powerful enabler within several of these domains. For instance, analytical and generative AI models can enhance knowledge acquisition by revealing patterns and opportunities not easily detectable by human actors (Alavi et al. 2024; Alghanemi and Al Mubarak, 2022; Kurup and Gupta, 2022), and NLP tools can support knowledge documentation through automated transcription, classification, and structuring of textual information (Kambala, 2023).

However, the literature presents a more cautious view regarding AI's role in knowledge sharing. Although intelligent search tools and recommendation systems can improve access to explicit knowledge, scholars emphasize that AI technologies face inherent limitations in supporting the socially embedded, relational, and tacit dimensions of knowledge exchange (Bratianu, 2025; Bratianu and Bejinaru, 2026). Tacit knowledge – rooted in context, experience, and interpersonal interaction (Nonaka, 1994; Nonaka and Takeuchi, 1995) – cannot be easily codified or inferred algorithmically, restricting AI's capacity to fully mediate or substitute human-driven sharing processes (Bejinaru, 2026). In contrast, AI's contribution to knowledge application is generally regarded as more substantial: predictive analytics and decision-support systems can assist employees in interpreting information and evaluating options, particularly in data-rich organizational environments (Alghanemi and Al Mubarak, 2022; Sumbal et al. 2024).

Alongside these opportunities, research consistently identifies a range of challenges associated with incorporating AI into knowledge-intensive organizational environments. Human barriers include resistance to new work practices, digital skill gaps, and cultural inertia that impede adoption (Arias-Pérez and Vélez-Jaramillo, 2022; Ivchyk, 2024; Romeo and Lacko, 2026). Technological barriers arise from limitations in infrastructure, system compatibility, and data quality, as well as complexities in integrating AI with existing information technologies (IT) architectures. Financial barriers reflect the high costs of implementation, customization, and ongoing maintenance (Dwivedi et al. 2021). Ethical-regulatory barriers encompass concerns related to privacy, bias, discrimination, accountability, and data governance as AI systems increasingly mediate knowledge-intensive activities (Arrieta et al 2020; Campos Zabala, 2023). These clusters of challenges underscore that AI does not simply extend KM capabilities but also surfaces organizational, technical, and normative tensions.

Taken together, the literature presents a nuanced picture: while AI offers meaningful opportunities to augment certain knowledge processes, its integration is accompanied by substantial constraints, particularly in domains involving tacit knowledge or complex organizational readiness. Although conceptual analyses are abundant (i.e., Böhm and Durst, 2026), empirical investigations that jointly examine perceptions of AI's usefulness for discrete KM processes and perceptions of the barriers that shape its implementation remain comparatively scarce. Understanding these perceptions is essential for illuminating how organizations navigate the emerging landscape of AI-enabled knowledge work and how employees reconcile expectations of technological benefit with awareness of implementation challenges.

3. Materials and Methods

An online quantitative survey was administered between May and June 2024 and completed by 378 respondents representing a diverse range of socio-demographic and occupational backgrounds from organizations of varying sizes and sectors. The survey consisted of three questionnaires. The first two were composed of closed-ended statements rated on a six-point Likert scale ranging from 1 ("strongly disagree") to 6 ("strongly agree"), while the third included single-choice demographic and organizational questions.

The first questionnaire assessed perceptions of the usefulness of artificial intelligence for enhancing KMPs. It included 20 Likert-scale items grouped into four dimensions: knowledge acquisition, knowledge documentation, knowledge sharing, and knowledge application (see Table 1) (Nakash and Bolisani, 2024b, 2025). The second questionnaire measured perceived barriers to implementing AI within KMSs through 20 items distributed across four domains: human, technological, financial, and ethical-regulatory barriers (see Table 2) (Nakash and Bolisani, 2026). Both scales demonstrated strong internal consistency, with Cronbach's alpha coefficients exceeding the accepted threshold of 0.70. Excellent internal reliability was observed for the overall scale of the first questionnaire ($\alpha = 0.92$) and the second questionnaire ($\alpha = 0.90$). Construct validity for both instruments was confirmed through Confirmatory Factor Analysis (CFA) within a Structural Equation Modeling (SEM) framework.

Table 1: Dimensions of AI-Supported KMPs and Their Conceptual Definitions

	Dimension	Conceptual Meaning	Example Item from Questionnaire 1
I	Knowledge Acquisition	The process of identifying, evaluating, and integrating new knowledge from internal and external sources to enhance organizational understanding and future decision-making	"Innovative ideas for products or services will be developed using AI"
II	Knowledge Documentation	The systematic recording, structuring, and organizing of knowledge to ensure its accessibility, accuracy, and long-term usability	"Knowledge from discussions, meetings, and conversations within an organization will be documented using AI-based NLP technologies"
III	Knowledge Sharing	The exchange and dissemination of insights, experiences, and expertise across organizational boundaries to promote collaboration, learning, and innovation	"The flow of knowledge among the organization's employees will be improved through AI"
IV	Knowledge Application	The utilization of acquired and shared knowledge to inform decisions, optimize operations, and improve organizational performance	"AI-powered decision support systems will make it easier to make smart choices by analyzing options and evaluating outcomes"

Table 2: Dimensions of Barriers to AI Implementation in KMSs and Their Conceptual Definitions

	Dimension	Conceptual Meaning	Example Item from Questionnaire 2
I	Human Barriers	Challenges stemming from employee resistance, skill gaps, lack of awareness, and cultural inertia that hinder the adoption of AI for KM	"Employees currently lack the necessary skills to fully utilize AI for enhancing KM"
II	Technological Barriers	Constraints related to system compatibility, data quality, integration complexity, and risks associated with AI-enabled IT infrastructures	"There is difficulty in integrating and interfacing AI applications with existing KMSs"
III	Financial Barriers	Economic limitations involving high upfront investment, customization costs, and ongoing maintenance required for AI deployment in KM	"The cost of purchasing, implementing, and maintaining AI solutions for KM is too high for my organization"
IV	Ethical-Regulatory Barriers	Legal, ethical, and governance concerns including privacy, bias, discrimination, accountability, and data ownership in AI-mediated KM	"Biases and hidden discrimination may seep into decision-making due to mistaken interpretation of reality by the algorithms"

The third questionnaire captured demographic and organizational characteristics of the respondents and revealed a heterogeneous sample. The participants included 52.6% women, and 67.5% held an academic degree. Respondents represented small (36%), medium-sized (33.6%), and large organizations (30.4%) across public, industrial, services, and high-tech sectors. Organizational roles included employees (43.9%) and managers (56.1%), while 34.1% reported specialization in knowledge management (KM). The average age of participants was 41.97 years ($SD = 10.68$), and 11.9% reported organizational tenure exceeding 20 years.

Prior to full distribution, the questionnaires were pilot-tested to ensure clarity and reliability. The survey protocol received approval from the Institutional Ethics Committee (Reference No. 200524103), ensuring compliance with established ethical research standards. Informed consent was obtained from all participants, participation was voluntary, and anonymity, confidentiality, and data privacy were fully maintained.

Questionnaire validation and statistical analyses were conducted using IBM SPSS Statistics (Version 28) and R (Version 4.3).

4. Findings

The results reveal a statistically significant positive relationship between the perceived usefulness of AI for improving KMPs and the perceived barriers and challenges associated with implementing AI technologies in KMSs. As illustrated in Figure 1, the scatterplot demonstrates a positive trend between the two composite variables, indicating that higher perceptions of AI usefulness tend to coincide with higher perceptions of implementation barriers.

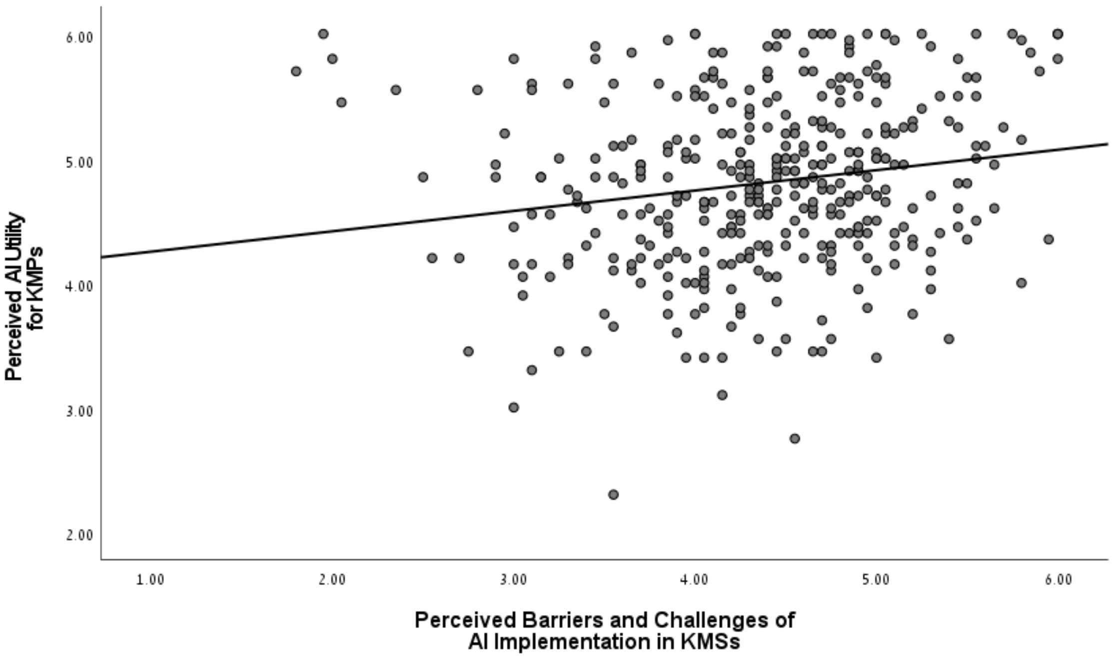

Figure 1: Relationship Between Perceived AI Usefulness for KMPs and Perceived Barriers to AI Implementation in KMSs

A more detailed view of these relationships is presented in Table 3, which reports the correlations between perceived AI usefulness across four KMPs – knowledge acquisition, knowledge documentation, knowledge sharing, and knowledge application – and four categories of implementation barriers: human, technological, financial, and ethical-regulatory.

Table 3: Pearson Correlation Matrix Between Perceived AI Usefulness Across KMPs and Perceived Barriers to AI Implementation in KMSs

		Perceived Barriers and Challenges of AI Implementation in KMSs				
		Human	Technological	Financial	Ethical-Regulatory	Total Score
Perceived AI Utility for KMPs	Knowledge Acquisition	.20***	.13*	.06	.11*	.15**
	Knowledge Documentation	.17**	.18***	.12*	.16**	.19***
	Knowledge Sharing	.12*	.10	.12*	.08	.13*
	Knowledge Application	.16**	.09	.09	.11*	.14**
	Total Score	.19***	.14**	.11*	.13**	.18***

*p<.05, **p<.01, ***p<.001.

Overall, the table shows that the perceived usefulness of AI across the different KMPs is positively associated with most categories of implementation barriers, although the strength and consistency of these relationships vary across processes:

1. Knowledge acquisition is positively associated with human, technological, and ethical-regulatory barriers, while its relationship with financial barriers is not significant.
2. Knowledge documentation shows positive relationships with all four categories of barriers and exhibits the strongest and most consistent associations among the four processes.
3. Knowledge sharing demonstrates fewer significant relationships with implementation barriers. Its associations appear mainly with human and financial barriers, while the relationships with technological and ethical-regulatory barriers are not significant.
4. Knowledge application is positively associated with human and ethical-regulatory barriers, whereas its relationships with technological and financial barriers are not significant.

Across the four KMPs, human barriers are the only category that shows significant associations with all processes, whereas technological, financial, and ethical-regulatory barriers appear more selectively. The total score of perceived AI usefulness for KMPs is also positively associated with the overall score of perceived implementation barriers, as well as with each barrier category.

5. Discussion

The results suggest that perceptions of AI in KM reflect a form of cognitive duality in which technological optimism coexists with heightened awareness of organizational complexity. Individuals who recognize the potential of AI to enhance knowledge processes also appear more attentive to the structural conditions required for embedding AI into KMSs. This pattern aligns with prior research on AI adoption and digital transformation, which shows that recognition of technological value often develops alongside awareness of the organizational adjustments required for effective implementation (Kirchner et al. 2025; Romeo and Lacko, 2026). In this sense, perceived implementation barriers may reflect not resistance but a more mature understanding of AI integration as an organizational transformation rather than merely a technological upgrade.

A second insight relates to the heterogeneous nature of KMPs. The differing patterns across knowledge acquisition, documentation, sharing, and application suggest that AI interacts unevenly with organizational knowledge activities. This observation is consistent with KM literature emphasizing that knowledge processes differ in their levels of codification and technological mediation (Alavi and Leidner, 2001; Nonaka and Takeuchi, 1995). Processes involving structured knowledge assets may expose the technological and organizational implications of AI integration more clearly, whereas processes centered on interpersonal knowledge exchange may appear less directly dependent on technological infrastructures. Accordingly, AI adoption in KM should be understood as a differentiated transformation across knowledge processes rather than a single organizational capability.

These findings also carry implications for both theory and practice. Theoretically, the results suggest that perceived usefulness and perceived barriers may develop simultaneously rather than acting as opposing determinants of adoption, thereby extending traditional technology adoption perspectives such as the Technology Acceptance Model (Davis, 1989) and supporting more systemic views of socio-technical alignment. Practically, the findings indicate that organizations should approach AI-enabled KM initiatives through integrated strategies that combine technological investment with organizational readiness, including employee capability development, supportive knowledge cultures, and governance mechanisms for responsible AI use.

Finally, the consistent prominence of human-related barriers underscores the enduring centrality of the human dimension in KM. Despite the growing capabilities of AI technologies, their effectiveness ultimately depends on employees' willingness and ability to integrate AI-generated outputs into knowledge work. This observation echoes long-standing KM scholarship emphasizing that technological infrastructures alone cannot ensure effective knowledge processes without complementary cultural and managerial conditions (Alavi and Leidner, 2001; Davenport and Prusak, 1998) and aligns with recent research highlighting the importance of human-AI collaboration in organizational knowledge practices (Jarrahi et al. 2023; Liu and Shen, 2025).

6. Conclusion

Our empirical study sheds light on a central tension in the organizational adoption of AI for KM: recognition of the technology's potential benefits tends to emerge alongside heightened awareness of the challenges involved in its implementation. Rather than representing conflicting perceptions, these two dimensions appear to develop in parallel, reflecting a more comprehensive understanding of AI as both an opportunity and an organizational challenge. By demonstrating this duality, the study contributes to a more nuanced perspective on AI adoption in KM and emphasizes that successful implementation requires coordinated attention to technological capabilities, organizational structures, and the human dimensions of knowledge work. Future research could further investigate how these perceptions evolve over time as organizations accumulate practical experience with AI-enabled KMSs. In addition, longitudinal and comparative studies across sectors could help clarify whether the relationship between perceived utility and perceived barriers changes as AI technologies and organizational capabilities mature.

AI Declaration: The authors confirm that no AI tools were used in the preparation of this manuscript. All research activities, analyses, and writing were carried out manually, in full adherence to the highest standards of academic integrity.

Ethics Declaration: This research project was approved by the Human Subjects Institutional Review Board (HSIRB), which examined the ethical aspects of the study (Approval No. 200524103).

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