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The transformative impact of AI on knowledge management processes

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Abstract

Purpose – This study seeks to explore the prospective strategic relationship between knowledge management (KM) and artificial intelligence (AI) by examining how AI technologies are currently perceived to enhance critical knowledge management processes (KMPs) in organizations.

Design/methodology/approach – An online survey of 378 employees and managers, representing a diverse range of sociodemographic and occupational backgrounds, evaluated the perceived usefulness of AI in key KMPs: knowledge acquisition, documentation, sharing and application. It also evaluated the perceived importance of AI implementation and trust in AI tools for KMPs, inspired by established theoretical frameworks for technology acceptance. Statistical tests included ANOVA, *t*-tests, MANOVA, Pearson and Spearman.

Findings – AI is perceived as highly beneficial across all KMPs, with varying degrees of usefulness. Specifically, managers generally see higher potential in AI for KM than regular employees. Positive attitudes toward AI were noted among knowledge managers for knowledge acquisition and graduated for knowledge application. The findings also show a positive correlation between the perceived usefulness of AI, the importance of its implementation and trust in AI tools. Surprisingly, the high-tech sector reported lower perceptions of AI's usefulness, especially for knowledge acquisition and sharing. Gender, age, seniority and organization size showed no significant impact.

Originality/value – Given that research on AI in KM is still in its early stages and largely theoretical, this empirical investigation is timely. The findings thus represent a pioneering effort in harnessing the potential of AI within knowledge-intensive organizational environments.

Keywords Artificial intelligence, AI adoption, Knowledge management processes, Knowledge acquisition, Knowledge documentation, Knowledge sharing, Knowledge application

Paper type Research paper

1. Introduction

Artificial intelligence (AI) refers to the capacity of systems to interpret external data, learn from it, and apply acquired knowledge to achieve specific goals through adaptive behavior (Kaplan and Haenlein, 2019). By emulating human cognitive functions—such as perception, reasoning, learning, and problem-solving—AI enables machines to perform tasks that are traditionally ascribed to human intelligence (Böhm and Durst, 2024; Chubb *et al.*, 2022; Glikson and Woolley, 2020; Secinaro *et al.*, 2023; Sheikh *et al.*, 2023). These capabilities are driven by advanced computational methods, including machine learning (ML), deep learning (DL), and neural networks, which facilitate the analysis of complex data patterns and support enhanced decision-making (Brynjolfsson and Mitchell, 2017). A key subfield, natural language processing (NLP), allows systems to understand and generate human language,

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thereby advancing human-computer interaction. Recent developments in generative AI (Gen-AI) have further broadened the technology's scope, establishing it as a transformative force across areas such as automation and decision-making (Chubb *et al.*, 2022; Kaczorowska-Spychalska *et al.*, 2024; Kelly *et al.*, 2023; Secinaro *et al.*, 2023).

The rapid expansion of AI technologies is driving significant transformations across industries, contributing to widespread technological disruption (Arias-Pérez and Vélez-Jaramillo, 2022; Güven *et al.*, 2024). Recent findings from the McKinsey Global Survey on AI suggest that this growth is fueled by the increasing integration of AI into diverse business functions at both strategic and operational levels (McKinsey, 2024). While AI offers substantial economic and operational potential (Taherdoost and Madanchian, 2023), its effectiveness ultimately depends on its alignment with specific business processes and user needs (Nakash and Bolisani, 2024a). Variations in AI adoption and utilization can also be found in connection with differences in employees' and managers' ability to effectively incorporate AI into their daily work, highlighting the importance of tailored implementation strategies (Ransbotham *et al.*, 2022).

Indeed, a key factor in the proliferation of AI, as with other information technologies (IT), is the intensity and speed of adoption by potential users, which, in turn, depend on their acceptance of the technology and its functionalities. The Technology Acceptance Model (TAM) is one of the most widely used theoretical frameworks for examining user acceptance of AI technologies (Kelly *et al.*, 2023). According to TAM, AI adoption in organizations is primarily influenced by user perceptions, particularly regarding its perceived usefulness and ease of use (Davis, 1989; Dwivedi *et al.*, 2021). Trust in AI, shaped by individual attitudes and experiences, is also a critical factor in determining the extent to which employees and managers integrate AI into their workflows (Akudjedu *et al.*, 2023; Glikson and Woolley, 2020).

Given that AI fundamentally replicates human cognitive functions in processing information and knowledge for decision-making, knowledge management (KM) provides a valuable theoretical lens for assessing its organizational impact, as well as its alignment with users' needs and their subsequent willingness to adopt it. In particular, knowledge management processes (KMPs)—the dynamic activities through which organizations acquire, store, share, and apply knowledge—constitute a core element of KM (Birzniece, 2011; Pinho *et al.*, 2012; Zbuchea *et al.*, 2019). In today's fast-paced business environment, effectively processing knowledge resources is critical not only for supporting informed decision-making and enhancing daily operations but also as a key driver of organizational competitiveness (Al Mansoori *et al.*, 2020; Areed *et al.*, 2020; Taherdoost and Madanchian, 2023).

In response to the growing complexity of knowledge-intensive environments, many organizations have implemented IT-based knowledge management systems (KMSs) to streamline knowledge creation, organization, and dissemination. However, despite the pivotal role of these systems, the effectiveness of KM has traditionally relied on human expertise and judgment (Alghanemi and Al Mubarak, 2022). The advent of AI has significantly reshaped this landscape, enabling both the automation and augmentation of various KMPs. Given the profound interconnection between AI and KM (Bencsik, 2021), understanding their evolving relationship is essential for organizations striving to navigate an increasingly data-driven and competitive business environment (Taherdoost and Madanchian, 2023).

2. Research purpose and questions

As mentioned, KM and AI can be seen as closely interrelated fields, both fundamentally linked to the concept of knowledge and its management (Bencsik, 2021). Edwards and Lönnqvist (2023) reinforce this interconnection by asserting that "AI desperately needs KM" (p.914) to unlock its full potential. Similarly, Iaia *et al.* (2024) highlight that the integration of AI into KM creates a mutually reinforcing dynamic that advances both domains. Historically, the handling of knowledge within organizations was an exclusively human-driven capability until the advent of AI (Alghanemi and Al Mubarak, 2022). While KM facilitates the comprehension of

knowledge, AI provides the tools necessary for its expansion, utilization, and the creation of new knowledge (Haenlein and Kaplan, 2019). As early as the 2000s, Liebowitz (2001) suggested that AI could enhance KM by improving KMPs, a notion that has gained increasing relevance with recent technological advancements. In particular, the emergence of powerful Gen-AI tools has ushered in a transformative era for organizational KM, redefining how knowledge is created, shared, and applied (Alavi *et al.*, 2024; Benbya *et al.*, 2024).

As AI technologies rapidly advance, KM is evolving into a more sophisticated and nuanced discipline, fundamentally altering traditional methodologies and enhancing its strategic importance. Jallow *et al.* (2020) highlight that AI can be developed and utilized to enhance the KMPs that businesses have already established. However, alongside these opportunities, AI-driven KMSs introduce notable challenges and risks, including data privacy concerns, algorithmic bias, knowledge verification difficulties, and the potential erosion of tacit knowledge due to over-reliance on AI-generated insights (Benbya *et al.*, 2024; Glikson and Woolley, 2020; Kaczorowska-Spychalska *et al.*, 2024; Jallow *et al.*, 2020; Liang *et al.*, 2022; Nakash and Bolisani, 2024a). Despite the growing scholarly interest in AI's role in KM (Al Mansoori *et al.*, 2020; Taherdoost and Madanchian, 2023), empirical research remains limited (Nakash and Bolisani, 2024a), often focusing on specific industries or communication processes within KM (AlQahtani, 2024; Iaia *et al.*, 2024; Jallow *et al.*, 2020). Understanding the evolving relationship between AI and KM is therefore critical for organizations seeking to harness AI's full potential in knowledge-intensive environments.

Integrating AI and KMSs for improved KMPs is thus regarded as a transformative development (Takyar, 2023). A study of 120 senior executives in Italian manufacturing firms found that AI adoption enhances KMPs but is ineffective without appropriate KMP integration (Leoni *et al.*, 2022). This inefficacy often stems from a lack of awareness regarding AI's KM applications, contributing to hesitancy in AI investment (Taherdoost and Madanchian, 2023). More broadly, uncertainty about AI's strategic advantages significantly affects organizational perceptions (Chen *et al.*, 2021).

This empirical study examines user perceptions of AI's potential to support KM in organizational settings, focusing on demographic and employment factors that may influence these perceptions. Rather than limiting the scope to a specific AI tool, the research adopts a broad perspective, considering various AI technologies and their applications within business and organizational contexts. Given the evolving attitudes toward AI (Secinaro *et al.*, 2023) and the need to assess its opportunities and challenges across industries (Güven *et al.*, 2024), we aim to explore how AI's potential in KM is recognized at different organizational levels. By identifying patterns in user perceptions, our findings may offer critical insights into the practical viability of AI-driven KM solutions within organizations. Understanding these perspectives is crucial for bridging the gap between theoretical advancements and real-world applications, ultimately shaping strategies for AI adoption in KM practices.

Since organizations apply different KMPs in distinct contexts, it is essential to distinguish between them to evaluate their effectiveness (Obeso *et al.*, 2020). Our study focuses on four primary KMPs frequently cited in KM literature: **knowledge acquisition,** the process of identifying, evaluating, and integrating new knowledge from internal and external sources; **knowledge documentation,** the systematic recording and structuring of knowledge to ensure accessibility and usability; **knowledge sharing,** the exchange of insights and expertise across organizational boundaries to enhance collaboration and innovation; and **knowledge application,** the utilization of acquired and shared knowledge to inform decision-making and drive organizational performance (Areed *et al.*, 2020; Kassaneh *et al.*, 2021; Nakash and Bolisani, 2024b; Scarso and Bolisani, 2023).

To address these issues, the study poses the following research questions:

RQ1. How do employees and managers perceive AI's potential to enhance KMPs in organizational settings?

RQ2. Do perceptions of AI benefits differ across distinct KMPs?

RQ3. Are there variations in AI perceptions based on demographic and occupational factors?

3. Literature review and hypothesis development

AI technologies offer diverse capabilities that can significantly vary in effectiveness depending on the complexity and context of each specific KMP (AlQahtani, 2024; Kaczorowska-Spychalska *et al.*, 2024; Takyar, 2023). For instance, AI is deemed to excel in knowledge acquisition due to its ability to process and analyze large datasets, identify patterns, and extract valuable insights (Alghanemi and Al Mubarak, 2022; Brynjolfsson and McAfee, 2014; Brynjolfsson and Mitchell, 2017; Ransbotham *et al.*, 2022). Recent advancements in ML, DL, and NLP have further expanded AI's capabilities, allowing it to mine unstructured data from diverse sources and derive actionable knowledge (Sheikh *et al.*, 2023; Waykar and Al Mubarak, 2022). The SECI theory (Socialization, Externalization, Combination and Internalization) by Nonaka and Takeuchi (1995) emphasizes that different KMPs require varying levels of social interaction. Knowledge sharing and application, for example, demand higher human interaction (Scarso and Bolisani, 2023; Toscani, 2023), while processes like knowledge acquisition and documentation often are more automated (AlQahtani, 2024; Brynjolfsson and Mitchell, 2017). Consequently, AI may be perceived as more beneficial in processes requiring less human interaction, which can influence how its usefulness is evaluated across different KMPs. Building on these insights, and acknowledging that KMPs affect company performance in different ways and degrees (Obeso *et al.*, 2020), we propose our initial hypothesis:

H1. There will be variations in evaluating the usefulness of AI across different KMPs.

The strategic importance of KM necessitates the development of long-term plans for effectively utilizing an organization's knowledge assets (Bolisani and Bratianu, 2017). Managers, as key decision-makers, are responsible for aligning organizational goals with technological advancements, ensuring that knowledge resources are leveraged for competitive advantage. AI has emerged as a transformative tool enhancing decision-making processes, automating routine tasks, and optimizing resource allocation (AlQahtani, 2024; Arias-Pérez and Vélez-Jaramillo, 2022; Davenport and Ronanki, 2018; Brynjolfsson and Mitchell, 2017; Iaia *et al.*, 2024; Ransbotham *et al.*, 2022; Taherdoost and Madanchian, 2023). Its ability to streamline processes and reduce operational costs may be particularly appealing to managerial jobs (Dwivedi *et al.*, 2021; Kaplan and Haenlein, 2019; Takyar, 2023). This aligns with their need for accurate, readily available, and comprehensive knowledge to inform strategies (Brynjolfsson and McAfee, 2014; Chen *et al.*, 2021). In contrast, employees without managerial responsibility may perceive AI as a significant threat to their roles (Arias-Pérez and Vélez-Jaramillo, 2022; Benbya *et al.*, 2024; Iaia *et al.*, 2024). This divergence in perspectives suggests that managerial roles, which emphasize long-term strategic planning and optimization, may foster more favorable attitudes toward AI adoption in KMPs. Considering this, we propose the following hypothesis:

H2. Managers will exhibit more favorable perceptions than regular employees concerning the usefulness of AI in KMPs.

Knowledge managers are people whose jobs and tasks are explicitly oriented to implement KMPs and improve KM capabilities within their organization. Given their expertise in managing knowledge flows, they are uniquely positioned to assess the limitations of traditional KM approaches and recognize the potential of AI-driven solutions (Nakash *et al.*, 2022). As strategic planners, knowledge managers leverage knowledge resources to gain a

competitive edge, aligning their interests with innovative technologies that enhance organizational capabilities (Liebowitz, 2001; McKeen and Staples, 2004; Schroeder *et al.*, 2012). Their familiarity with AI's ability to automate and optimize KMPs, particularly in knowledge acquisition, positions them as key advocates for AI integration in KM practices. Since knowledge acquisition is the initial and often most resource-intensive stage of the KM cycle (Nonaka and Takeuchi, 1995), knowledge managers may prioritize its enhancement to ensure a steady inflow of relevant and high-quality knowledge. Therefore, we formulated the following research hypothesis:

H3. Knowledge managers will exhibit more positive perceptions than non-knowledge managers regarding the usefulness of AI in KMPs, with a particularly strong perception of its usefulness in knowledge acquisition.

Individuals with academic degrees often possess greater awareness of AI's advanced capabilities due to their exposure to cutting-edge research and technological developments, and can better comprehend and appreciate the potential applications of AI across various domains. Furthermore, AI has become increasingly integrated into higher education, with many academic institutions incorporating AI-driven tools into curricula and research (Chubb *et al.*, 2022; Crompton and Burke, 2023). As a result, graduates frequently develop hands-on experience with AI technologies, fostering a deeper understanding of their practical benefits and reliability. Moreover, people with academic backgrounds typically possess strong critical thinking and analytical skills, which can allow them to evaluate the potential of AI to enhance knowledge application by providing insights, identifying patterns, and supporting decision-making processes (Chubb *et al.*, 2022; Secinaro *et al.*, 2023). Therefore, they are more likely to recognize the strategic benefits of leveraging AI to achieve knowledge-based organizational goals. In light of these considerations, we hypothesize as follows:

H4. Graduated will exhibit more positive perceptions than non-graduated regarding the usefulness of AI for knowledge application.

The Cognitive Evaluation Theory posits that intrinsic motivation is driven by an individual's perception of competence and autonomy, highlighting the significance of feeling capable and self-directed in one's engagement with technology (Deci and Ryan, 1985). Studies have demonstrated that higher perceived usefulness leads to greater trust in technology, as users associate usefulness with reliability and effectiveness. Consequently, when employees perceive AI technologies positively, it can enhance both cognitive and emotional trust in the technology and its use, playing a pivotal role in the integration and acceptance of AI within organizations (Choung *et al.*, 2023; Glikson and Woolley, 2020; Güven *et al.*, 2024). Furthermore, according to the TAM, the more beneficial a technology is perceived to be, the stronger the motivation to integrate it within organizational practices (Davis, 1989). This implies that when employees recognize AI as advantageous for KMPs, they are more likely to commit to its implementation. Based on these explanations, we formulated the following research hypothesis:

H5. There will be a positive relationship between the perceived usefulness of AI for KMPs, the importance attributed to implementing AI in the organization, and the level of trust placed in AI tools for KMPs. As the perception of usefulness increases, so will the importance of implementation and the level of trust.

The high-tech sector is widely recognized for its strong culture of innovation and early adoption of emerging technologies (Baram and Ben-Israel, 2019). A knowledge-sharing organizational culture is particularly critical to success in this sector, as it facilitates collaboration and accelerates technological advancements (Toscani, 2023). High-tech companies are often at the forefront of technological advancements, with employees generally more familiar with advanced technologies compared to those in other sectors (Baram and Ben-Israel, 2019; Maggor and Frenkel, 2022). Additionally, these companies typically

have better access to resources, including financial investments and skilled personnel, to implement and support new business initiatives and processes. Artificial intelligence is expected to be a key factor influencing the development and growth of this industry (Israel Innovation Authority, 2024). Consequently, we propose the following hypothesis:

H6. The high-tech sector will exhibit more positive perceptions than other sectors regarding the usefulness of AI for KMPs.

Research shows that employees prioritize practical benefits such as efficiency, accuracy, and productivity when evaluating new technologies (Davis, 1989; Güven *et al.*, 2024; Venkatesh *et al.*, 2003). The TAM framework identifies perceived usefulness and ease of use as the primary determinants of technology adoption across diverse user groups (Davis, 1989). Expanding on TAM, the Unified Theory of Acceptance and Use of Technology (UTAUT) incorporates additional factors, such as social influence and facilitating conditions, which further shape technology adoption behaviors (Venkatesh *et al.*, 2003). In line with these models, if AI tools are perceived as easy to use and are accompanied by adequate training and support, employees are likely to find them beneficial, regardless of gender, age, or seniority. Based on these considerations, we propose the following hypotheses:

H7. There will be no significant differences in the perceived usefulness of AI for KMPs between men and women.

H8. There will be no significant differences in the perceived usefulness of AI for KMPs across different age groups.

H9. There will be no significant differences in the perceived usefulness of AI for KMPs across different levels of seniority.

Empirical evidence suggests that small and medium-sized enterprises (SMEs) typically manage their knowledge informally and often unconsciously (Bolisani *et al.*, 2016). This is largely due to limited resources such as budgets, personnel, and infrastructure, which distinguish these organizations from larger ones (Alavi *et al.*, 2024; Nakash and Bouhnik, 2023). These constraints may pose significant barriers to effective KMPs (Pinho *et al.*, 2012). Additionally, SMEs often prioritize daily operations and short-term planning over strategic thinking. In contrast, the complexity of large organizations drives them to invest in KMSs and be more agile in introducing KM initiatives. Consequently, individuals in large organizations are more likely to experience the benefits of advanced technologies firsthand (Sytnik and Kravchenko, 2021). Furthermore, the strategic imperative of maintaining a sustainable competitive advantage and fostering innovation through accumulated business knowledge may be more pronounced in large organizations (Nonaka and Takeuchi, 1995). Organization size can thus function as a key variable in understanding how resource availability influences AI adoption in KM practices. Based on these considerations, we propose the following hypothesis:

H10. Large organizations will exhibit more positive perceptions than small and medium-sized organizations regarding the usefulness of AI in KMPs.

4. Procedures

4.1 Research design

Our objective was to assess the perceived potential of AI technologies in enhancing KMPs within organizations. To achieve this goal, we opted for a quantitative questionnaire approach, specifically designed to gauge respondents' opinions on this matter. We chose an online survey methodology due to its advantages in terms of broad reach, cost-effectiveness, and convenience (Queirós *et al.*, 2017; Zickar and Keith, 2023). Furthermore, the online survey

method was preferred for its capacity to swiftly collect a large volume of responses (Fowler, 2013; Mohajan, 2020), allowing us to capture a wide spectrum of opinions on the integration of AI in KMPs.

The questionnaire was structured into three primary sections: the first focused on the intersection of AI and KMPs, the second on participants' occupational specifics, and the third on their demographic information (see Appendix). It incorporated various question formats, including closed statements rated on a 6-point Likert scale (ranging from 1 – definitely no, to 6 – definitely yes), multiple-choice questions, and an open-ended query. This mixed-method approach was chosen to comprehensively capture insights into how AI is perceived to impact KMPs.

The survey protocol received approval from the Institutional Ethics Committee (Reference number: 200524103), ensuring adherence to ethical research standards. Data collection was conducted in Israel between May and June 2024, with this setting chosen for its unique characteristics that enhance the study's international relevance. Firstly, Israel's diverse and multicultural population (Mendelson-Maoz, 2015) provided a heterogeneous sample, allowing for an examination of AI perceptions across various demographic and organizational contexts. This diversity strengthens the study's ability to capture insights that may be applicable to other multicultural and globally interconnected work environments, particularly those in technologically advanced economies.

Secondly, Israel's highly developed technological infrastructure, strong culture of innovation (Katz, 2018) and growing public and private investments in AI, make this country a global leader in AI research and adoption. The country's status as a "Start-Up Nation" (Baram and Ben-Israel, 2019; Maggor and Frenkel, 2022) underscores its role as an early adopter of emerging digital technologies, offering a valuable case study for understanding how AI integration unfolds in organizations (Debowy *et al.*, 2024). Consequently, insights gained from Israel are highly relevant for organizations worldwide.

To ensure a diverse respondent pool, the questionnaire was distributed among employees and managers from organizations of varying sizes and sectors. We employed a multi-channel distribution strategy, leveraging colleagues, acquaintances, organizational networks, and social media platforms. This approach aimed at maximizing response rates and encompassing viewpoints from a wide array of organizational contexts. Specifically, we employed the "snowball" sampling technique in virtual communities to increase sample size, representativeness, and external validity (Baltar and Brunet, 2012). This method involves initial respondents inviting members of their social circles to participate. The survey was administered through Google Forms. All participants gave their informed consent by selecting the consent option on the survey form. Participation was voluntary and anonymous, thereby encouraging participants to share their perspectives candidly and ensuring confidentiality. This methodological choice was crucial in obtaining authentic feedback without concerns about privacy (Mohajan, 2020).

4.2 Reliability and validity

Before distributing the questionnaire to the full sample, it was administered to a pilot group of 52 participants. This preliminary phase aimed to evaluate and enhance the instrument's clarity, refine item wording, and ensure internal consistency and structural validity, thereby strengthening its overall quality for broader deployment.

The initial section of the questionnaire comprised 20 statements rated on a Likert scale. This section was structured into four subscales, each consisting of five items that assessed knowledge acquisition, documentation, sharing, and application within KMPs. Additionally, a composite score was computed to evaluate the overall perceived benefit of AI across all KMPs collectively.

The subscales demonstrated strong internal consistency, with Cronbach's alpha coefficients of 0.82 for knowledge acquisition, 0.71 for knowledge documentation, 0.81 for

knowledge sharing, and 0.82 for knowledge application. Excellent internal consistency was observed for the total scale ($\alpha = 0.92$). To assess the questionnaire's construct validity, we employed Confirmatory Factor Analysis (CFA) within a Structural Equation Modeling (SEM) framework. The analysis was conducted using R software (version 4.3) and its interface R-Studio (R Core Team, 2023).

We utilized the Lavaan package (Rosseel, 2012) to build a second-order model. In this model, each questionnaire subscale served as a latent construct, and ultimately, the total usefulness perception was modeled as a second-order construct encompassing all four subscales. The results, presented in Figure 1, indicate an acceptable model fit, evidenced by CFI (0.950), TLI (0.929), RMSEA (0.069), and SRMR (0.064). These findings provide evidence for our questionnaire's good construct validity.

Moreover, Construct validity was supported by a significant correlation ($r = 0.56$, $p < 0.001$) between the total score of the 20 items and a dedicated question assessing respondents' perceptions of AI's benefits for KMPs in organizational contexts.

Furthermore, participants were queried on their trust levels in AI applications across the four KMP domains. Internal consistency of the trust measure was assessed using Cronbach's alpha. The alpha coefficient was excellent ($\alpha = 0.85$), indicating a high level of reliability for the four items measuring trust in AI applications.

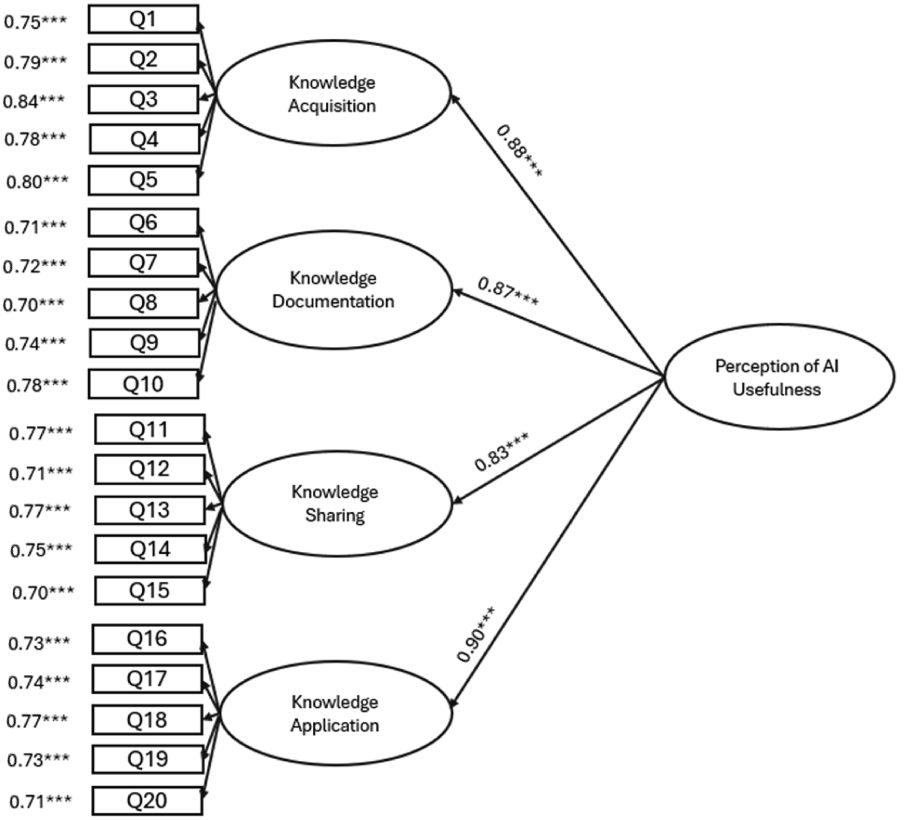

Figure 1. CFA model for assessing the quality of the research questionnaire. ***$p < 0.001$. Source: Authors' own work

4.3 Sample description

A total of 378 subjects completed the study questionnaire, a sample size that meets established recommendations for robust statistical analysis in organizational research (Zickar and Keith, 2023) and aligns with previous studies on technology adoption and AI perceptions (Akudjedu *et al.*, 2023; Baskaran *et al.*, 2020). The socio-demographic and organizational characteristics of the sample are detailed in Table 1. The sample exhibited a nearly equal gender distribution (52.6% females and 47.4% males) and a slight predominance of individuals with academic backgrounds (67.5%). Among the graduates, respondents included those with a bachelor's degree ($n = 139$), a master's degree ($n = 102$), or a doctoral degree ($n = 14$). Regarding organizational characteristics, participants were distributed across various sizes, with the service sector (33.1%) and the public sector (27.8%) being the most represented. Over half of the respondents held managerial positions (56.1%), while a smaller portion specialized in KM (34.1%). The most common seniority level was 2–5 years (28.1%), followed by 5–10 years (18.8%). The average age of the participants was 41.97 years ($SD = 10.68$).

4.4 Statistical analysis

Data analysis was performed using two statistical software packages: IBM SPSS Statistics (Version 28) and R (Version 4.3). The internal consistency of the study questionnaire was assessed using Cronbach's alpha coefficients. CFA was employed to evaluate the construct validity of the questionnaire. To address the specific research questions, a range of statistical tests were conducted, including repeated-measures ANOVA, independent-samples *t*-tests, multivariate analysis of variance (MANOVA), Pearson's correlations, and Spearman's rank-order correlations. A significance level of $\alpha = 0.05$ was adopted for all statistical analyses.

Table 1. Socio-demographic and organizational characteristics of the research sample ($N = 378$)

Item	Value	*N*	%
Sex	Female	199	52.6
	Male	179	47.4
Education	Non-graduated	123	32.5
	Graduated	255	67.5
Organization size	Small	136	36.0
	Medium	127	33.6
	Large	115	30.4
Business sector	Public	105	27.8
	Industrial	65	17.2
	Services	125	33.1
	High-tech	59	15.6
	Other	24	6.3
Role	Employee	166	43.9
	Manager	212	56.1
Specialize in KM	No	249	65.9
	Yes	129	34.1
Seniority	<2	61	16.1
	2≤5	106	28.1
	5≤10	71	18.8
	10≤15	61	16.1
	15≤20	34	9.0
	20+	45	11.9
Age	<30	66	17.5
	30–39	96	25.4
	40–49	118	31.2
	50–59	74	19.6
	60+	24	6.3

5. Results

To assess the differential perceptions of AI technologies' potential benefits across the four KMP sub-scales, we conducted a repeated-measures ANOVA. The analysis revealed a significant main effect for the sub-scale ($F(3, 1131) = 28.22$, $p < 0.001$). Bonferroni pairwise comparison indicated that respondents perceived AI technologies as significantly more beneficial for improving knowledge acquisition ($M = 4.92$, $SD = 0.77$) and knowledge documentation ($M = 4.91$, $SD = 0.73$) compared to knowledge sharing ($M = 4.72$, $SD = 0.84$) and knowledge application ($M = 4.67$, $SD = 0.86$), with *all p-values* < 0.001. These findings are further illustrated in Figure 2.

To further explore variations in perceptions, independent samples *t*-tests were conducted to examine the effects of organizational role (employee vs. manager) and expertise in KM (yes vs. no) on the perceived usefulness of AI for KMPs. All five perception scores (total score and four sub-scales) served as dependent variables. The results revealed a significant main effect of organizational role, with managers perceiving greater benefits of AI for knowledge acquisition ($t(376) = 2.99$, $p = 0.001$), knowledge documentation ($t(376) = 2.22$, $p = 0.014$), knowledge application ($t(376) = 2.00$, $p = 0.023$), and the total score ($t(376) = 2.39$, $p = 0.009$) compared to employees. Notably, differences in knowledge sharing did not reach significance ($t(376) = 1.07$, $p = 0.141$). Similarly, expertise in KM was found to influence perceptions, with knowledge managers reporting AI as significantly more beneficial for knowledge acquisition ($t(376) = 1.86$, $p = 0.031$) compared to non-knowledge managers. These findings are detailed in Tables 2 and 3, respectively.

An additional independent samples *t*-test investigated the influence of educational background (graduates vs. non-graduates) on the perceived usefulness of AI for KMPs. The analysis encompassed all five perception scores (total score and four sub-scales) as dependent variables. The results indicated a significant main effect of education for knowledge application only ($t(376) = 1.82$, $p = 0.035$), with graduates perceiving AI as more beneficial for this sub-scale compared to non-graduates. No significant differences were observed in knowledge acquisition, knowledge documentation, or knowledge sharing among respondents of different educational backgrounds. These findings are detailed in Table 4.

To investigate broader relational dynamics, Pearson correlation coefficients were calculated between the perceived usefulness of AI for KMPs (all five perception scores;

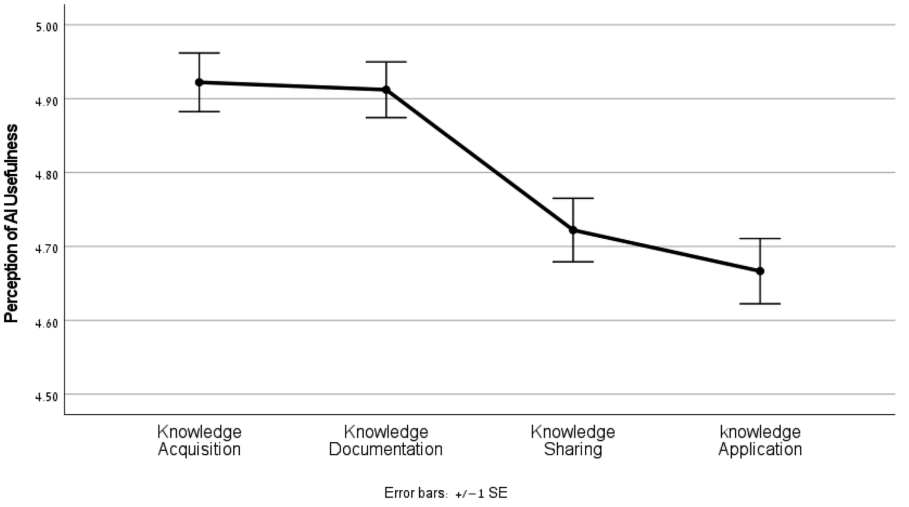

Figure 2. Differential perceptions of AI's benefits across KMPs sub-scales. Source: Authors' own work

Table 2. Differences in perception of AI usefulness for KMPs by organizational role ($N = 378$)

Perceived AI usefulness for KMPs; organizational role	Employees $n = 166$ M	SD	Managers $n = 212$ M	SD	*t*-value	*p*-value
Knowledge acquisition	4.79	0.82	5.03	0.72	2.99**	0.001
Knowledge documentation	4.82	0.77	4.99	0.70	2.22*	0.014
Knowledge sharing	4.67	0.81	4.76	0.86	1.07	0.141
Knowledge application	4.57	0.82	4.74	0.88	2.00*	0.023
Total score	4.71	0.70	4.88	0.66	2.39**	0.009

Note(s): *$p < 0.05$, **$p < 0.01$

Table 3. Differences in perception of AI usefulness for KMPs by expertise in KM ($N = 378$)

Perceived AI usefulness for KMPs; KM expertise	No $n = 249$ M	SD	Yes $n = 129$ M	SD	*t*-value	*p*-value
Knowledge acquisition	4.87	0.79	5.02	0.73	1.86*	0.031
Knowledge documentation	4.88	0.75	4.98	0.70	1.20	0.115
Knowledge sharing	4.70	0.83	4.76	0.85	0.62	0.266
Knowledge application	4.63	0.85	4.74	0.87	1.19	0.118
Total score	4.77	0.69	4.87	0.67	1.41	0.080

Note(s): *$p < 0.05$

Table 4. Differences in perception of AI usefulness for KMPs by education ($N = 378$)

Perceived AI usefulness for KMPs; education	Non-graduated $n = 123$ M	SD	Graduated $n = 255$ M	SD	*t*-value	*p*-value
Knowledge acquisition	4.79	0.82	5.03	0.72	1.00	0.159
Knowledge documentation	4.82	0.77	4.99	0.70	0.63	0.265
Knowledge sharing	4.67	0.81	4.76	0.86	0.11	0.457
Knowledge application	4.57	0.82	4.74	0.88	1.82*	0.035
Total score	4.71	0.70	4.88	0.66	1.05	0.147

Note(s): *$p < 0.05$

total score and four sub-scales), the perceived importance of AI implementation for KMPs, and trust levels in AI. All correlations were positive and statistically significant (*all p-values* < 0.001). These results indicate that individuals who perceive AI as more beneficial for KMPs also tend to place greater importance on its implementation within their organizations and exhibit higher trust in AI applications for these processes. Table 5 presents the detailed correlation coefficients.

To examine sector-based differences, a MANOVA was conducted to assess the influence of the business sector (public, industry, services, and high-tech) on the perceived usefulness of AI for KMPs. The analysis encompassed all five perception scores (total score and four sub-scales) as dependent variables. Significant main effects emerged for sector on knowledge acquisition ($F(3, 353) = 2.65$, $p = 0.049$) and knowledge sharing ($F(3, 353) = 2.64$, $p = 0.049$). Bonferroni post-hoc tests revealed that respondents from the high-tech sector reported significantly lower perceptions of AI's benefit for knowledge acquisition compared to the public ($p = 0.006$) and service sectors ($p = 0.031$), while no significant difference was

Table 5. Pearson correlation matrix between perception of AI usefulness to improve KMPs, AI implementation importance in organizations, and trust levels in AI applications ($N = 378$)

Perceived AI usefulness for KMPs	Importance of AI implementation	Trust levels in AI applications
Knowledge acquisition	0.33***	0.42***
Knowledge documentation	0.34***	0.44***
Knowledge sharing	0.34***	0.46***
Knowledge application	0.35***	0.52***
Total score	0.39***	0.54***

Note(s): ***$p < 0.001$

found with the industrial sector ($p = 0.377$) (see Figure 3). Similarly, perceived AI usefulness for knowledge sharing was lower in the high-tech sector compared to the public ($p = 0.025$), service ($p = 0.022$), and industry sectors ($p = 0.009$) (see Figure 4). No significant differences were observed between the industrial sector and the public and service sectors (*all p-values* > 0.05).

Finally, our analysis revealed no significant effects of gender, age, seniority, or organizational size on the perceived usefulness of AI across all four sub-scales and the total perception score (*all p-values* > 0.05). Independent samples *t*-tests were conducted for gender, while multivariate analysis of variance (MANOVA) examined the effect of organization size. Spearman's rank-order correlation coefficients were used to assess the relationships between the age of the respondent or their seniority in the organization with the perceived usefulness of AI to improve KMPs.

6. Discussion

In line with the work of Leoni *et al*. (2022), our results affirm that AI is broadly perceived as beneficial across all KMPs, albeit with varying degrees of perceived usefulness. The full

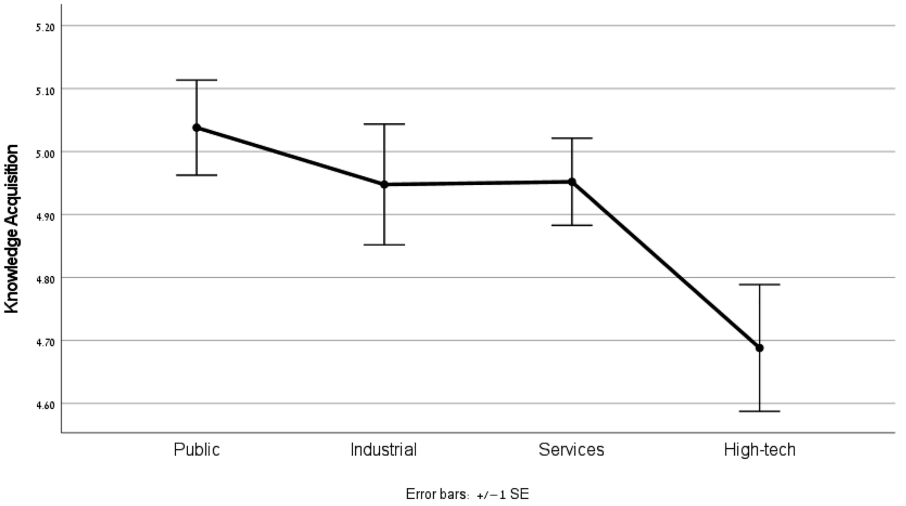

Figure 3. Differences between business sectors in perceived AI usefulness to benefit knowledge acquisition. Source: Authors' own work

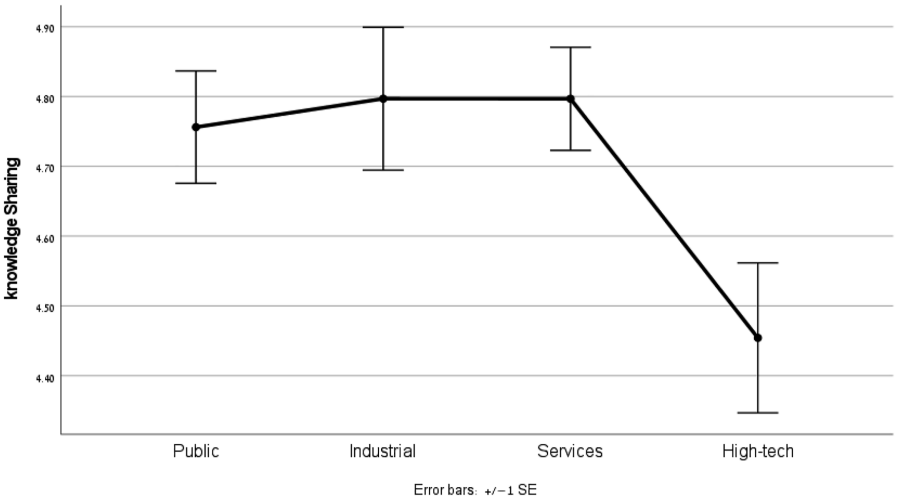

Figure 4. Differences between business sectors in perceived AI usefulness to benefit knowledge sharing. Source: Authors' own work

confirmation of hypothesis *(H1)*, which posited variations in AI perceptions regarding different KMPs, underscores respondents' awareness of AI's differential impact. This highlights the necessity of a strategic AI implementation approach that considers organizational needs and contextual nuances. This is consistent with the literature that emphasizes the need for tailored AI applications to maximize business value (Enholm *et al.*, 2022). For instance, while AI may significantly enhance knowledge acquisition through advanced data analytics and pattern recognition, its role in knowledge sharing is perceived to be relatively less significant. This differentiation is crucial for maximizing the benefits of AI in KM, as it allows organizations to tailor AI applications to the specific characteristics of each KMP.

The partial confirmation of hypothesis *(H2)*, which proposed that managers perceive AI more positively than regular employees, suggests that job roles influence AI's perceived utility in enhancing KMPs. However, while managers generally view AI more favorably than regular employees, this relationship can vary depending on the specific KMPs involved. For example, the two categories have substantially the same opinion regarding knowledge sharing. This could be attributed to the widespread recognition that KM involves human-social elements, which may fit the characteristics of AI less. In fact, knowledge sharing, unlike other KMPs, inherently relies on interpersonal interactions and social dynamics within an organization and involves not only the transfer of explicit knowledge but also tacit knowledge, which may require informal interactions, mentorship, and collaborative efforts (Kassaneh *et al.*, 2021; Scarso and Bolisani, 2023). Consequently, both regular employees and managers seem to share the same awareness and perception that AI may be less beneficial to knowledge sharing or, at best, may support human-social interactions but not replace them.

Hypothesis *(H3)* was fully supported, revealing that knowledge managers hold more positive attitudes toward AI compared to individuals without KM expertise, particularly in knowledge acquisition. This can be attributed to the deep familiarity of knowledge managers with KMPs, as well as their heightened awareness of knowledge gaps within their organizations related to traditional practices (Nakash *et al.*, 2022). Their consistent understanding of the strategic knowledge needs of business units likely shapes their distinct stance on the unique potential of AI to generate new insights from vast datasets, while reducing

the cognitive load associated with knowledge acquisition. In short, KM experts apparently fully support the prospects of AI.

Our findings also support hypothesis *(H4)*, indicating that graduates have more positive perceptions of AI's role in knowledge application within organizational settings compared to non-graduates. From our viewpoint, this trend can be attributed to the fact that graduates are often at the forefront of exploring technical innovations and are accustomed to leveraging advanced technologies to enhance their work. This mindset makes graduates more receptive to adopting AI, as they recognize its potential to facilitate the application of knowledge in solving complex problems, generating new insights, and improving overall outcomes (Chubb *et al.*, 2022; Crompton and Burke, 2023; Secinaro *et al.*, 2023). Additionally, graduates are uniquely positioned to recognize how AI can effectively leverage knowledge in ways that may be more challenging with conventional methods.

Additionally, we observed a positive correlation between three key variables: the perceived usefulness of AI in enhancing KMPs, the perceived importance of AI implementation, and trust in AI tools. This finding supports the hypothesis *(H5)* and underscores the interconnectedness of these factors in influencing AI adoption, in a manner that aligns with the TAM (Davis, 1989). Understanding these dynamics offers valuable insights for managers and decision-makers seeking to implement AI in their organizations. By recognizing the pivotal roles of perceived usefulness, importance, and trust in technology, organizations can devise strategies that effectively address potential barriers to AI adoption and capitalize on its transformative potential in KM.

Interestingly, our findings reveal that the high-tech sector reported lower perceptions of AI usefulness for knowledge acquisition and sharing, contrary to expectations and leading to the refutation of hypothesis *(H6)*. This unexpected outcome may reflect a more discerning and critical stance among high-tech professionals, who, due to their technical expertise and deeper exposure to AI systems, may be more aware of the limitations, risks, or immature capabilities of current AI tools in handling complex, context-dependent knowledge tasks. Such individuals might also hold higher performance expectations for AI systems and therefore assess their contribution more stringently compared to professionals from other sectors. Additionally, it is possible that the high degree of digital infrastructure and automation already present in high-tech organizations (Debowy *et al.*, 2024; Madanchian and Taherdoost, 2024) reduces the marginal perceived value that AI contributes to existing KMPs. However, it is worth noting that this finding may also be attributed to the relatively low representation of this sector in the current sample ($n = 59$, 15.6%). The limited sample size may not fully capture the diverse perspectives within the high-tech industry, potentially skewing the results, constraining the generalizability of the findings, and obscuring intra-sectoral variation (Mohajan, 2020; Queirós *et al.*, 2017; Zickar and Keith, 2023). To sum up, it is a point that requires further investigation.

Furthermore, our study found no significant differences in AI perceptions based on gender, age, or seniority, fully confirming hypotheses *(H7)*, *(H8)*, and *(H9)*. This finding indicates that attitudes toward AI in the context of KMPs are relatively consistent across these variables, regardless of personal or professional backgrounds. This is consistent with the TAM and UTAUT models, which imply that individual differences may not necessarily influence technology perceptions (Davis, 1989; Venkatesh *et al.*, 2003). However, to some extent, it contrasts with the common opinion that younger generations are, *per se*, more prone to new IT applications including AI. Instead, as AI becomes increasingly integrated into everyday tools and systems, it appears that a homogeneous perception of AI's value is emerging across diverse demographic groups. Additionally, the consistent perceptions across these variables suggest that organizations may be successfully promoting an inclusive and equitable environment for AI adoption.

Finally, contrary to our expectations, our research found no significant relationship between organization size and AI usefulness perceptions, leading to the rejection of hypothesis *(H10)*. This result underscores the need to reconsider the traditional assumption and common view about the relationship between organization size and technology adoption. Theoretically

speaking, it also challenges theories like the resource-based view (RBV) (Barney, 1991), which posits that larger organizations are better positioned to capitalize on technological innovations due to their greater resources and capabilities (Alavi *et al.*, 2024; Nonaka and Takeuchi, 1995). One possible explanation for this unexpected result is that the rapid pace of technological advancement—and the availability at least until now of "free trial" versions of many AI systems—has democratized access to AI tools and solutions, thereby leveling the playing field. In particular, the proliferation of cloud-based and subscription-based AI services has reduced the need for substantial in-house infrastructure, making these technologies accessible to organizations of all sizes. This finding also suggests that perceptions of AI usefulness may be influenced more by organizational culture, leadership, and strategic priorities than by firm size alone.

7. Conclusions

As research on AI in KM remains in its early stages, with previous studies primarily presenting conceptual frameworks, this study contributes a pioneering empirical analysis of the interplay between these domains within organizational settings. By elucidating the nuanced ways in which AI is perceived across different roles and sectors, the collected evidence significantly advances the literature on AI's role in enhancing KMPs. In doing so, we extend prior theoretical discussions by grounding them in quantitative data and offering nuanced insights into the conditions that shape AI acceptance in KM contexts. The results challenge existing assumptions of classic theories of innovation, like the RBV, by showing that organizational size does not necessarily predict variations in perceptions of AI's usefulness for KMPs. Conversely, the findings support the TAM and UTAUT models, emphasizing the importance of perceived usefulness and trust of single individuals in AI tools as key factors for their adoption in KM contexts. The research also underscores the differential impact of AI on various KMPs, thereby reinforcing the need for a nuanced approach to integrating AI in KM.

From a practical standpoint, our findings offer several actionable insights for organizations aiming to leverage AI to enhance KMPs. Firstly, the particularly positive perceptions of AI among knowledge managers and graduates suggest that these groups can be key advocates for AI adoption to drive organizational change toward KM excellence. Targeted training and professional development initiatives should be designed to empower these individuals as change agents, facilitating the successful implementation of AI-driven KM solutions. Secondly, the findings underscore the importance of fostering a culture that supports AI adoption at all organizational levels, regardless of gender, age, seniority, or organizational size. To optimize KM outcomes, organizations should actively promote trust in AI technologies and clearly communicate their benefits, ensuring broad acceptance and seamless integration into existing KMSs. In particular, we recommend prioritizing the deployment of AI tools in knowledge creation and documentation processes, where perceived usefulness is especially high. Such strategic alignment is likely to yield significant returns by enhancing the value, accessibility, and sustainability of organizational knowledge assets.

While this study provides valuable insights, it is not without limitations. Firstly, the relatively low representation of the high-tech sector in the sample may limit the generalizability of the findings to this industry, and additional investigations should be performed to verify the counter-intuitive results that we have obtained. Secondly, considering that this investigation was conducted in a single country, future research should aim to include a more balanced and broader representation of various industries, geographical regions, and cultural contexts to provide a more comprehensive understanding. Thirdly, as this study relies on self-reported data, it is susceptible to biases such as social desirability and response bias. To enhance the robustness of future studies, researchers should consider employing mixed-method approaches, integrating surveys with qualitative methods such as in-depth interviews or case studies. Fourthly, the use of the "snowball" sampling technique, while effective in increasing sample size and representativeness, may introduce biases due to the non-random

nature of the sampling process. Future studies should consider alternative sampling methods to mitigate this limitation. Fifthly, while this study highlights AI's benefits in KMPs, it does not fully account for variations in AI maturity. In organizations where AI is still developing, expected benefits in certain KMPs may not yet materialize. Future research should examine how different stages of AI adoption impact KM effectiveness.

Future research should delve into the implementation and long-term effects of integrating AI into KMPs. Longitudinal studies could yield valuable insights into how perceptions of technology evolve over time and the impact of AI integration on knowledge-based organizational success. Additionally, it is advisable for future research to focus on understanding the spectrum of challenges and barriers associated with the implementation of AI technologies in KMSs. Finally, future studies could examine the role of specific AI applications in KM, exploring how different AI solutions are utilized across various organizational contexts.

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Appendix
The research questionnaire

Part I – AI and KM processes

(1) Please estimate *the likelihood* of each of the following statements:

I believe that in the business environment, in the near future . . .

	1 Definitely not	2 Almost certainly not	3 Possibly, but unlikely	4 Possibly, but likely	5 Almost certainly yes	6 Definitely yes
Knowledge acquisition						
1. Innovative ideas for products or services will be developed using AI						
2. New business opportunities will be identified through AI						
3. Future forecasts will be produced in the professional field of the organization, relying on AI-based simulation models						
4. Lessons from various organizational events will be automatically derived through AI						
5. Comparative analysis of competitors' status and generation of new knowledge about the organization's competitive advantage will be enabled through AI						

(*continued*)

Continued

	1 Definitely not	2 Almost certainly not	3 Possibly, but unlikely	4 Possibly, but likely	5 Almost certainly yes	6 Definitely yes
Knowledge documentation						
6. Personal knowledge of experts in the organization will be elicited through AI-based chatbots that will conduct dialogues with them						
7. Knowledge from discussions, meetings, and conversations within an organization will be documented using natural language processing technologies powered by AI						
8. The human effort required for classifying knowledge items in organizational systems will be reduced through AI						
9. Navigation and search in organizational knowledge databases will be improved thanks to AI capabilities						
10. The knowledge stored in organizational systems will be up-to-date, relevant, and accurate thanks to AI capabilities						
Knowledge sharing						
11. AI-driven search engines will facilitate the retrieval of knowledge items and shorten search times						
12. Employees will automatically receive relevant knowledge in a personalized manner thanks to the use of AI advanced algorithms						
13. The flow of knowledge among the organization's employees will be improved through AI						
14. Collaborations between teams from different departments or geographical areas will be promoted through AI						
15. A positive culture of knowledge sharing will be cultivated through AI						
Knowledge application						
16. AI-powered decision support systems will make it easier to make smart choices by analyzing options and evaluating outcomes						
17. Organizational performance improvement will be achieved by AI machine learning, based on the analysis of work patterns						
18. Employees will receive advice from AI-based robots on how to utilize the existing knowledge in an organization for their routine work tasks						
19. Leveraging knowledge for business continuity in emergencies and crises will be achieved through AI						
20. The prevention of recurring faults and errors will be enabled through the analysis of accumulated knowledge by AI						

(2) Please rate your *level of agreement* with each of the following statements:

I Believe that . . .	1 Definitely not	2 Almost certainly not	3 Possibly, but unlikely	4 Possibly, but likely	5 Almost certainly yes	6 Definitely yes
1. AI is capable of contributing to knowledge management processes in the organizational context						
2. It is important to me that my organization will implement applications of AI						

(3) Please mark how much you estimate that *you will trust* AI applications in knowledge management processes in the organizational context:

	1 Definitely not	2 Almost certainly not	3 Possibly, but unlikely	4 Possibly, but likely	5 Almost certainly yes	6 Definitely yes
1. I will rely on AI applications for *knowledge acquisition* – meaning, to collect, identify, and develop knowledge from various sources						
2. I will rely on AI applications for *knowledge documentation* – meaning, to organize, structure, and store knowledge in a way that will allow its retrieval in the future						
3. I will rely on AI applications for *knowledge sharing* – meaning, to disseminate and transfer relevant knowledge to employees and teams across the organization						
4. I will rely on AI applications for *knowledge application* – meaning, for practical use of knowledge and leveraging it for the benefit of the organization						

Part II – Occupational details

(1) **What is your seniority in your current organization?**

- Up to Two Years
- Over 2 years and up to 5 years
- Over 5 years and up to 10 years

- Over 10 years and up to 15 years
- Over 15 years and up to 20 years
- Over 20 years

(2) **What is the approximate number of employees in the organization you belong to?**

- A small organization, with less than 100 employees
- Medium-sized organization, between 100 and 2,500 employees
- A large organization, with over 2,500 employees

(3) **Which business sector does your organization belong to? [Choose the most suitable definition in your opinion]**

- Public sector (An organization maintained by the state or local authority)
- Industrial sector (An organization engaged in manufacturing and industry)
- Services sector (An organization that provides various services, including financial, health, education, and more)
- High-tech sector (Technology, research, and development organization)
- Other ___

(4) **Which division do you work in within the organization? [Choose the definition that best fits your opinion]**

- Digital and Information
- Human Resources, Training, and Professional Development
- Marketing and Sales
- Operations and Logistics
- Finance and Accounting
- Research and Development
- Customer Service
- Legal
- Communications and Public Relations
- Strategy and Headquarters

(5) **What is your role in the organization?**

- Employee, without managerial responsibility
- Middle management level manager
- Senior management level manager

(6) **Do you specialize in KM in your role?**

- Yes
- No

(7) [If the respondent indicated that they have KM expertise]:

How many years of accumulated experience do you have in the KM field?

_____

Part III – Demographic Details

(1) **Sex:**

- Male
- Female

(2) **Age:**

_____

(3) **Education:**

- High school or lower level
- Post-secondary or certificate studies
- Bachelor's degree
- Master's degree
- Doctorate degree

Do you have anything to add regarding the opportunities for integrating AI into KM in the organizational context?

_____
_____
_____

Thank you very much for your cooperation!

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