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# Artificial intelligence in knowledge management: Identifying and addressing the key implementation challenges

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A B S T R A C T

In today's digital landscape, Knowledge Management (KM) is crucial for organisational competitiveness. Artificial Intelligence (AI) offers transformative potential for KM practices, yet its integration presents multifaceted challenges. This study addresses significant gaps in the literature by identifying and prioritising critical challenges associated with AI integration in KM.

Employing a tripartite methodological approach, this research combines a literature review on KM and AI's challenges, a Delphi study with domain experts, and confirmatory factor analysis (CFA) across four KM processes. Data from retail sector professionals validate the challenges identified by experts.

Findings reveal a comprehensive landscape of challenges, categorised into technological, organisational, and ethical domains, with variations across different KM processes. The study contributes to the field by comprehensively exploring AI-related challenges in KM, offering a quantitative ranking, and enhancing understanding of the AI-KM interplay.

This research provides valuable insights for business leaders, facilitating the development of strategies to foster robust knowledge ecosystems. By addressing these challenges proactively, organisations can enhance their KM practices, leveraging AI to maintain competitiveness in an increasingly digital business environment. The study contributes to theoretical discourse and offers practical implications for organisations navigating AI integration in their KM practices.

## 1. Introduction

In the rapidly evolving landscape of the digital age, Artificial Intelligence (AI) has emerged as a transformative force, fundamentally reshaping Knowledge Management (KM) paradigms across diverse industries (Jarrahi et al., 2023; Ghamgui et al., 2025; Fowler, 2000). As organisations strive to harness the full potential of their intellectual capital, AI technologies offer unprecedented opportunities to enhance the creation, dissemination, and utilisation of knowledge (Duan et al., 2019). With its advanced capabilities to automate complex tasks, extract critical insights from extensive data repositories (Bag et al., 2021), store and manage knowledge efficiently (Wu et al., 2023), and seamlessly facilitate its transition and application (Rezaei et al., 2024a), AI has significantly transformed how organisations navigate and optimise their knowledge resources, empowering them to achieve more effective and sophisticated decision-making processes (Jarrahi et al., 2023; Sanzogni et al., 2017).

However, despite its vast potential, the integration of AI into KM systems is fraught with significant challenges (Fosso Wamba et al., 2022). These multifaceted challenges span technological, organisational, and ethical dimensions, each presenting unique obstacles that can impede the successful implementation and adoption of AI-driven KM solutions. Technological challenges encompass issues related to data quality, algorithmic biases, and the complexity of integrating AI with existing KM infrastructures (Janssen et al., 2020). Organisational challenges include resistance to change, skill gaps, and the imperative for robust governance frameworks (Borges et al., 2021). Ethical considerations, such as data privacy and the responsible use of AI, further complicate this already intricate landscape (Shrestha et al., 2019). Mastering these challenges is pivotal for organisations to realise AI's potential dividends fully within the realm of KM.

The extant literature has begun grappling with the multifaceted challenges of integrating AI into KM systems. For example, Dwivedi et al. (2021) provided a broad, multidisciplinary perspective on AI integration's key challenges and opportunities, laying a strong theoretical foundation. However, their analysis lacked a specific focus on the KM context, potentially limiting the depth of insights. Building on this foundational work, Jarrahi et al. (2023) explicated the potential role of

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AI in supporting the fundamental dimensions of KM, proposing practical ways to build the partnership between humans and AI. While their study narratively outlined some challenges for KM, it did not provide a rigorous analysis of the specific challenges encountered in AI-driven KM systems.

Taherdoost and Madanchian (2023) further contributed by examining challenges such as data quality, integration issues, and ethical considerations in workplace KM through a systematic review. However, their research did not extend to empirical validation of the identified challenges, leaving a critical gap in actionable insights. Similarly, Siau and Wang (2020) made a valuable contribution by deeply exploring the challenge of trust in AI systems, which is a critical factor for successful KM integration. Yet, their study just focused on the trust dimension without comprehensively examining the broader array of challenges that organisations face when incorporating AI into KM practices.

Some studies have explored AI's broader implications for KM but have not addressed the challenges and barriers directly. For instance, works by Sanzogni et al. (2017), Birzniece (2011), and Liebowitz (2001) analysed AI's impact on KM from different theoretical perspectives but lacked specificity in tackling the obstacles organisations encounter. Moreover, De Bruyn et al. (2020) analysed the pitfalls and opportunities of AI in marketing through the lenses of KC and knowledge transfer. However, their work was a theoretical analysis without numerical or empirical support and focused narrowly on marketing-related KM issues. Sharma et al. (2023) took a historical perspective, examining how AI could support key aspects of KM. Although insightful, their work remained descriptive rather than analytical, offering limited depth in exploring specific challenges. Peng et al. (2023) systematically analysed knowledge graphs, a key AI technology for KM. However, their study focused narrowly on this technology and provided a high-level overview of challenges without delving into empirical data or case studies. Sanzogni et al. (2017) explored the tacit-explicit knowledge dichotomy in AI-KM contexts. While their work offered a valuable theoretical discourse, it lacked practical application and empirical evidence. Furthermore, their discussion was limited in addressing ethical, regulatory, and organisational challenges, which are increasingly critical in the context of AI in KM.

These studies reflect the growing interest in understanding AI's role and challenges in KM but suffer from three significant limitations. First, they are mainly theoretical, lacking empirical validation and practical applicability, which limits their relevance to real-world organisational contexts. Second, they focus narrowly on specific challenges, such as ethical issues or trust, while failing to address the broader challenges that span the entire KM lifecycle. Third, their scope is restricted by prioritising KS, leaving critical gaps in understanding how AI can integrate seamlessly across all KM processes, including KC, storage, and application. This absence of holistic analysis and actionable insights underscores the need for more comprehensive and empirically grounded research to bridge the gap between theory and practice in this domain.

This paper addresses this critical gap by identifying and analysing the key implementation challenges of AI in KM, providing a comprehensive overview to guide organisations in managing the complexities of adoption. By exploring the current state of AI in KM and shedding light on the primary hurdles, this research seeks to answer essential questions: What are the most pressing challenges in leveraging AI within KM? How do professionals perceive these challenges? How do managers and decision-makers understand and navigate these obstacles in practical, real-world contexts? To address these questions, this study employs a rigorous multi-method approach. It begins with a review of prior research on AI's impact on KM to establish foundational insights, followed by the Delphi method to explore theoretical perspectives on challenges. Finally, CFA is used to validate these challenges.

Situated at the nexus of theory and practice, this research offers a robust and comprehensive framework for integrating AI into KM systems. It advances academic discourse by addressing critical gaps in understanding AI's role within KM while simultaneously delivering actionable strategies for fostering KC, sharing, and application in complex and dynamic organisational contexts. This study equips organisations with the necessary tools and insights to achieve sustainable and effective KM in the evolving AI landscape by bridging the divide between AI's theoretical promise and its practical implementation.

This paper is structured as follows: It begins with a review of the literature on AI and KM, highlighting the potential challenges at their intersection. Study One then employs the Delphi method to identify and categorise key ethical challenges in AI-driven KM across various models. Building on these findings, Study Two conducts a confirmatory factor analysis (CFA) to validate and refine the identified categories. The paper concludes with a comprehensive discussion of the results, along with practical and theoretical implications, limitations, and directions for future research.

## 2. Literature review

### 2.1. *The impact of AI on KM*

The evolution of AI has fundamentally transformed the way organisations approach KM. As technologies advance, AI has emerged as a central enabler of more efficient, dynamic, and intelligent KM processes. It automates core functions such as information retrieval (Guo et al., 2020; Smith, 2019), content generation (Barriga, 2019; Liu et al., 2021), and the categorisation of large volumes of knowledge (Pettersen, 2019). Furthermore, AI enhances the extraction of latent meanings and relationships within unstructured data, allowing for deeper insights and more accurate interpretation of organisational knowledge (Sanzogni et al., 2017). AI also contributes to the secure management and distribution of knowledge across departments and teams, fostering real-time access and cross-functional collaboration. In parallel, technologies like augmented reality complement AI systems by enabling immersive and experiential training environments. The combined effect is a KM system that not only stores and organises information but also adapts, learns, and improves continuously. This results in greater efficiency, better-informed decision-making, and increased organisational innovation (Cockburn et al., 2018; Botega and da Silva, 2020). More recently, the rise of generative AI (GenAI)—particularly large language models (LLMs) such as ChatGPT—has marked a new phase in AI-enabled KM (Alavi et al., 2024). These models dramatically expand accessibility, allowing non-specialists to engage in knowledge work that previously required expert input. Tools like ChatGPT support organisations in generating tailored content, summarising complex documents, retrieving context-specific knowledge, and personalising user interactions (Gupta et al., 2024). As Storey (2025) points out, GenAI tools are now embedded in everyday workflows, transforming how knowledge is produced and consumed. Sumbal and Amber (2025) similarly emphasise ChatGPT's capacity to act as a real-time knowledge assistant, enabling faster decision-making, improved collaboration, and continuous learning across organisational levels. These developments illustrate how AI, particularly generative AI, has shifted KM from a static, storage-oriented function to a dynamic, interactive capability. AI systems no longer just support KM processes; they actively shape how knowledge is created, shared, and applied in real-time, fundamentally redefining the boundaries and potential of KM in modern organisations.

#### 2.1.1. *Knowledge creation and AI*

Knowledge creation (KC) is the dynamic process of generating new knowledge, insights, ideas, and understanding through various means, including exploration, discovery, experimentation, reflection, and analysis (Nonaka and Toyama, 2015). This process involves synthesising existing information, generating new patterns and relationships, and producing innovative insights that advance and enrich knowledge within a particular field or domain (North and Kumta, 2018). KC occurs through multiple avenues, such as research endeavours, experimentation, collaborative efforts, and critical thinking, all aimed at enhancing our understanding of the environment and devising novel solutions to complex challenges (Nonaka and Toyama, 2015).

Meanwhile, AI operates on principles of continuous improvement and relies heavily on data to refine and enhance its performance (Jarrahi et al., 2023). AI shares the same ultimate goal as KC: generating fresh insights through data collection from diverse sources (Bag et al., 2021). Thus, AI emerges as a potent ally in the KC process, streamlining data collection by automating the gathering and analysis of information (Bag et al., 2021). Nowadays, AI is impressively integrated into KC processes across various fields, including healthcare research and development (Leone et al., 2021), educational technology (Gupta and Jain, 2017), environmental sustainability (Chopra et al., 2021), business intelligence (Bag et al., 2021), scientific research, creative industries, urban planning (Seo, 2022), and customer service (Jarrahi et al., 2023). AI algorithms analyse vast datasets to identify and accelerate optimal outcomes more efficiently, creating new knowledge for the faster development of products, such as medications in healthcare or machinery in the industry (Bag et al., 2021). Recent advancements in GenAI, especially LLMs, have significantly extended the role of AI in KC. These models, such as those powering generative tools, can assist users in synthesising complex information, generating ideas, drafting content, and facilitating real-time interaction with large-scale knowledge repositories (Alavi et al., 2024; Storey, 2025). Their ability to process and respond to natural language inputs enables both technical and non-technical users to engage in creative and analytical knowledge work more effectively.

AI systems also personalise learning experiences by adapting content based on real-time analysis of users' performance and engagement (Jarrahi et al., 2023). This capability enhances the creation of new approaches, methods, and knowledge flows in education, effectively addressing individual needs, such as those of students in educational settings or employees in continuous learning processes. Scientists and scholars use AI-based models to predict future impacts based on current and historical data (Nasseef et al., 2022). This provides new knowledge that leads to better strategies for mitigating the side effects of crises like climate change, global warming, and pandemics.

In the creative industries, writers, artists, and musicians conceptualise new content ideas, while AI tools assist by generating drafts, suggesting improvements, and even creating original pieces based on input parameters. This collaboration enhances creativity and productivity, allowing creators to explore new styles and ideas, thus expanding the horizons of artistic expression (Anantrasirichai and Bull, 2022).

Organisations leverage AI to amass substantial data from various sources, including social media, customer feedback, and secondary data, to create informed business strategies, product development, and marketing campaigns (Rezaei et al., 2024a). An illustrative example of AI's pivotal role is the application of AI-powered Natural Language Processing (NLP) tools (Dessì et al., 2021). These tools excel in analysing unstructured data, such as customer feedback, social media posts, and online reviews, enabling organisations to decipher customer sentiments, gain new insights, and identify emerging trends in KC processes (Juhn and Liu, 2020). Additionally, they can improve customer service efficiency, freeing human agents to focus on more complex issues essential for creating new knowledge (Rezaei, 2023).

#### 2.1.2. Knowledge storage and AI

Knowledge storage (KST) encompasses the intricate processes and technological infrastructure employed for capturing, preserving, organising, and retrieving knowledge within an organisation, ensuring it is readily accessible and employable when needed (Rezaei et al., 2020). Traditionally, KST involves using databases, data warehouses, and other data storage systems to meticulously catalogue substantial volumes of information in a structured manner. These systems employ techniques such as indexing, compression, and caching to optimise the storage and retrieval of knowledge (Ranjbarfard et al., 2014).

AI significantly enhances KST processes by automating data organisation, improving search and retrieval, and optimising data management. AI algorithms can automatically organise and categorise vast amounts of data, making it easier to store and retrieve information (Wu et al., 2023). NLP can analyse text data to classify documents based on content, context, and relevance, reducing the time and effort required for manual data sorting and ensuring consistent and accurate categorisation (Juhn and Liu, 2020). AI-powered search engines improve the efficiency of retrieving stored knowledge by using advanced algorithms to understand the context and intent behind search queries, providing more accurate and relevant results (Hill et al., 2024). AI can also personalise search experiences by learning user preferences and behaviour patterns. For example, intelligent Electronic Health Records (EHR) systems can improve patient care in healthcare records management through better diagnosis, treatment recommendations, and preventive care strategies (Lin et al., 2019). More recently, GenAI has addressed previous challenges in KST by enabling automatic synthesis, summarisation, and the capture of information from diverse sources. It not only leverages existing knowledge but also generates and organises new knowledge for future access (Alavi et al., 2024). AI techniques can compress data without significant loss of information, reducing storage requirements and costs. Machine learning (ML) algorithms can identify and eliminate redundant or duplicate data, optimising storage space and improving data management efficiency (Delen et al., 2013). For example, this enhanced efficiency and accuracy in legal research in the legal industry supports better case preparation and legal strategies (Lin et al., 2019).

AI can automate tagging and annotating data, adding metadata that enhances the context and usability of stored information (Arunachalam et al., 2021). This is particularly useful for multimedia content like images, videos, and audio files. AI can recognise and label objects, faces, and spoken words, enhancing user experience through personalised content delivery and improved content management (Pan et al., 2022). AI facilitates the integration of data from various sources, ensuring that stored knowledge is comprehensive and cohesive. ML models can detect and resolve inconsistencies, harmonise data formats, and merge datasets, creating a unified knowledge base (Liu et al., 2022). Security is also bolstered through AI's ability to detect unauthorised access and unusual activity patterns, safeguarding sensitive information in financial institutions. Moreover, AI-driven predictive data management helps organisations anticipate storage needs, ensuring scalability (Wu et al., 2023). Therefore, by integrating data from various sources and maintaining real-time processing capabilities, AI enables seamless and efficient KST, enhancing accessibility, performance, efficiency, and security.

#### 2.1.3. Knowledge sharing and AI

Knowledge sharing (KS) is a fundamental process in organisational dynamics, facilitating the exchange of information, skills, experiences, and insights among individuals (Rezaei et al., 2022; Mojtaba, 2022). This exchange occurs through a spectrum of channels, encompassing both formal mechanisms—such as structured training sessions, workshops, meetings, and documentation—and informal interactions, including spontaneous conversations, collaborative projects, and peer mentoring (Davenport and Prusak, 1998; Rezaei et al., 2021a).

Enhancing the efficacy of KS within an organisational context necessitates a multifaceted approach. This approach includes developing interpersonal competencies among community members, such as fostering a sense of belonging and nurturing a collaborative ethos (Cabrera and Cabrera, 2005); cultivating organisational attributes, including the propagation of collective culture and mutual trust (Rezaei et al., 2023); and implementing facilities that streamline KS processes, mainly through the deployment of innovative technologies (Alavi and Leidner, 2001). Integrating advanced technologies is thus pivotal in promoting and incentivising KS practices and augmenting collaborative tools (von Krogh, 2012). Indeed, achieving and sustaining effective KS within organisations would be virtually unattainable without technological advancements (Kane et al., 2014).

Among the most transformative technological innovations in this domain is the deployment of AI. AI significantly enhances KS through various mechanisms, including the automation of content analysis, provision of personalised recommendations, and facilitation of efficient collaboration (Jarrahi, 2018). For instance, AI-enhanced intranets in corporate environments analyse shared documents and insights to suggest relevant information to employees, thereby fostering productivity and innovation (Sundaresan and Zhang, 2022). Moreover, AI algorithms demonstrate proficiency in identifying pertinent knowledge, recommending it to relevant experts, and streamlining collaboration among individuals and teams (Rezaei et al., 2024b).

In academic research, AI tools integrated into digital libraries recommend relevant papers and identify potential collaborators, thereby accelerating interdisciplinary studies and facilitating the dissemination of knowledge (Venkatesh, 2022). A salient illustration of AI's impact on KS is the deployment of chatbots and virtual assistants. These AI-driven tools provide expeditious and personalised responses to common queries, automating routine tasks and consequently liberating time for individuals to engage in higher-order KS activities, such as problem-solving and innovation (Luo et al., 2019).

ML, a subset of AI, further augments organisational capabilities by identifying patterns and extracting insights from extensive datasets (Delen et al., 2013). ML algorithms analyse data to uncover trends, offering individuals opportunities for more effective and rapid exchanges of thoughts and skills (Ghasemaghaei and Calic, 2020). Recent advancements in AI, particularly the emergence of GenAI, have significantly improved knowledge transfer within organisations. GenAI facilitates personalised onboarding, supports interactive and hands-on learning experiences, and provides immediate access to relevant information. Furthermore, it reduces communication barriers by enabling employees to seek information more freely, thereby ensuring consistent and efficient KS across geographically dispersed teams and time zones (Alavi et al., 2024).

Additionally, AI-based technologies demonstrate proficiency in curating personalised learning experiences and adapting the pace and content of educational materials to meet individual requirements and learning styles, thereby facilitating the transfer of new knowledge (Lee et al., 2022).

In customer support, AI-powered knowledge bases that continuously update based on customer feedback ensure the provision of accurate and up-to-date information (Zhu et al., 2010). Furthermore, AI-driven e-learning platforms tailor educational resources to diverse learning styles, thereby enhancing educational outcomes and facilitating more effective knowledge transfer (Zawacki-Richter et al., 2019).

This comprehensive integration of AI across various facets of KS underscores its transformative potential in revolutionising organisational learning, collaboration, and innovation (Dwivedi et al., 2021). As AI technologies continue to evolve, their impact on KS practices is likely to become even more pronounced, potentially redefining the landscape of organisational KM in the coming years (Rezaei et al.,2024b).

#### 2.1.4. *Knowledge application and AI*

Knowledge Application (KA) is a critical process within KM that involves using knowledge to address challenges, inform decision-making, and generate novel products or services. As such, it occupies a central role in the KM framework, given that knowledge without effective application holds limited value (Alavi and Leidner, 2001). KA necessitates a comprehensive understanding of the context in which knowledge must be applied, encompassing individual and organisational needs and objectives (Dilling and Lemos, 2011). The efficacy of KA is contingent upon seamless communication, collaboration, and the exchange of experiences and expertise among stakeholders (Ode and Ayavoo, 2020).

The capacity for practical KA emerges as a critical determinant of organisational success in the contemporary, rapidly evolving business environment. Entities proficient in leveraging their knowledge assets are better positioned to innovate, adapt, and thrive in the face of emerging challenges and opportunities (Liebowitz, 2001).

KA is frequently conceptualised as the enabler that facilitates the practical implementation of knowledge following its retrieval or dissemination, often involving reconfiguring existing knowledge resources, such as best practices and applicable solutions, or delivering new products and services within novel contexts (Bhatt, 2001). AI is an exemplar in this domain, streamlining KA through various mechanisms. For instance, AI can rapidly analyse vast volumes of data, uncovering patterns and relationships that may elude human perception, thereby facilitating the extraction of actionable insights for decision-making processes (Hardaker et al., 2004).

AI demonstrates strong capabilities in processing and analysing text and speech by deconstructing language into its constituent elements to extract meaning. This allows for identifying relevant information and uncovering latent insights from unstructured data (Liebowitz, 2001). Additionally, AI can personalise learning experiences by leveraging users' individual preferences and learning styles, recommending targeted learning materials, and tailoring KA processes to specific needs, thereby improving efficiency and effectiveness (Sundaresan and Zhang, 2022). The advent of GenAI has further advanced organisational KA by enabling faster, more consistent access to stored knowledge through natural language interactions (Alavi et al., 2024). Emerging research and case studies demonstrate notable improvements in productivity and service quality. For example, Brynjolfsson et al. (2023) reported that integrating GenAI into customer support operations led to a 14 % overall increase in productivity, a 30 % gain among novice agents, and a measurable improvement in customer satisfaction.

Automation represents a prime illustration of AI's facilitative role in KA, as it streamlines repetitive tasks such as data entry and analysis, thereby liberating human capital for more strategic endeavours (Davenport and Kirby, 2016). Furthermore, AI excels in prediction, a vital component in implementing new organisational strategies and processes. By harnessing its predictive capabilities based on historical data, AI identifies trends and patterns, simplifying the use of knowledge for any future decision-making processes (North and Kumta, 2018).

Incorporating AI into KA processes represents a crucial advancement in KM, enabling organisations to optimise using their knowledge assets in innovative ways. With the continuous evolution of AI technologies, their ability to refine and improve KA practices is expected to expand, bringing transformative changes to how organisations manage and apply knowledge in the future (Dwivedi et al., 2021).

### 2.2. *AI and KM: Challenges and concerns*

The intersection of AI and KM represents a frontier of immense potential and significant complexity for contemporary organisations. As firms increasingly leverage AI technologies to enhance their KM processes, they encounter a multifaceted landscape of challenges and concerns that warrant critical examination (Dwivedi et al., 2021). These challenges span across technological, organisational, and ethical dimensions, each presenting unique obstacles to the effective integration of AI within KM frameworks (Asrar-ul-Haq and Anwar, 2016; Hu et al., 2023; Owoc et al., 2019; Zaraté et al., 2008). The technological challenges encompass issues related to data quality, system integration, and the adaptability of AI algorithms to diverse organisational contexts (Janssen et al., 2020). Organisational challenges, on the other hand, revolve around the structural and cultural shifts required to accommodate AI-driven KM systems, including changes in work processes, skill requirements, and decision-making paradigms (Brynjolfsson and Mitchell, 2017). Ethical challenges, perhaps the most complex and far-reaching, involve navigating the implications of AI use on privacy, fairness, transparency, and accountability in KM practices (Martin et al., 2022).

#### 2.2.1. *Technological challenges*

Implementing AI in KM systems presents various technological challenges for organisations. These challenges stem from AI technologies' intricate nature and complex interactions with existing KM infrastructures (Davenport and Ronanki, 2018).

A primary concern revolves around data quality and integrity, which are fundamental to the efficacy of AI-driven knowledge systems (Ghasemaghaei and Calic, 2020). Organisations frequently encounter issues related to data inconsistency, incompleteness, and inherent biases, all of which can significantly impact the accuracy and reliability of AI-generated insights (Janssen et al., 2020). The dispersal of knowledge across diverse sources and restrictions imposed by data privacy and security regulations further exacerbate these challenges, potentially compromising the effectiveness of AI algorithms that rely heavily on high-quality data. The significance of data quality cannot be overstated, as it directly impacts the efficacy and precision of AI models and, subsequently, KM processes. Data quality encompasses various dimensions, including accuracy, completeness, consistency, timeliness, and relevance (McGilvray, 2021). A myriad of factors can contribute to poor data quality, including human errors, system glitches, data integration complexities, and inaccuracies in data entry. Inaccurate or incomplete data can lead to skewed or erroneous insights and decisions, posing particular challenges when handling sensitive or critical information (Kees et al., 2017).

Another significant challenge lies in the integration of AI with legacy systems. Many organisations operate legacy KM systems that were not originally designed to interface seamlessly with AI technologies. The process of integrating AI-based systems with these legacy counterparts can prove arduous, demanding substantial resources and expertise. It often necessitates significant modifications to existing workflows, resulting in time-consuming and cost-intensive endeavours (Qin et al., 2021). Scalability represents a formidable challenge in AI-based KM systems. These systems must be architected to accommodate an organisation's evolving needs, expanding their capabilities without compromising performance as data volumes surge. Achieving this scalability mandate requires specialised skills in developing scalable systems and a profound comprehension of an organisation's data requirements (Davenport and Ronanki, 2018). Transparency and explainability constitute additional hurdles in AI-driven KM systems. AI models must maintain transparency and explainability to ensure users comprehend the decision-making processes. A lack of transparency or explainability can engender user scepticism towards the outputs generated by AI systems. Developing models that can be elucidated and comprehended by users mandates considerable expertise (Angelov et al., 2021).

Reliability and robustness further underscore the challenges at hand. AI models must exhibit unwavering reliability and robustness, capable of handling outliers, noise, and missing data without faltering. Reliability lapses can lead to suboptimal decision-making, diminishing KM systems' effectiveness. Developing dependable and resilient models necessitates a deep well of expertise in ML and data science (Balagurunathan et al., 2021). Security and privacy concerns constitute a formidable aspect of the technological challenges. AI-based KM systems must be fortified to ensure data security and privacy. They must safeguard sensitive data, conform to privacy regulations, and thwart unauthorised access. Addressing these challenges requires a comprehensive understanding of cybersecurity principles and data privacy regulations (Li, 2018; Radulov, 2019).

Algorithm complexity introduces a significant layer of intricacy in AI's role within KM. AI algorithms often possess complex and opaque structures that can be difficult to interpret or explain, which poses challenges for understanding how decisions are made and evaluating the reliability and validity of AI-generated outputs. The core concern surrounding algorithmic complexity lies in its tendency to obscure the rationale behind system recommendations, thereby potentially undermining user trust (Kosovskaya, 2018). This issue is particularly critical in high-stakes domains such as healthcare, finance, and national security, where decisions based on inaccurate or biased outputs may lead to severe consequences (Ceylan et al., 2021). Furthermore, managers and organisational leaders may reject algorithmic recommendations if they cannot comprehend the underlying logic or perceive the outcomes as misaligned with expectations. They may also dismiss AI-generated insights if those are based on negative trends or sensitive underlying data, regardless of the technical accuracy of the system (Abbas, 2025). These concerns highlight the importance of explainable AI and transparent system design in fostering user trust and facilitating the effective adoption of AI in KM.

#### *2.2.2. Organisational challenges*

Adopting AI for KM presents organisations with a multifaceted array of challenges deeply embedded in their structural and cultural fabric. These challenges, called organisational challenges, transcend mere technological implementation, encompassing issues of organisational readiness, employee acceptance, and strategic alignment (Rezaei, 2024; Dwivedi et al., 2021).

A significant organisational hurdle is the resistance to change among employees. Implementing AI-based KM systems often necessitates comprehensive alterations to existing processes and workflows. This can engender employee resistance, potentially impeding adoption rates and the system's overall success (Ferreira et al., 2018a, 2018b; Shrestha et al., 2019). Such resistance is frequently exacerbated by a lack of trust in AI systems, particularly when their decision-making processes lack transparency or appear to contradict human intuition (Siau and Wang, 2020). This phenomenon aligns with the broader concept of technological frames, as proposed by Orlikowski and Gash (1994), which posits that individuals' interpretations of technology significantly influence its adoption and use within organisations.

Developing and implementing AI-based KM systems demands substantial proficiency in ML, data science, and information technology. Consequently, many organisations face a critical challenge in the form of a dearth of requisite expertise. This skills gap often compels organisations to seek external consultants or partners, potentially incurring significant costs that can strain budgetary constraints (Hebbar and Vandana, 2023). This challenge is compounded by the rapid evolution of AI technologies, necessitating continuous organisational learning and adaptation (Brynjolfsson and McAfee, 2014). For example, in the same but specific field, Dehkhodaei et al. (2023) found that the lack of sufficient knowledge and learning is a serious problem in big data analysis (BDA), which consequently impacts progress in AI employment. Interdepartmental collaboration represents another formidable challenge. AI-based KM systems frequently mandate collaboration among diverse departments, such as IT and KM. This necessitates seamless communication and cooperation between these departments, which can prove challenging in the presence of departmental silos or communication barriers (Allal-Chérif et al., 2021). The concept of "boundary objects" (Star and Griesemer, 1989) becomes particularly relevant here, because AI-based KM systems must serve as effective interfaces between different organisational units with potentially divergent perspectives and priorities.

Ensuring alignment between the AI-based KM system and the organisation's overarching goals and values is a pivotal requirement. The system must be meticulously crafted to bolster the organisation's overall strategic objectives and resonate with its cultural values (Davenport and Ronanki, 2018). Failure to achieve this alignment may compromise the system's effectiveness and potentially prove detrimental to organisational operations. This challenge is reminiscent of the "strategic fit" concept in information systems research (Venkatraman et al., 1993), emphasising the need for congruence between technological initiatives and organisational strategy.

The financial implications of developing and implementing AI-based KM systems present another significant challenge. These initiatives often take a considerable financial toll, requiring organisations to allocate substantial resources to the project. This can pose a formidable challenge, particularly when organisations grapple with limited budgets or competing priorities vie for resources (Goirand et al., 2021). This financial burden is further complicated by the concept of the "IT productivity paradox" (Brynjolfsson, 1993), which highlights the complex and often non-linear relationship between IT investments and organisational performance outcomes.

#### 2.2.3. Ethical challenges

Ethical challenges in integrating AI into KM systems represent a critical dimension that organisations must navigate with the utmost care and consideration. These challenges carry considerable weight, impacting various facets of an organisation's operations (Goirand et al., 2021). They extend beyond mere compliance issues, touching upon fundamental questions of fairness, transparency, privacy, and human autonomy in an AI-augmented workplace.

A primary concern revolves around the potential for AI systems to perpetuate or exacerbate existing biases in organisational knowledge bases and decision-making processes (Ntoutsi et al., 2020). AI algorithms can become tainted with bias when trained on data that perpetuates historical prejudices or stereotypes. Such bias can culminate in discriminatory and inequitable decision-making processes (DeCamp and Lindvall, 2020; Martin et al., 2022).

The issue of transparency, accountability and explainability in AI-driven knowledge systems presents another substantial ethical challenge. As AI algorithms become more complex, the 'black box' nature of their decision-making processes raises concerns about accountability and trust (Rezaei et al., 2024b; Doshi-Velez and Kim, 2017). Organisations grapple with the ethical implications of relying on systems whose rationale may be opaque, particularly in contexts where decisions significantly impact individuals or organisational outcomes (Mazurek and Małagocka, 2019; Murdoch, 2021). This lack of transparency affects employee trust and raises questions about legal and ethical responsibility when AI-informed decisions lead to adverse outcomes (Felzmann et al., 2020; Robinson, 2020).

Privacy concerns loom large in the ethical landscape of AI-enhanced KM (Gündüz et al., 2023). The vast amounts of data required to train and operate effective AI systems often include sensitive personal and organisational information. Organisations face the ethical challenge of balancing the need for comprehensive data with the imperative to protect individual privacy rights and maintain data security (Zuboff, 2023). This challenge is further complicated by evolving data protection regulations and the global nature of many organisations' operations, necessitating compliance with diverse legal frameworks.

The potential for AI to diminish human agency and autonomy in knowledge work presents a profound ethical challenge. As AI systems become more advanced in generating, analysing, and applying knowledge, organisations must grapple with questions about the appropriate balance between AI and human decision-making (Jarrahi, 2018). The ethical implications of over-reliance on AI in knowledge processes include the potential erosion of human expertise, the devaluation of tacit knowledge, and the psychological impact on employees who may feel displaced or devalued.

Moreover, the long-term societal implications of AI in KM raise ethical questions about organisational responsibility. The potential for AI to exacerbate economic inequalities through job displacement or skill polarisation poses ethical challenges that extend beyond organisational boundaries (Brynjolfsson and McAfee, 2014). Organisations must consider their role in mitigating these broader societal impacts while pursuing AI-driven innovation in their KM practices.

## 3. Study one: Delphi method

### 3.1. The Delphi method

The Delphi method is a structured communication technique that employs multiple rounds of questionnaires or surveys to gather expert opinions and build consensus on a specific topic. A defining feature of this method is its anonymity to participants, allowing experts—panellists—to contribute freely without fear of criticism, which reduces the influence of dominant individuals and fosters independent thought. This iterative process enables participants to refine their views based on group feedback, promoting convergence of expert opinions over successive rounds (Humphrey-Murto et al., 2020; Steurer, 2011; Okoli and Pawlowski, 2004).

Widely valued for eliciting informed perspectives and attaining consensus on complex and uncertain issues, the Delphi method is applied across various disciplines (Rezaei et al., 2021b). For instance, Hasson et al. (2000) used it to develop nursing research guidelines. In the digital health field, Rezaei et al. (2021c) applied a mixed-method Delphi approach to validate ethical indicators, and Deveci et al. (2020) used a fuzzy-rough Delphi method to evaluate offshore wind farm siting criteria in environmental management. Flostrand et al. (2020) and Martinuzzi and Krumay (2013) have highlighted its relevance in emerging fields like sustainability, CSR, and corporate strategy.

In healthcare, a comprehensive review by Schifano and Niederberger (2025) analysed 287 Delphi studies, underscoring its widespread use in developing clinical guidelines and policy frameworks. In environmental governance, López-Gunn et al. (2024) used it to assess information system roles in groundwater management. In climate change policy, Flood et al. (2023) utilised a layered Delphi panel to co-develop visions of a low-carbon, climate-resilient future. Likewise, in marine science, Cunha et al. (2022) applied the method to assess technologies for marine litter reduction.

These diverse and contemporary applications further highlight the Delphi method's adaptability, methodological robustness, and value in generating collective insights for decision-making in fields such as healthcare, education, environmental management, sustainability, and information systems.

### 3.2. The panel of experts

In the Delphi method, the expert panel comprises individuals with deep expertise and experience in a field relevant to the research question. Their selection is based on professional background, academic credentials, and practical engagement in the subject area. For this study, invitations were extended to senior professionals holding managerial, founder, or ownership roles in the e-retail sector and to scholars specialising in AI and KM, including professors and researchers affiliated with universities and R&D institutions. After carefully reviewing the responses, 17 experts (7 industry professionals and 10 scholars) confirmed their participation in the Delphi panel.

### 3.3. The procedures

The Delphi procedure embarked on a preliminary phase where 17 items, spanning three dimensions—technological, organisational, and ethical—were identified through a review of prior studies. Subsequently, participants were queried about the perceived importance of these factors in challenging AI in KM, utilising a 5-point Likert scale. For instance, participants were asked to assess how much they concurred with the statement, "Algorithm complexity represents a significant challenge for Knowledge Creation (KC)." This approach was applied across all KM dimensions.

The results from each round were aggregated, analysed, and presented to the experts as a summary report without revealing individual responses. The analysis encompassed the computation of two primary indices: the mean value and standard deviation for each item, along with the determination of Kendall's Coefficient of Concordance (Kendall's W). Kendall's coefficient, also known as Kendall's W, assesses the level of agreement or consensus among a group of raters or judges concerning a set of rankings or ratings. It spans a range from 0 to 1, with higher values denoting greater consensus. It is pertinent to acknowledge that Kendall's coefficient solely gauges the extent of concordance among experts and does not inherently reflect the accuracy or validity of their opinions or prognostications. Empirical experience designates a minimum value of 0.5 for Kendall's W Coefficient to indicate consensus. Based on empirical evidence, consensus typically materialises after three or four rounds (Fig. 1) (De Loë et al., 2016; Toma and Picioreanu, 2016).

(Source: Author's calculation)

### 3.4. Results

The Delphi method was applied across all four dimensions of KM, spanning three rounds. Every panellist actively participated during all three rounds in the four knowledge areas. As previously mentioned, the degree of agreement among panellists was quantified using Kendall's W statistic. The results demonstrate that panellists could progressively converge towards a consensus across all four knowledge areas. This consensus became particularly evident in the third round, as indicated by the substantially high values of Kendall's W. This consensus achievement was observed across all models and was indicative of a collective agreement among the experts.

Concerning the identified indicators, those that exhibited a mean value surpassing 3.5 were deemed significant by the conclusion of the third round. In summary:

- KC presented thirteen significant indicators: scalability, resistance to change, accountability, and privacy.
- KST encompassed fifteen significant indicators: scalability, data quality and availability, security and privacy, resistance to change, and budget constraints.
- KS featured fourteen significant indicators: scalability, resistance to change, budget constraints, and a lack of job security.
- KA revealed fourteen significant challenges, with scalability, resistance to change, and accountability standing out as the most prominent among them.

Furthermore, the chi-square statistic was utilised to assess whether the distribution of responses diverged significantly from what would be anticipated by random chance alone. Notably, the results underscored that the differences in responses between the panellists were statistically significant and not merely attributable to chance.

Tables 1.1, 1.2, 1.3, and 1.4 present an overview of the principal challenges within KM concerning AI, while Table 2 concisely summarises the Delphi results.

## 4. Study two: Confirmatory factor analysis (CFA)

The second study focuses on statistically validating the structure derived from the Delphi method outputs from the first study. The Delphi method was employed to gather expert consensus on key constructs and their relationships, refining the theoretical framework through an iterative and collaborative process. This phase aimed to identify the principal challenges associated with integrating AI into the four independent models of KM.

Building on this foundation, CFA was conducted in the second phase to provide a robust quantitative assessment of the measurement model. CFA was employed to validate and affirm the findings obtained through the Delphi method by testing the model's reliability and construct validity, ensuring its statistical soundness. By integrating the Delphi method's expert-driven refinement with the quantitative rigour of CFA, the framework is theoretically grounded and empirically validated, providing a reliable basis for exploring the research objectives.

Accordingly, as part of the CFA process, a meticulously designed questionnaire was developed based on the indicators identified in the Delphi study. The questionnaire was tailored to each of the four KM models (refer to Fig. 2) and presented to participants. Respondents were invited to share their perspectives using a 5-point Likert scale, evaluating the significance of specific challenges, such as "data quality and availability" for AI integration within the KS model. Ratings ranged from 1 (very low) to 5 (very high), quantifying their opinions for subsequent analysis.

### 4.1. Industry selection

The retail sector holds profound significance within the global economy, serving as the gateway through which consumers access an extensive array of products and services. Retailers operate across diverse landscapes, spanning traditional brick-and-mortar establishments to virtual online marketplaces, and employ a broad spectrum of strategies to attract and retain customers. Consequently, the retail industry operates in a highly competitive environment, with companies perpetually striving to distinguish themselves through product quality, pricing, convenience, and overall customer experience. Accordingly, the retail industry has undergone rapid transformation in recent years, extensively embracing AI to elevate operational capabilities, enhance customer experiences, and drive growth (Shankar, 2018). AI technologies, notably ML and NLP, are utilised in various facets of retail operations, including supply chain management, inventory control, pricing optimisation, and personalised marketing initiatives (Weber and Schütte, 2019).

AI-powered chatbots and virtual assistants facilitate customer interactions by providing product recommendations, addressing inquiries, and delivering round-the-clock support (Huang and Rust, 2018). Moreover, AI's analytical capabilities enable extracting valuable

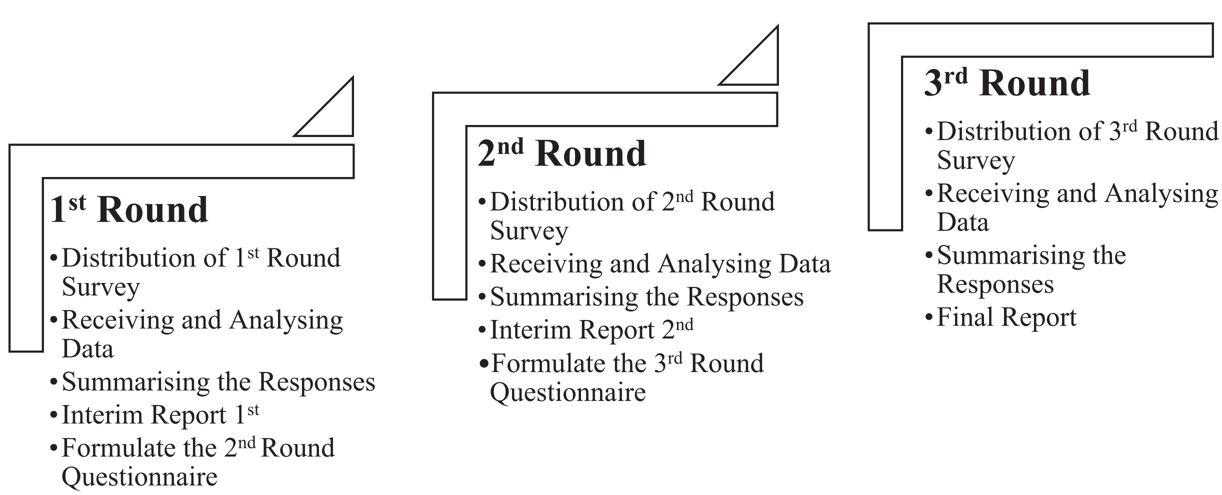


**Fig. 1.** Overview of the Delphi Method.

**Table 1.1**
AI challenges in KC.

| Key Challenges | | 1st Round | | 2nd Round | | 3rd Round | |
|---|---|---|---|---|---|---|---|
| | | Mean | SD | Mean | SD | Mean | SD |
| Technological Challenges (TC) | **data quality and availability** | **4.2941** | **0.58787** | **4.3529** | **0.49259** | **4.4706** | **0.62426** |
| | integration with legacy systems | 3.5294 | 0.62426 | 3.4118 | 0.61835 | 3.2941 | 0.58787 |
| | **scalability** | **4.6471** | **0.49259** | **4.7059** | **0.46967** | **4.7647** | **0.43724** |
| | **transparency and explainability** | **4.0588** | **0.65865** | **4.1176** | **0.60025** | **4.2353** | **0.43724** |
| | **reliability and robustness** | **3.7059** | **0.58787** | **3.8235** | **0.52859** | **3.9412** | **0.55572** |
| | **security and privacy** | **4.2941** | **0.46967** | **4.3529** | **0.49259** | **4.4118** | **0.71229** |
| | algorithm complexity | 3.3529 | 0.49259 | 3.2353 | 0.43724 | 3.1765 | 0.39295 |
| Organisational Challenges (OC) | **resistance to change** | **4.7059** | **0.46967** | **4.7059** | **0.46967** | **4.7647** | **0.43724** |
| | **lack of expertise** | **4.1765** | **0.63593** | **4.2353** | **0.66421** | **4.3529** | **0.60634** |
| | **interdepartmental collaboration** | **3.8235** | **0.63593** | **3.9412** | **0.55572** | **4.0000** | **0.61237** |
| | aligning with the organisation's values | 3.7647 | 0.75245 | 3.5882 | 0.71229 | 3.4706 | 0.62426 |
| | **budget constraints** | **4.3529** | **0.49259** | **4.3529** | **0.49259** | **4.4706** | **0.51450** |
| Ethical Challenges (EC) | bias | 3.2941 | 0.91956 | 3.0588 | 0.82694 | 3.0000 | 0.79057 |
| | **accountability** | **4.2353** | **0.75245** | **4.3529** | **0.60634** | **4.4118** | **0.61835** |
| | **privacy** | **3.7647** | **1.03256** | **3.9412** | **0.89935** | **4.0000** | **0.86603** |
| | **transparency** | **3.7647** | **0.56230** | **3.8824** | **0.48507** | **3.9412** | **0.65865** |
| | **lack of job security** | **4.4118** | **0.61835** | **4.4706** | **0.51450** | **4.5294** | **0.62426** |

Source: Author' calculation.

**Table 1.2**
AI challenges in KST.

| Key Challenges | | 1st Round | | 2nd Round | | 3rd Round | |
|---|---|---|---|---|---|---|---|
| | | Mean | SD | Mean | SD | Mean | SD |
| Technological Challenges (TC) | **data quality and availability** | **4.1765** | **0.52859** | **4.2353** | **0.43724** | **4.2941** | **0.46967** |
| | integration with legacy systems | 3.4118 | 0.61835 | 3.3529 | 0.60634 | 3.2941 | 0.58787 |
| | **scalability** | **4.5294** | **0.51450** | **4.4706** | **0.51450** | **4.5294** | **0.51450** |
| | **transparency and explainability** | **3.9412** | **0.55572** | **4.0000** | **0.50000** | **4.0000** | **0.50000** |
| | **reliability and robustness** | **3.6471** | **0.60634** | **3.7059** | **0.58787** | **3.7647** | **0.56230** |
| | **security and privacy** | **4.1765** | **0.52859** | **4.2353** | **0.43724** | **4.2353** | **0.43724** |
| | algorithm complexity | 3.3529 | 0.49259 | 3.4118 | 0.50730 | 3.4706 | 0.51450 |
| Organisational Challenges (OC) | **resistance to change** | **4.5882** | **0.50730** | **4.6471** | **0.49259** | **4.7059** | **0.46967** |
| | **lack of expertise** | **4.0588** | **0.55572** | **4.1176** | **0.48507** | **4.1765** | **0.52859** |
| | **interdepartmental collaboration** | **3.8235** | **0.52859** | **3.8824** | **0.48507** | **3.9412** | **0.55572** |
| | **aligning with the organisation's values** | **3.8235** | **0.72761** | **3.8824** | **0.69663** | **3.9412** | **0.65865** |
| | **budget constraints** | **4.2941** | **0.46967** | **4.3529** | **0.49259** | **4.4118** | **0.50730** |
| Ethical Challenges (EC) | **bias** | **3.4706** | **0.71743** | **3.5294** | **0.62426** | **3.5882** | **0.61835** |
| | **accountability** | **4.1765** | **0.63593** | **4.2353** | **0.56230** | **4.2941** | **0.46967** |
| | **privacy** | **3.7647** | **0.75245** | **3.8824** | **0.69663** | **3.9412** | **0.65865** |
| | **transparency** | **3.7647** | **0.43724** | **3.8824** | **0.33211** | **3.9412** | **0.55572** |
| | **lack of job security** | **4.3529** | **0.60634** | **4.4118** | **0.50730** | **4.4706** | **0.51450** |

Source: Author's calculation.

**Table 1.3**
AI challenges in KS.

| Key Challenges | | 1st Round | | 2nd Round | | 3rd Round | |
|---|---|---|---|---|---|---|---|
| | | Mean | SD | Mean | SD | Mean | SD |
| Technological Challenges (TC) | **data quality and availability** | **4.2353** | **0.43724** | **4.2941** | **0.58787** | **4.2941** | **0.58787** |
| | integration with legacy systems | 3.4706 | 0.62426 | 3.4706 | 0.62426 | 3.4118 | 0.61835 |
| | **scalability** | **4.5882** | **0.50730** | **4.6471** | **0.49259** | **4.6471** | **0.60634** |
| | **transparency and explainability** | **4.0588** | **0.65865** | **4.1176** | **0.60025** | **4.1765** | **0.63593** |
| | **reliability and robustness** | **3.7647** | **0.56230** | **3.8235** | **0.52859** | **3.9412** | **0.55572** |
| | **security and privacy** | **4.2353** | **0.43724** | **4.2353** | **0.43724** | **4.3529** | **0.49259** |
| | algorithm complexity | 3.2941 | 0.46967 | 3.2353 | 0.43724 | 3.2941 | 0.58787 |
| Organisational Challenges (OC) | **resistance to change** | **4.4706** | **0.51450** | **4.5294** | **0.51450** | **4.5294** | **0.62426** |
| | **lack of expertise** | **4.0000** | **0.50000** | **4.0588** | **0.55572** | **4.1176** | **0.69663** |
| | **interdepartmental collaboration** | **3.8824** | **0.48507** | **3.8235** | **0.52859** | **3.9412** | **0.55572** |
| | **aligning with the organisation's values** | **3.6471** | **0.70189** | **3.5882** | **0.61835** | **3.5294** | **0.62426** |
| | **budget constraints** | **4.2353** | **0.43724** | **4.2941** | **0.46967** | **4.3529** | **0.60634** |
| Ethical Challenges (EC) | bias | 3.5294 | 0.62426 | 3.4706 | 0.62426 | 3.4118 | 0.79521 |
| | **accountability** | **4.1176** | **0.60025** | **4.1765** | **0.52859** | **4.2353** | **0.56230** |
| | **privacy** | **3.8824** | **0.69663** | **4.0000** | **0.70711** | **4.0588** | **0.74755** |
| | **transparency** | **3.8824** | **0.60025** | **3.8235** | **0.52859** | **3.8824** | **0.69663** |
| | **lack of job security** | **4.2941** | **0.46967** | **4.2941** | **0.58787** | **4.3529** | **0.70189** |

Source: Author's calculation.

**Table 1.4**
AI challenges in KA.

| Key Challenges | | 1st Round | | 2nd Round | | 3rd Round | |
|---|---|---|---|---|---|---|---|
| | | Mean | SD | Mean | SD | Mean | SD |
| Technological Challenges (TC) | **data quality and availability** | **4.2353** | **0.43724** | **4.2941** | **0.58787** | **4.2941** | **0.58787** |
| | integration with legacy systems | 3.4706 | 0.62426 | 3.4706 | 0.62426 | 3.4118 | 0.61835 |
| | **scalability** | **4.5882** | **0.50730** | **4.6471** | **0.49259** | **4.6471** | **0.60634** |
| | **transparency and explainability** | **4.0588** | **0.65865** | **4.1176** | **0.60025** | **4.1765** | **0.63593** |
| | **reliability and robustness** | **3.7647** | **0.56230** | **3.8235** | **0.52859** | **3.9412** | **0.55572** |
| | **security and privacy** | **4.2353** | **0.43724** | **4.2353** | **0.43724** | **4.3529** | **0.49259** |
| | algorithm complexity | 3.2941 | 0.46967 | 3.2353 | 0.43724 | 3.2941 | 0.58787 |
| Organisational Challenges (OC) | **resistance to change** | **4.4706** | **0.51450** | **4.5294** | **0.51450** | **4.5294** | **0.62426** |
| | **lack of expertise** | **4.0000** | **0.50000** | **4.0588** | **0.55572** | **4.1176** | **0.69663** |
| | **interdepartmental collaboration** | **3.8824** | **0.48507** | **3.8235** | **0.52859** | **3.9412** | **0.55572** |
| | **aligning with the organisation's values** | **3.6471** | **0.70189** | **3.5882** | **0.61835** | **3.5294** | **0.62426** |
| | **budget constraints** | **4.2353** | **0.43724** | **4.2941** | **0.46967** | **4.3529** | **0.60634** |
| Ethical Challenges (EC) | bias | 3.5294 | 0.62426 | 3.4706 | 0.62426 | 3.4118 | 0.79521 |
| | **accountability** | **4.1176** | **0.60025** | **4.1765** | **0.52859** | **4.2353** | **0.56230** |
| | **privacy** | **3.8824** | **0.69663** | **4.0000** | **0.70711** | **4.0588** | **0.74755** |
| | **transparency** | **3.8824** | **0.60025** | **3.8235** | **0.52859** | **3.8824** | **0.69663** |
| | **lack of job security** | **4.2941** | **0.46967** | **4.2941** | **0.58787** | **4.3529** | **0.70189** |

Source: Author's calculation.

**Table 2**
Summarise the Delphi Rounds.

| | Delphi Rounds | Summarise activities and results | | | | | Chi-Square | Kendall W | Need to next round? |
|---|---|---|---|---|---|---|---|---|---|
| | | Invited/ Participated panellists | N | Indicators (mean > 3.5) | df | Sig. | | | |
| KC | 1st round | 17/17 | 17 | 15 | 16 | 0.000 | 44.819 | 0.284 | Yes |
| | 2nd round | 17/17 | 17 | 14 | 16 | 0.000 | 79.785 | 0.349 | Yes |
| | **3rd round** | **17/17** | **17** | **13** | **16** | **0.000** | **137.202** | **0.538** | **No** |
| KST | 1st round | 17/17 | 17 | 14 | 16 | 0.000 | 43.434 | 0.188 | Yes |
| | 2nd round | 17/17 | 17 | 15 | 16 | 0.000 | 82.322 | 0.329 | Yes |
| | **3rd round** | **17/17** | **17** | **15** | **16** | **0.000** | **139.406** | **0.564** | **No** |
| KS | 1st round | 17/17 | 17 | 15 | 16 | 0.000 | 45.518 | 0.202 | Yes |
| | 2nd round | 17/17 | 17 | 14 | 16 | 0.000 | 85.217 | 0.339 | Yes |
| | **3rd round** | **17/17** | **17** | **14** | **16** | **0.000** | **148.624** | **0.602** | **No** |
| KA | 1st round | 17/17 | 17 | 15 | 16 | 0.000 | 45.112 | 0.269 | Yes |
| | 2nd round | 17/17 | 17 | 14 | 16 | 0.000 | 82.744 | 0.347 | Yes |
| | **3rd round** | **17/17** | **17** | **14** | **16** | **0.000** | **138.029** | **0.548** | **No** |

Source: Author's calculation.

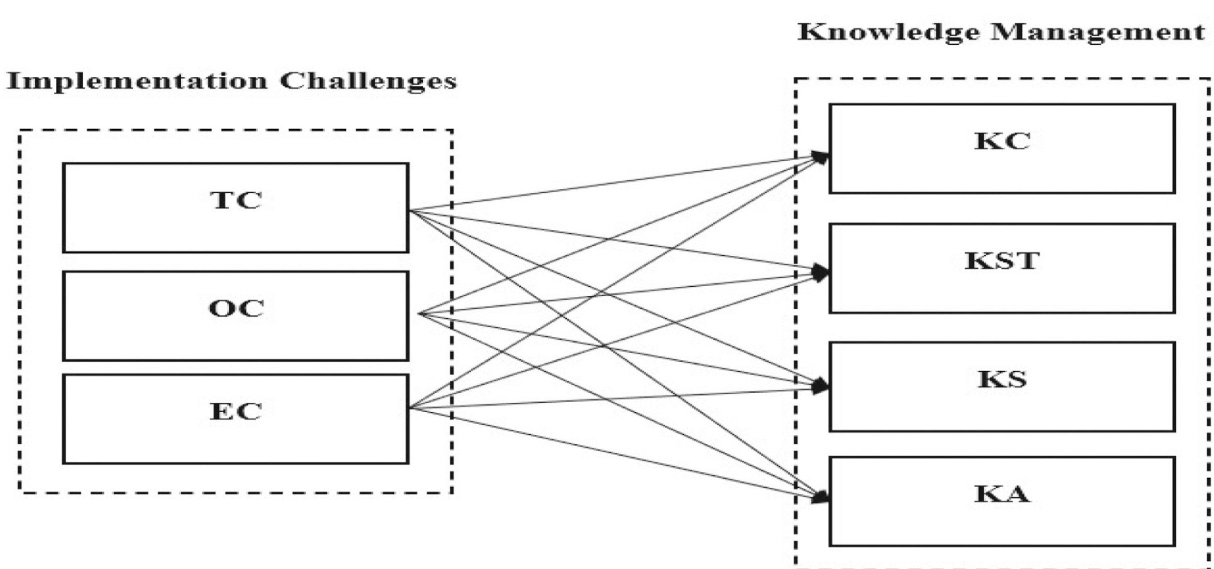


**Fig. 2.** The Conceptual model for CFA.

insights from customer data, empowering e-retailers to make informed decisions regarding product development, pricing strategies, and marketing campaigns (Kaur et al., 2020). Consequently, AI adoption in the e-retail sector can potentially reduce operational costs, enhance efficiency, and improve precision.

However, integrating AI into the online retail sector presents challenges, including ethical considerations, data privacy concerns, and the need for a skilled workforce adept at developing and implementing AI solutions (Cao, 2021).

This study focuses on the e-retail landscape in Iran, a relatively nascent yet rapidly expanding sector. According to Statista (2025), the e-commerce market in Iran is projected to grow by 11.87 % between 2025 and 2029, reaching a market volume of approximately US$24.39 billion by 2029. This growth trajectory is underpinned by Iran's youthful and tech-savvy population, increasing smartphone penetration, and a burgeoning appetite for online shopping (Emami et al., 2023). Although the e-retail sector in Iran is similar in concept and implementation to those in other countries, there are differences due to unique economic, technological, regulatory, and cultural factors (Yasin et al., 2014). In Iran, local e-commerce platforms like Digikala Co., dominate the market, with international giants like Amazon Co., absent due to sanctions and regulatory barriers (Donovan et al., 2023; Motamedi, 2019). Payment systems in Iran rely heavily on local banking methods and cash on delivery, reflecting limited access to international financial networks (Emami et al., 2023). Conversely, US online retailers benefit from advanced logistics, diverse payment options, and strong consumer protections, allowing seamless transactions and rapid delivery (Gauri et al., 2021). These differences also highlight unique opportunities for growth in AI utilisation. Despite economic sanctions, technological infrastructure challenges, and regulatory constraints, Iranian e-commerce platforms have significant potential to expand the scope and sophistication of their AI implementations, drawing inspiration from the advanced AI applications seen in developed countries (Ghobakhloo and Ching, 2019).

Nowadays, despite all the barriers, Iranian e-retail firms have recorded significant growth (ECDCI, 2023). Online marketplaces have emerged as key players within the Iranian e-retail landscape, offering a broad spectrum of products and services and making strategic investments in logistics and payment infrastructure to address the distinctive challenges posed by the Iranian market (Mivehchi, 2019).

A preliminary roster of Iran's top 60 thriving e-retail enterprises was meticulously compiled, comprising 16 large firms and the remainder categorised as SMEs. The selections were based on key metrics such as sales volume, customer base, satisfaction indices, Customer Acquisition Cost (CAC), Customer Lifetime Value (CLV), and Average Order Value (AOV). The curated list was strategically designed to encompass various industry sectors, including vehicle sales, sporting goods, general e-commerce, online book sales, medical supplies, home appliances, cosmetics, electronics, fashion and apparel, and groceries and food.

An additional focus of this research was to determine the extent to which companies in the sample used AI. Leveraging comprehensive data, which included information from company websites, annual reports, self-reported activity details, and scholarly research, the application of AI within these enterprises was assessed across seven primary categories (Table 3).

Following the compilation process, we distributed 427 questionnaires to key decision-makers within the selected enterprises. The questionnaires targeted professionals from diverse domains, including production, sales, and marketing, who are directly or indirectly engaged with AI-driven KM processes within their organisations. These participants were selected based on their involvement in implementing, managing, or utilising AI tools for KC, storage, sharing, or application. For instance, production managers contributed insights into AI-powered automation and data-driven decision-making, sales professionals discussed AI-assisted customer insights and predictive analytics, and marketing specialists shared perspectives on AI-driven content curation and consumer engagement (Ref. Table 3). After a rigorous vetting of the responses, we identified 202 fully completed questionnaires deemed suitable for comprehensive analysis. Tables 4 and 5 provide detailed statistical insights into the second survey community and industry segmentation of participants for reference.

**Table 3**
Areas of AI Utilisation.

| AI Use Scope | Firms Using AI* | AI Use Case* | Firms Per Use Case** |
|---|---|---|---|
| Customer Experience & Personalisation | 25 | Product Recommendations | 9 |
| | | Customer Reviews Analysis | 8 |
| | | Personalised Marketing | 2 |
| | | Chatbots and Virtual Assistants | 14 |
| | | Customer Behaviour Analysis | 4 |
| Inventory and Demand Management | 15 | Demand Forecasting | 10 |
| | | Inventory Optimisation | 1 |
| | | Dynamic Pricing | 3 |
| | | SCM (Supply Chain Management) | 3 |
| Operational Efficiency | 29 | Auto-Support | 15 |
| | | Fraud Detection | 3 |
| | | Sales Data Analysis | 13 |
| | | Content Creation | 7 |
| User Experience Enhancement | 15 | Search and Filtering | 2 |
| | | Visual Search | 14 |
| | | Voice Search | 1 |
| Image and Video Analysis | 6 | Image Recognition | 5 |
| | | Virtual Try-Ons | 2 |
| Natural Language Processing | 5 | Sentiment Analysis | 5 |
| | | Voice Assistants | 1 |
| Predictive Analytics | 7 | Customer Lifetime Value Prediction | 6 |
| | | Churn Prediction | 3 |

Source: Author's calculation.
* Firms that use AI in this scope (Out of 60 studied).
** Firms use AI within this particular case (Out of firms that use AI in this scope).

### 4.2. Common method Bias and data quality assessment

Common Method Bias (CMB) represents a potential source of systematic error in research using a single data collection method to measure multiple constructs. This bias can lead to spurious correlations between variables and misestimating actual effects, thereby threatening the validity of research findings (Podsakoff et al., 2003). To address this concern, this study employed Harman's Single-Factor Test, a widely recognised research approach facilitated through SPSS software.

The Harman's Single-Factor Test involves consolidating all items into a single factor, with CMB considered present if this factor accounts for over 50 % of the variance in all variables under consideration. The analysis revealed that the results ranged between 33 % and 39 % for the four distinct models in this study, indicating that common method bias did not pose a significant threat to the validity of the findings (Podsakoff et al., 2003).

### 4.3. Multivariate normality and multicollinearity assessment

A critical preliminary step in statistical analysis involves assessing the normality of data distribution. To evaluate the normality of the Likert scale data, skewness and kurtosis tests were conducted, following Keller's (2015) recommendations. Data values between -2 and + 2 in these tests indicate a normal distribution. The results affirmed that the data satisfied the acceptable normality criteria, ensuring subsequent parametric analyses' appropriateness.

In addition to normality checks, scrutinising multicollinearity is essential to ensure the independence of descriptive variables. This assessment was achieved by examining the variance inflation factors (VIF), calculated as VIF $= (1\text{-}R^2)^{-1}$ (Field, 2013). With $R^2$ values falling below 0.8, the resulting VIF values remained below 5, well within the acceptable range stipulated by Field (2013). Consequently, multicollinearity was not deemed a significant concern within this study,

**Table 4**
Descriptive of the Second Survey Community.

| | Education Level | | | Work Experience (Year) | | | | Gender | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | UG | PG | PhD | <1 | 1-3 | 3-5 | 5< | M | F | NA. |
| Sales Managers | 12 | 13 | 4 | 5 | 9 | 8 | 7 | 13 | 10 | 6 |
| Marketing Managers | 9 | 12 | 7 | 5 | 11 | 9 | 4 | 11 | 8 | 10 |
| Operations Managers | 9 | 11 | 4 | 2 | 4 | 10 | 8 | 9 | 6 | 9 |
| IT Managers | 15 | 37 | 14 | 12 | 22 | 16 | 16 | 24 | 21 | 21 |
| Customer Service Managers | 9 | 15 | 4 | 8 | 11 | 6 | 3 | 10 | 11 | 7 |
| Finance Managers | 5 | 4 | 1 | 0 | 2 | 5 | 3 | 4 | 5 | 1 |
| Other | 4 | 10 | 3 | 3 | 7 | 3 | 3 | 9 | 3 | 4 |
| Total | **63** | **102** | **37** | **35** | **66** | **57** | **44** | **80** | **64** | **58** |
| | **202** | | | **202** | | | | **202** | | |

Source: Author's calculation.

**Table 5**
The Spectrum of Industry Sectors and Participants.

| Industry Sectors | Participants | Industry Sectors | Participants |
|---|---|---|---|
| Vehicle Sales | 17 | Home Appliances Sales | 21 |
| Sporting Goods Sales | 16 | Cosmetics Sales | 26 |
| General E-Commerce | 48 | Electronics E-commerce | 25 |
| Online Book Sales | 19 | Fashion and Apparel | 8 |
| Medical Supplies | 16 | Groceries and Food | 6 |

Source: Author's calculation.

further supporting the robustness of the statistical analyses.

### 4.4. *Assessing reliability and validity*

Ensuring the consistency and accuracy of measurement instruments is paramount in pursuing robust research findings. Therefore, a comprehensive approach was employed to assess the reliability and validity.

The reliability of a measurement instrument refers to its consistency in measuring the intended construct across multiple applications. This study employed a multi-faceted approach to reliability assessment, encompassing internal reliability, composite reliability (CR), and Average Variance Extracted (AVE).

Internal reliability was evaluated using Cronbach's alpha, with values exceeding 0.7 indicating acceptable internal consistency (Cho and Kim, 2015). Composite Reliability (CR), which assesses the internal consistency of a latent construct while accounting for measurement error, was also calculated. Concurrently, the Average Variance Extracted (AVE) was analysed, representing the average percentage of variation explained by the measuring items. Following established guidelines, acceptable values for CR and AVE should surpass 0.7 and 0.5, respectively (Hair et al., 2019; Field, 2013).

Validity assessment is crucial in determining the extent to which a scale or set of measures effectively represents the targeted concept. This study conducted a comprehensive validity analysis encompassing convergent, discriminant, and content validity, utilising CFA to validate the dimensionality of the constructs.

Convergent validity was evaluated via CR and AVE values, which indicate the degree to which indicators of a specific construct converge or share a high proportion of variance in common. As per established criteria, CR and AVE should exceed 0.7 and 0.5, respectively, with CR surpassing AVE (Fornell and Larcker, 1981). These results are presented in Table 6 of the manuscript.

Discriminant validity was examined through AVE and factor correlation analysis, assessing the distinctiveness of constructed measures and ensuring differentiation between factor-related questions compared to those related to other factors. This assessment adhered to two critical criteria: (1) the AVE value must exceed 0.50 to ensure construct validity adequacy, and (2) the AVE should surpass the squared factor correlation ($R^2$) (Lomax and Schumacker, 2012). The results of this analysis are detailed in Table 7 of the manuscript.

### 4.5. *Model fit assessment*

The evaluation of model fit constitutes a critical component in CFA, determining the degree of congruence between the hypothesised model and empirical data. This assessment entails a comparative analysis of the observed covariance matrix against the predicted covariance matrix generated by the proposed model. Given the study's focus on the influence of AI across four distinct dimensions of KM, it is imperative to scrutinise fitness indicators for each model individually.

A comprehensive battery of statistical tests and fit indices was systematically applied to assess model fit rigorously. This multifaceted approach thoroughly evaluates the model's adequacy in representing the underlying data structure. The selection of fit indices was guided by current best practices in structural equation modelling, encompassing both absolute and incremental fit measures. These indices collectively provide a nuanced understanding of the model's performance across various aspects of fit. The detailed outcomes, including specific fit indices and their respective threshold values, are presented in Table 8.

### 4.6. *Results*

The findings unveil a comprehensive landscape of challenges posed by integrating AI within KM. These challenges have been categorised into three distinctive domains: technological, organisational, and ethical.

#### 4.6.1. *Technological challenges*

Within this category, six distinct factors have been identified, each representing a significant hurdle. These factors include data quality and availability, scalability, transparency and explainability, reliability and robustness, security and privacy, and algorithm complexity. All these factors exhibit robust factor loadings, spanning from 0.749 to 0.894.

#### 4.6.2. *Organisational challenges*

Four key factors constitute this segment of challenges. These encompass resistance to change, lack of expertise, interdepartmental collaboration, and budget constraints. Each factor demonstrates strong factor loadings, ranging from 0.755 to 0.894. It is worth noting that alignment with the organisation's values, while a notable challenge, displayed a factor loading of 0.709 for the KST model.

#### 4.6.3. *Ethical challenges*

In this domain, five significant factors emerge. These include bias, accountability, privacy, transparency, and lack of job security. Four (of five) factors exhibit robust factor loadings, ranging from 0.712 to 0.901. However, while a concern, bias shows a slightly lower factor loading of 0.699 for the KST model.

These findings highlight organisations' complex and multifaceted challenges in implementing AI-driven KM. While technological

**Table 6**
Construct Reliability and Convergent Validity.

| Construct | Indicators | SRW[1] | CA[2] | CR[3] | AVE[4] | Is Construct Reliability Established? | Is Convergent Validity Established? |
|---|---|---|---|---|---|---|---|
| KC Model | **TC** | | | **0.910** | **0.669** | **Yes** | **Yes** |
| | data quality and availability | 0.829 | 0.809 | | | | |
| | scalability | 0.814 | 0.799 | | | | |
| | transparency and explainability | 0.802 | 0.787 | | | | |
| | reliability and robustness | 0.841 | 0.802 | | | | |
| | security and privacy | 0.803 | 0.789 | | | | |
| | **OC** | | | **0.905** | **0.704** | **Yes** | **Yes** |
| | resistance to change | 0.869 | 0.824 | | | | |
| | lack of expertise | 0.817 | 0.789 | | | | |
| | interdepartmental collaboration | 0.805 | 0.783 | | | | |
| | budget constraints | 0.863 | 0.812 | | | | |
| | **EC** | | | **0.904** | **0.702** | **Yes** | **Yes** |
| | accountability | 0.793 | 0.742 | | | | |
| | privacy | 0.832 | 0.801 | | | | |
| | transparency | 0.842 | 0.812 | | | | |
| | lack of job security | 0.882 | 0.846 | | | | |
| KST Model | **TC** | | | **0.898** | **0.638** | **Yes** | **Yes** |
| | data quality and availability | 0.799 | 0.709 | | | | |
| | scalability | 0.701 | 0.699 | | | | |
| | transparency and explainability | 0.821 | 0.754 | | | | |
| | reliability and robustness | 0.799 | 0.741 | | | | |
| | security and privacy | 0.864 | 0.801 | | | | |
| | **OC** | | | **0.916** | **0.686** | **Yes** | **Yes** |
| | resistance to change | 0.874 | 0.789 | | | | |
| | lack of expertise | 0.892 | 0.802 | | | | |
| | interdepartmental collaboration | 0.755 | 0.701 | | | | |
| | aligning with the organisation's values | 0.709 | 0.684 | | | | |
| | budget constraints | 0.894 | 0.834 | | | | |
| | **EC** | | | **0.907** | **0.663** | **Yes** | **Yes** |
| | bias | 0.699 | 0.654 | | | | |
| | accountability | 0.712 | 0.675 | | | | |
| | privacy | 0.849 | 0.789 | | | | |
| | transparency | 0.888 | 0.812 | | | | |
| | lack of job security | 0.901 | 0.832 | | | | |
| KS Model | **TC** | | | **0.924** | **0.670** | **Yes** | **Yes** |
| | data quality and availability | 0.814 | 0.769 | | | | |
| | scalability | 0.802 | 0.749 | | | | |
| | transparency and explainability | 0.855 | 0.717 | | | | |
| | reliability and robustness | 0.789 | 0.712 | | | | |
| | security and privacy | 0.894 | 0.782 | | | | |
| | algorithm complexity | 0.749 | 0.702 | | | | |
| | **OC** | | | **0.891** | **0.672** | **Yes** | **Yes** |
| | resistance to change | 0.823 | 0.789 | | | | |
| | lack of expertise | 0.811 | 0.762 | | | | |
| | interdepartmental collaboration | 0.812 | 0.748 | | | | |
| | budget constraints | 0.832 | 0.724 | | | | |
| | **EC** | | | **0.898** | **0.688** | **Yes** | **Yes** |
| | accountability | 0.772 | 0.701 | | | | |
| | privacy | 0.842 | 0.792 | | | | |
| | transparency | 0.808 | 0.746 | | | | |
| | lack of job security | 0.891 | 0.812 | | | | |
| KA Model | **TC** | | | **0.883** | **0.601** | **Yes** | **Yes** |
| | data quality and availability | 0.719 | 0.641 | | | | |
| | scalability | 0.792 | 0.702 | | | | |
| | transparency and explainability | 0.785 | 0.731 | | | | |
| | reliability and robustness | 0.764 | 0.702 | | | | |
| | security and privacy | 0.814 | 0.744 | | | | |
| | **OC** | | | **0.897** | **0.635** | **Yes** | **Yes** |
| | resistance to change | 0.811 | 0.771 | | | | |
| | lack of expertise | 0.803 | 0.743 | | | | |
| | interdepartmental collaboration | 0.792 | 0.747 | | | | |
| | aligning with the organisation's values | 0.729 | 0.687 | | | | |
| | budget constraints | 0.845 | 0.801 | | | | |
| | **EC** | | | **0.910** | **0.716** | **Yes** | **Yes** |
| | accountability | 0.872 | 0.812 | | | | |
| | privacy | 0.832 | 0.784 | | | | |
| | transparency | 0.814 | 0.768 | | | | |
| | lack of job security | 0.865 | 0.818 | | | | |

Source: Author's calculation.
[1] Standardised Regression Weight
[2] Cronbach Alpha.
[3] Composite Reliability
[4] Average Variance Extracted.

**Table 7**
Discriminant Validity.

| Models | Factor Correlation(R) | $R^2$ | AVE1 and AVE2 | Is it established? ($AVE_i > R^2$) |
|---|---|---|---|---|
| First Construct-KA | | | | |
| TC �→ OC | 0.723 | 0.523 | 0.602,0.693 | Yes |
| TC �→ EC | 0.735 | 0.540 | 0.624,0.625 | Yes |
| OC �→ EC | 0.712 | 0.507 | 0.688,0.634 | Yes |
| Second Construct-KST | | | | |
| TC �→ OC | 0.741 | 0.549 | 0.602,0.683 | Yes |
| TC �→ EC | 0.709 | 0.503 | 0.608,0.634 | Yes |
| OC �→ EC | 0.764 | 0.584 | 0.612,0.675 | Yes |
| Third Construct-KS | | | | |
| TC �→ OC | 0.729 | 0.531 | 0.618,0.714 | Yes |
| TC �→ EC | 0.727 | 0.529 | 0.678,0.642 | Yes |
| OC �→ EC | 0.766 | 0.587 | 0.683,0.644 | Yes |
| Fourth Construct-KA | | | | |
| TC �→ OC | 0.745 | 0.555 | 0.598,0.602 | Yes |
| TC �→ EC | 0.738 | 0.545 | 0.622,0.594 | Yes |
| OC �→ EC | 0.744 | 0.554 | 0.593,0.602 | Yes |

Source: Author's calculation.

challenges remain the most prominent, context-specific factors such as alignment with organisational values and bias also play a critical role. This underscores the importance of a nuanced approach to AI integration within different KM models. For a detailed breakdown, refer to Table 9 and Fig. 3.

## 5. Discussion

The examination of the results, delineated in Table 3, entails their interpretation from two distinct analytical perspectives.

Primarily, we will embark upon a vertical analysis, wherein the results are contextualised within the framework of the pertinent model from which they originated. This methodological approach facilitates the identification of behavioural trends exhibited by challenges within each specific model.

Subsequently, we will undertake a horizontal analysis, necessitating a comprehensive exploration of the challenges. Through this evaluative process, we endeavour to discern the behaviour of challenges across varying models. By meticulously examining each challenge in isolation, we aim to elucidate its significance across diverse models, thereby attaining a more nuanced understanding of its impact.

### *5.1. Vertical Consideration*

- KC Model:

For the KC model, the predominant challenges include resistance to change (factor loading of 0.869) and lack of job security (factor loading of 0.882). These challenges necessitate a focus on overcoming cultural and organisational barriers while providing job security to employees for the effective implementation of AI in knowledge capture.

Resistance to change often stems from a fear of the unknown or a perception of a threat to existing processes and job roles. Addressing this requires fostering a culture that embraces change and innovation, which can be achieved through effective communication, training programs, and demonstrating the tangible benefits of AI integration to the staff. Involving employees in the transition process and offering reassurance and support can reduce resistance and create a more collaborative environment.

Emphasising AI's augmentation aspect can address concerns over job security and its potential to replace human roles. By offering opportunities for upskilling and reskilling, organisations can ensure that their workforce remains valuable contributors in an AI-driven environment.

- KST Model:

In the KST model, the most significant hurdles include a lack of expertise (factor loading of 0.892), budget constraints (factor loading of 0.894), and privacy concerns (factor loading of 0.849). Tackling these issues necessitates securing critical knowledge and assets for effective data management and storage, as well as taking steps to alleviate budget restrictions and resolve privacy issues.

Budget constraints highlight the financial challenges faced during AI adoption. These can be mitigated by exploring funding options like grants, partnerships, or cost-sharing models and prioritising AI projects based on their potential impact and feasibility.

Privacy concerns underline the importance of data protection and privacy in AI-KM integration. Establishing robust data governance policies, stringent security measures, and compliance with data protection regulations can alleviate these concerns and foster a more secure environment for data management.

- KS Model:

Within the KS model, the paramount challenges are security and privacy (factor loading of 0.894) and transparency and explainability (factor loading of 0.855). Security and privacy concerns are paramount in AI-KM integration. Addressing these challenges involves implementing robust security protocols, regular audits, and possibly employing data encryption technologies to maintain confidentiality, integrity, and data availability.

Transparency and explainability challenges require adopting explainable AI (XAI) technologies and practices to make AI models more understandable and interpretable for users, fostering trust and understanding. Navigating these obstacles within the KS model is vital for promoting trust and understanding among stakeholders while ensuring secure and responsible data management.

**Table 8**
Fitness Indices.

| Fit Indices | Reference Value | KA | | KST | | KS | | KA | |
|---|---|---|---|---|---|---|---|---|---|
| | | Value | Result | Value | Result | Value | Result | Value | Result |
| $\chi^2$/df | <3 | 1.544 | Achieved | 1.621 | Achieved | 1.920 | Achieved | 1.432 | Achieved |
| RMSEA | 0.03 < x < 0.08 | 0.064 | Achieved | 0.061 | Achieved | 0.048 | Achieved | 0.072 | Achieved |
| GFI | > 0.90 | 0.93 | Achieved | 0.94 | Achieved | 0.93 | Achieved | 0.91 | Achieved |
| NNFI | > 0.90 | 0.90* | Achieved | 0.90* | Achieved | 0.91 | Achieved | 0.92 | Achieved |
| NFI | > 0.90 | 0.91 | Achieved | 0.90* | Achieved | 0.92 | Achieved | 0.91 | Achieved |
| CFI | > 0.90 | 0.90* | Achieved | 0.90* | Achieved | 0.91 | Achieved | 0.89* | Achieved |

Source: Author's calculation.
* Almost accepted.

**Table 9**
CFA result- four models.

| | Challenges | KC Model | KST Model | KS Model | KA Model |
|---|---|---|---|---|---|
| **Technological Challenges (TC)** | data quality and availability | **0.829** | 0.799 | ***0.814*** | 0.719 |
| | scalability | **0.814** | 0.701 | ***0.802*** | 0.792 |
| | transparency and explainability | 0.802 | ***0.821*** | **0.855** | 0.785 |
| | reliability and robustness | **0.841** | ***0.799*** | 0.789 | 0.764 |
| | **security and privacy** | 0.803 | ***0.864*** | **0.894** | 0.814 |
| | algorithm complexity | – | – | **0.749** | – |
| **Organisational Challenges (OC)** | resistance to change | ***0.869*** | **0.874** | 0.823 | 0.811 |
| | lack of expertise | ***0.817*** | **0.892** | 0.811 | 0.803 |
| | interdepartmental collaboration | ***0.805*** | 0.755 | **0.812** | 0.792 |
| | **budget constraints** | 0.863 | **0.894** | 0.832 | 0.845 |
| | aligning with the organisation's values | – | 0.709 | – | **0.729** |
| **Ethical Challenges (EC)** | bias | – | **0.699** | – | |
| | accountability | ***0.793*** | 0.712 | 0.772 | **0.872** |
| | privacy | 0.832 | **0.849** | ***0.842*** | 0.832 |
| | transparency | ***0.842*** | **0.888** | 0.808 | 0.814 |
| | **lack of job security** | 0.882 | **0.901** | ***0.891*** | 0.865 |

Source: Author's calculation.
Source: Author's calculation.

- KA Model:

Focusing on the KA model, we identify two main challenges for the effective implementation of AI in KA: lack of job security (factor loading of 0.865) and budget constraints (factor loading of 0.845).

The lack of job security in the KA model emphasises employee concerns about AI technologies potentially replacing human roles. Mitigating this challenge involves focusing on the complementarity of AI and human skills, demonstrating how AI can augment human capabilities rather than replace them. Investing in employee development and providing opportunities for skill enhancement can bolster job security and foster a positive perception of AI integration (De Cremer and Kasparov, 2021).

Budget constraints in the KA model point to financial limitations during AI adoption. Addressing this involves strategic financial planning and prioritising AI projects based on their potential impact and alignment with organisational goals. Exploring various funding options, such as partnerships, grants, or crowdsourcing, can alleviate budget constraints and ensure optimal resource allocation.

These findings align with prior research. For instance, resistance to change and job insecurity, observed in the KC and KA models, reflects earlier findings by Shrestha et al. (2019), Dwivedi et al. (2021), and Brynjolfsson et al. (2023), who identified cultural barriers and workforce anxieties as key obstacles to AI integration. Similarly, privacy concerns and budget constraints in the KST and KA models are consistent with the observations of Wu et al., 2023 and Davenport and Ronanki (2018), who emphasised the need for strong data governance and financial planning in AI adoption. Furthermore, the emphasis on explainability in the KS model resonates with Siau and Wang (2020) and Angelov et al. (2021), who highlighted transparency as critical for trust

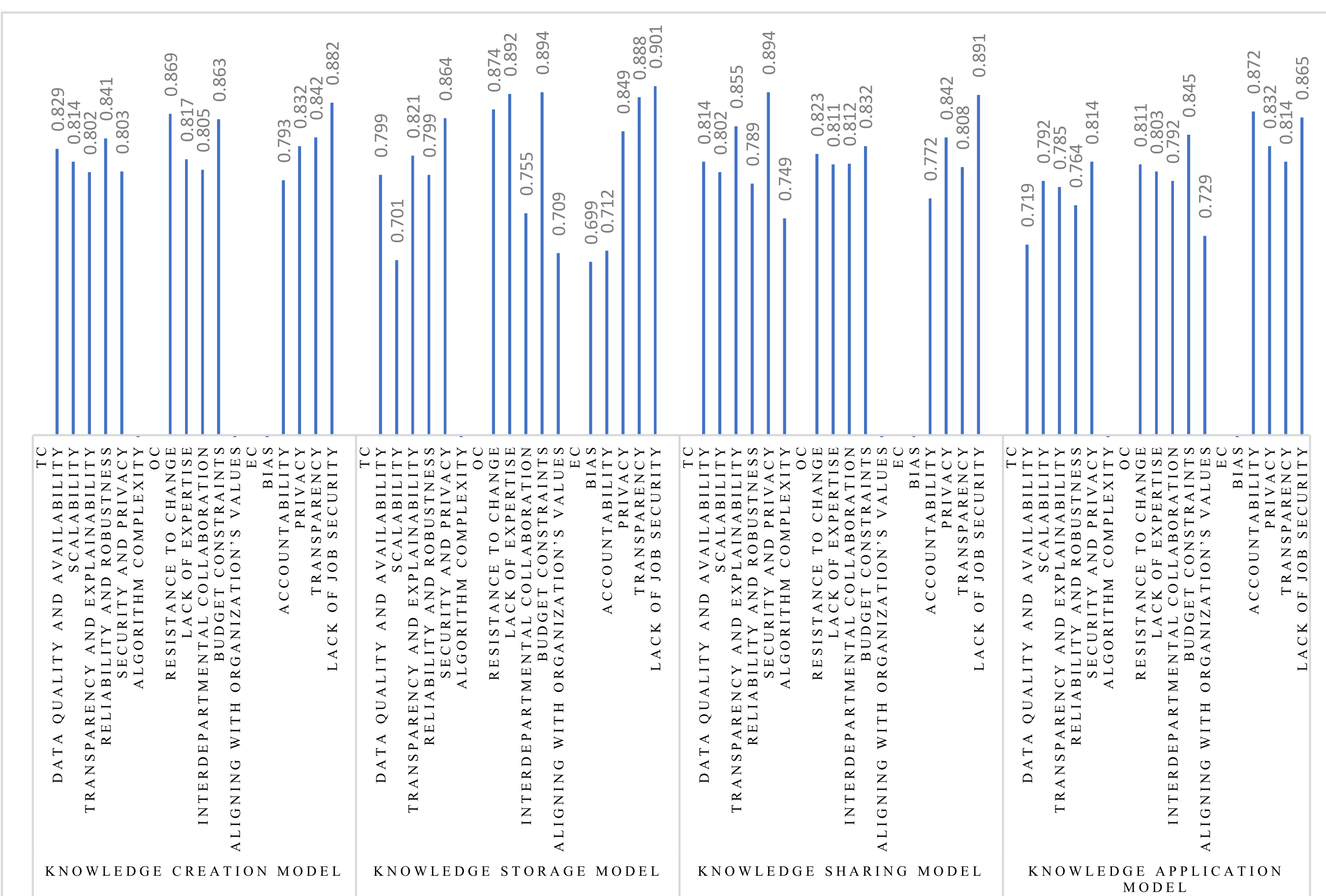


**Fig. 3.** SRW (factor loaded).

in AI systems.

### 5.2. Horizontal consideration

Upon a horizontal analysis, it becomes evident that specific challenges transcend the boundaries of individual KM models, showcasing their general applicability and significance. Security and privacy stand out as critical concerns, consistently presenting high factor loadings across all four models. This accentuates the vital data security and privacy needs, irrespective of the specific KM model. Safeguarding sensitive information and ensuring confidentiality is paramount, given the data-driven nature of AI applications in KM.

Similarly, the challenge of lack of job security holds substantial weight across all four models, signalling the widespread apprehension among employees regarding the potential impact of AI on their job roles. Ensuring job security is crucial for the employees' mental well-being and is integral for maintaining a productive and motivated workforce. By emphasising the complementary role of AI, organisations can alleviate these concerns and foster a more inclusive approach to AI implementation.

Budget constraints also pose substantial challenges in three of the four models, emphasising the need for organisations to have adequate resources and financial backing to deploy AI in KM successfully. Economic and financial considerations play a crucial role in determining the feasibility and sustainability of AI projects. Hence, strategic financial planning and exploration of various funding avenues become essential.

However, it is noteworthy that some challenges exhibit a more pronounced presence in a specific model. For instance, the KC model grapples predominantly with resistance to change and a lack of expertise, reflecting the cultural and knowledge gaps that need to be bridged for successful AI integration. The KST model, on the other hand, is significantly affected by a lack of expertise and privacy concerns, highlighting the need for skilled professionals and robust data protection measures.

In the KS model, transparency and explainability emerge as key hurdles alongside the general challenges of security and privacy. Ensuring that AI systems are understandable and interpretable by stakeholders is crucial for fostering trust and acceptance. Lastly, the KA model faces challenges related to a lack of job security and budget constraints. This emphasises the importance of employee-centric strategies and financial prudence in successfully applying knowledge through AI.

From a horizontal perspective, these findings are also consistent with previous literature. Security and privacy as universal concerns echo the findings of Radulov (2019) and Gündüz et al. (2023), who emphasised the importance of trust and data protection in AI integration. The repeated appearance of job insecurity across models mirrors workforce anxieties identified by Brynjolfsson and McAfee (2014) and Rezaei et al. (2024b), highlighting AI deployment's psychological and organisational implications. Similarly, budgetary concerns resonate with studies by Goirand et al. (2021) and Cao (2021), which discuss the financial hurdles in AI adoption. The model-specific reflections also find support in prior work, such as Ferreira et al., 2018a, 2018b and Bag et al. (2021) for KC, Wu et al. (2023) for KST, and Martin et al. (2022) for KS.

## 6. Implications

This study carries significant implications for both practical applications and theoretical advancements within the field of AI-based KM in the e-retail industry. The findings offer valuable insights to inform strategic decision-making, operational improvements, and future research directions.

### 6.1. Practical implications

This study illuminates the multifaceted challenges organisations face when implementing AI-based KM systems, encompassing technological, organisational, and ethical dimensions. The findings underscore organisations' need to develop a nuanced understanding of these challenges to formulate targeted mitigation strategies. Practical measures may include enhancing data quality and accessibility, ensuring algorithmic transparency and explainability, and addressing ethical concerns such as bias and privacy protection.

The research advocates for developing tailored strategies to address challenges specific to each KM model. Organisations must cultivate a deep understanding of the distinct KM models (KC, KST, KS, and KA) and the unique challenges associated with each. For instance, while data quality and availability may be paramount in the KC model, transparency and explainability might be critical in the KS model. Crafting strategies aligned with these model-specific challenges is crucial for effective AI implementation within respective KM frameworks.

Furthermore, the study highlights the interdependence of challenges within individual models. Addressing one challenge can potentially have cascading positive effects on other challenges within the same model. For example, mitigating expertise shortages in the KST model may concurrently alleviate privacy concerns. This finding underscores the importance of adopting a holistic approach that accounts for these intricate relationships, moving beyond isolated problem-solving that may yield suboptimal outcomes.

### 6.2. Theoretical implications

From a theoretical perspective, this study significantly enriches the literature on AI-based KM by meticulously identifying and categorising the primary challenges confronting organisations. This comprehensive taxonomy contributes to a more nuanced understanding of this critical domain, providing a solid foundation for future research. The empirical evidence underpinning the relationships between different challenges and their associations with specific KM models validates existing theories and extends the theoretical understanding of AI integration in KM processes.

The findings emphasise the imperative of exploring the intricate interplay between challenges and their impact on specific KM models. This opens up new avenues for research, inviting scholars to delve deeper into these complex relationships. Future studies could focus on developing more comprehensive theoretical models that account for the multifaceted interrelationships among different challenges, potentially leading to a more holistic understanding of AI implementation in KM systems.

Moreover, this research contributes to the broader theoretical discourse on technological integration in organisational knowledge processes. This study calls for a more integrated theoretical approach to understanding AI adoption in KM by highlighting the interconnected nature of technological, organisational, and ethical challenges. This perspective aligns with and extends socio-technical systems theory, suggesting that successful AI implementation in KM requires a balanced consideration of technological capabilities, organisational structures, and ethical implications.

## 7. Conclusion

This study comprehensively analyses the challenges in integrating AI into KM across four key processes: creation, storage, sharing, and application. These challenges are categorised into three primary domains—technological, organisational, and ethical—using a multi-method approach that combines the Delphi method and CFA to identify, refine, and validate them.

The findings reveal that while ethical challenges are a shared concern across all KM models, each model demonstrates distinct responses to technological and organisational issues. In the KC model, resistance to change and job security concerns underscore the need for cultural adaptation and workforce upskilling to foster AI acceptance.

The KST model faces challenges such as lack of expertise, budget constraints, and privacy concerns, highlighting the importance of skilled professionals, robust data governance, and strategic resource allocation. For the KS model, security, privacy, and transparency issues necessitate the adoption of explainable AI technologies and stringent data protection measures to build trust and enable secure knowledge dissemination. Meanwhile, the KA model emphasises budget constraints and job security concerns, stressing the importance of financial planning and demonstrating AI's role as a complement to human capabilities.

### 7.1. Limitations and future research directions

While this study provides valuable insights into the challenges of implementing AI-based KM systems, it is essential to acknowledge its limitations and identify promising avenues for future research.

Firstly, the study focused on the challenges identified through the Delphi method and CFA. While this approach provided a structured analysis of key challenges, it may not fully capture the rapidly evolving nature of AI technologies and their implications for KM. Future research could adopt a longitudinal approach to track how these challenges evolve over time as AI technologies advance and organisations gain more experience in their implementation.

Secondly, while this study aimed to provide a comprehensive overview of challenges across various industries and organisational contexts, it may not fully capture the nuances of specific sectors or sizes. Future research could delve deeper into industry-specific challenges, comparing and contrasting the implementation of AI in KM across different sectors such as healthcare, finance, manufacturing or organisational scales (e.g., SMEs vs large corporations).

Thirdly, the research primarily focused on identifying and ranking challenges. Future studies could extend this work by exploring effective strategies for overcoming these challenges. Case studies of firms that have successfully navigated these challenges could provide valuable insights into best practices and practical solutions.

Furthermore, while we touched upon ethical considerations, the rapidly evolving landscape of AI ethics in business contexts warrants further investigation. Future research could focus specifically on developing ethical frameworks for AI implementation in KM, considering aspects such as algorithmic fairness, transparency, and long-term societal impacts. Another limitation is that the study primarily focused on the challenges from an organisational perspective. Future research could explore the effects of AI-driven KM systems on individual employees, examining how these systems affect job roles, skill requirements, and employee satisfaction.

Lastly, while this study provided insights into the interplay between KM and AI, future research could delve deeper into how emerging technologies, particularly GenAI and LLMs, reshape traditional KM models. As these advanced systems increasingly influence knowledge creation, dissemination, and application, it becomes essential to investigate their transformative impact on KM practices. Future studies could explore the development of new hybrid KM models that strategically balance AI capabilities with human expertise, while also examining the organisational implications and emerging challenges associated with integrating GenAI and LLMs into KM systems.

Therefore, while this study provides a comprehensive overview of the challenges in implementing AI-based KM systems, it also opens up numerous avenues for future research. By addressing these limitations and exploring these research directions, scholars can continue to advance a general understanding of this critical area, ultimately leading to more effective and ethical integration of AI in organisational KM practices.

## CRediT authorship contribution statement

**Mojtaba Rezaei:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology.

## Data availability

The data that has been used is confidential.

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