Vilniaus universiteto leidykla

Contents lists available at Vilnius University Press

Information & Media
2026, vol. 105, pp. 8–29

eISSN 2783-6207
DOI: https://doi.org/10.15388/Im.2026.105.1

Integrating Artificial Intelligence into Knowledge Management: The Case of Lithuanian Business Organizations

Indrė Stasiūnaitė

Vilnius University, Faculty of Communication
stasiunaite.indre@gmail.com
https://ror.org/03nadee84

Daiva Siudikienė

Vilnius University, Faculty of Communication
daiva.siudikiene@kf.vu.lt
https://orcid.org/0000-0002-0412-6028
https://ror.org/03nadee84

Abstract. This article presents a study aiming to determine how artificial intelligence (AI) can be integrated into knowledge management (KM) processes in business organizations – from knowledge creation, storage, and dissemination to its use, while addressing practical challenges and problems related to the implementation of AI. The study is based on a qualitative research approach, involving semi-structured interviews with 13 experts with professional experience in AI, KM, and digital transformation. The interview data were analyzed by using content analysis in order to reveal the specifics of AI applications across different KM processes and the organizational conditions that shape them. The results of the study revealed that AI can be applied across various KM processes, including knowledge creation, storage, search, sharing, and application, creating opportunities for more efficient information processing, knowledge structuring and generalization, idea generation, access to organizational knowledge, and decision support. It has been found that the outcomes of AI integration depend on the organization's technological and organizational readiness, employee competencies, data quality, organizational culture, and appropriate governance mechanisms. The study also highlighted challenges related to data privacy and security, the reliability of AI-generated information, algorithmic bias, transparency, and employee competencies. The study complements research on the interaction between knowledge management and AI by providing empirical insights into the possibilities and constraints of integrating AI into everyday HR processes in Lithuanian business organizations.

Keywords: knowledge; knowledge management; artificial intelligence; business organizations; AI integration; knowledge management processes.

Dirbtinio intelekto integracija į žinių valdymą: Lietuvos verslo organizacijų atvejis

Santrauka. Šiame straipsnyje pristatomas tyrimas, kuriuo siekta nustatyti, kaip dirbtinis intelektas (DI) gali būti integruotas į žinių valdymo (ŽV) procesus verslo organizacijose – nuo žinių kūrimo, saugojimo ir sklaidos iki jų naudojimo, kartu sprendžiant praktinius iššūkius ir problemas, susijusias su DI diegimu. Tyrimas

Received: 2026-02-25. **Accepted:** 2026-08-31.

grindžiamas kokybiniu tyrimo požiūriu – atlikti pusiau struktūruoti interviu su 13 ekspertų, turinčių profesinės patirties DI, ŽV ir skaitmeninės transformacijos srityse. Interviu duomenys analizuoti taikant turinio analizę, siekiant atskleisti DI taikymo skirtinguose ŽV procesuose ypatumus ir juos lemiančias organizacines sąlygas. Tyrimo rezultatai atskleidė, kad DI gali būti taikomas įvairiuose ŽV procesuose, įskaitant žinių kūrimą, saugojimą, paiešką, dalijimąsi ir taikymą, t. y. DI gali sudaryti galimybes efektyviau apdoroti informaciją, struktūruoti ir apibendrinti žinias, generuoti idėjas, palengvinti prieigą prie organizacinių žinių ir palaikyti sprendimų priėmimą. Nustatyta, kad DI integravimo rezultatai priklauso nuo organizacijos technologinio ir organizacinio pasirengimo, darbuotojų kompetencijų, duomenų kokybės, organizacinės kultūros ir tinkamų valdymo mechanizmų. Tyrimas taip pat išryškino duomenų privatumo ir saugumo, DI generuojamos informacijos patikimumo, algoritminio šališkumo, skaidrumo ir darbuotojų kompetencijų iššūkius. Tyrimas papildo žinių valdymo ir DI sąveikos tyrimus, pateikdamas empirinių įžvalgų apie DI integravimo į kasdienius ŽV procesus Lietuvos verslo organizacijose galimybes ir ribojančias sąlygas.

Pagrindiniai žodžiai: žinios; žinių valdymas; dirbtinis intelektas; verslo organizacijos; dirbtinio intelekto integracija; žinių valdymo procesai

Introduction

In the context of modern organizations, *Artificial Intelligence* (AI) is becoming a transformative technology (Khadivar et al., 2025; Aldoseri et al., 2024; Taherdoost & Madanchian, 2023; Füller et al., 2022) that can process large datasets, generate insights from unstructured data, and automate repetitive tasks (de la Torre-López et al., 2023). If AI tools are effectively integrated into business and society, they could stimulate a significant global GDP growth and enhance labor productivity (Taylor, 2023).

AI enables organizations to enhance *Knowledge Management* (KM) processes by reducing inefficiencies, accelerating knowledge dissemination, and improving employees' access to knowledge. As organizations implement remote or hybrid work arrangements, the need for reliable, AI-powered KM systems becomes even more pronounced, ensuring that employees can effectively access and utilize knowledge regardless of their location or time zone (Taherdoost & Madanchian, 2023). It has been recognized that knowledge is a dynamic resource that can be continuously created and improved, and AI technologies can help identify new patterns, trends, and opportunities for innovation (Haefner et al., 2021). In an environment of rapidly evolving technologies, speed and focus on the competitive environment are gaining more importance than ever before.

Despite AI's potential, organizations often lack a clear understanding of how to strategically leverage it to create business value (Cui, 2025; Nveke & Adalusi, 2025; Borges et al., 2021; Chatterjee et al., 2020). Business competitiveness increasingly depends on effective KM, and if AI can optimize these processes, it can significantly improve organizational performance (Taherdoost & Madanchian, 2023). AI technologies are evolving rapidly, but organizations often face numerous challenges regarding their applicability, implementation conditions, and business value creation (Enholm et al., 2022; Mikalef & Gupta, 2021). Therefore, it is essential to explore how AI can be effectively integrated into the full spectrum of KM processes in business organizations, from knowledge creation, storage, and dissemination to its utilization, while addressing the challenges and problems associated with implementing AI. Previous studies have focused more on the mediating role of AI processes in the effective use of AI (Leoni et al., 2022), the general application of AI in business (Canhot & Clear, 2020; Paschen et al., 2019), the synergy between employees and AI applications (Sowa et al., 2021), and AI has also been presented as one of the technologies of the fourth industrial revolution that exerts an impact on the transformation of traditional business models and AI strategies (Kolyasnikov & Kelchevskaya, 2020). Although AI is considered a transformative technology that can change the KM processes of business organizations (Majumder & Dey, 2022), there is a lack of research on how to effectively integrate AI into daily knowledge management processes (Storey, 2025), and the failure to identify and manage potential risks delays the implementation of these technologies, thereby preventing them from fulfilling their full potential (Vining et al., 2022; Canhoto & Clear, 2020). These processes raise many questions about the ethics of AI use, AI-human interaction, and related issues (Rezaei et al., 2025; Bankins, 2021).

Although AI is getting increasingly integrated into organizational knowledge management, it remains unclear how AI affects the processes through which organizational knowledge is created, shared, transformed, and retained. In particular, existing research provides limited empirical evidence on how AI-mediated practices relate to the interaction between tacit and explicit knowledge, and how human and AI capabilities are combined across different KM processes. This gap is particularly evident in the Lithuanian business context, where empirical qualitative research that links AI-enabled KM practices to established knowledge management frameworks remains scarce. Therefore, the research problem concerns the way(s) how artificial intelligence changes organizational knowledge management processes in business organizations, with the aim of identifying the roles of human and artificial intelligence in these processes, as well as the organizational conditions that influence the effectiveness and risks of such collaboration.

The methods applied in the present research include scientific literature analysis, synthesis, comparison, generalization, and inductive qualitative content analysis, which are cumulatively applied to analyze the expert interviews. The study reveals how to bridge the gap between explicit and tacit knowledge, while adding more value to KM processes. As organizations increasingly rely on knowledge as a key competitive asset, effective integration of AI into KM can improve decision-making, innovation, and operational efficiency. It is worth noting that Lithuania is often regarded internationally as a highly digitized country, denoted by rapid adoption of AI and technological initiatives in business, while also creating a unique environment for research and academic discussions on how to effectively address the challenges of applying AI to KM in business organizations. Existing Lithuanian research has examined KM practices and digital transformation, but there is still insufficient empirical understanding of how contemporary AI technologies are integrated into everyday KM processes, and how this integration affects knowledge creation, sharing, storage, retrieval, and application. This study addresses this gap by providing qualitative evidence from expert perspectives within Lithuanian business organizations.

Literature Review

Knowledge is defined as well-founded beliefs held by individuals and an organization as a whole (Nonaka, 1994). The use of knowledge creates value in solving problems, forming, evaluating, making, and implementing decisions (Raudeliūnienė & Račinskaja, 2014). It is noted that knowledge is an intangible asset whose acquisition involves complex cognitive processes of perception, learning, and communication, significantly influenced by both individual and collective experiences (Epetimehin & Ekundayo, 2011). Knowledge is transferable, and it can be accumulated, adapted, and specialized, thus making it useful throughout the organization (Dalkir, 2013). In organizations, knowledge is embedded not only in documents or repositories, but also in organizational routines, processes, practices, established norms, and culture.

The process of generating, disseminating, using, and managing an organization's information and knowledge is known as knowledge management (Taherdoost & Madanchian, 2023). KM is the planning, organization, and control of people, processes, and systems within an organization with an intent to ensure that knowledge assets are developed and used effectively (King, 2009). In other words, it is a system for managing an organization's strategy, structures, and processes, enabling it to leverage its knowledge, learn, and create economic and social value for its customers and society while ensuring long-term business success. People face emerging knowledge needs integral to their daily tasks or routines, and these needs must be met through tools, processes, systems, and protocols that integrate and apply relevant knowledge. According to O. Omotayo (2015), in order to effectively manage knowledge, attention must be paid to four main components: knowledge, people, processes, and technologies. K. Dalkir (2013) noted that KM can facilitate the recruitment of new employees, reduce the loss of organizational memory due to employee departure, identify the most important resources so that the organization knows what and why it is doing, and create a methodology to stop the potential loss of intellectual capital. W. King (2009) stated that the significance of KM processes is directly related to the improvement of organizational processes, such as innovation, collaborative decision-making, individual and collective learning – all of which help to improve the management of organizational behavior, products, services, and relationships.

Knowledge is generally divided into two types: tacit and explicit knowledge (King, 2009; Alavi & Leidner, 2001), which possess unique characteristics and play a crucial role in the daily operations of business organizations. Tacit knowledge encompasses skills, insights, and intuition that individuals acquire over time and are often difficult to articulate because they are deeply rooted in personal experience and social interaction. R. Borges et al. (2019) identified that strong social ties are crucial for sharing tacit knowledge. Unlike explicit knowledge, tacit knowledge is often shared informally, through collaboration or observation. M. Addis (2016) stated that development and usage of tacit knowledge can lead to greater operational efficiency at all levels of the organization, while R. Muthuveloo et al. (2017) added that the use of tacit knowledge in an organization can contribute to better organizational performance, which can lead to a higher return on investment. For tacit knowledge to be more widely utilized, it must be conveyed and transformed into explicit knowledge.

Explicit knowledge is objective, formalized, codified, and easily documented, making it more accessible. It supports the technological and managerial procedures of an organization that requires a structured, standardized knowledge format (Muthuveloo et al., 2017). The transmission of knowledge in a clear, fixed format reduces the possibility of misinterpretation and thus ensures its more effective use. Due to the structured nature of this knowledge, it is well-suited for storage in KM systems, which allow organizations to effectively store, organize, and search for the necessary knowledge, and which make it easy to transfer from one system to another. Explicit knowledge is readily accessible and crucial to an organization's activities, as it can be reused, leading to more efficient work and reduced time spent on routine tasks. KM processes in organizations turn knowledge into valuable resources. Some works examine only one, subjectively most important KM process – that of knowledge sharing (Yi, 2009; Yang, 2007), while others provide more detailed lists of knowledge processes, such as creation, storage, and retrieval, transfer, and application (Alavi et al., 2024). By leveraging both explicit and implicit knowledge, organizations can create a dynamic, adaptive system that continuously learns and uses its intellectual assets to achieve a sustainable competitive advantage and long-term success.

One of the most significant perspectives on this process is the SECI model, proposed by I. Nonaka and H. Takeuchi (1995), which explains the creation of organizational knowledge as a continuous process of conversion between tacit and explicit knowledge. The model consists of four interrelated stages: *socialization*, when tacit knowledge is shared through experience and interpersonal interaction; *externalization*, when tacit knowledge is expressed and formalized; *combination*, when different types of expressed knowledge are integrated and systematized; and *internalization*, when expressed knowledge is internalized and becomes part of the practices of employees and the organization. Thus, the SECI model treats knowledge creation as a cyclical and continuous process, during which, individual knowledge is transformed into organizational resources and is again used to create new knowledge (Nonaka & Takeuchi, 1995; Nonaka, Toyama, & Konno, 2000). Rather than constituting a new mode of knowledge conversion, AI may be understood as an enabling infrastructure that transforms the conditions under which SECI processes occur. Its contribution, therefore, lies in augmenting human capabilities to articulate, combine, disseminate, and internalize knowledge, while raising new questions about the role of human experience and tacit knowledge in AI-mediated knowledge creation.

In the era of the Fourth Industrial Revolution, AI technologies are expected to drive business automation, enhance employee productivity, and reduce operational costs (Javaid et al., 2022). It is planned that all this will be achieved through cooperation between machines and people. AI is defined as a set of technological components that collect, process, and act on data in ways that mimic human intelligence (Canhoto & Clear, 2020). An important aspect of this definition is the technological components, indicating that AI is closely related to information technology. M. Haenlein and A. Kaplan (2019) defined AI as the ability of a system to rationally interpret data, learn from the data, and flexibly adapt their use to achieve specific goals and tasks. The most important aspect of this definition is rationality, namely, this approach to AI demonstrates that AI acts in a manner that achieves the best result or, in the presence of uncertainty, the best expected result (Paschen et al., 2019). Although there are many applications of AI, all AI systems can be explained by using a common model of input, process, and output: AI information systems request data from the environment (input), process this data in value-creating ways (processes), and transmit information (output) back to the environment (Canhoto & Clear, 2020; Paschen et al., 2019). AI is an umbrella term encompassing a variety of computational algorithms capable of performing tasks that typically require human intelligence, such as understanding human language, making decisions, and learning from experience. Its development has been driven by several key technologies, including machine learning, which encompasses natural language processing and computer vision, as well as deep learning and generative models (Balasubramanian et al., 2022).

Despite the abundance of AI technologies, most AI researchers and practitioners are focusing on breakthroughs in generative AI. This technology can generate original text, images, programming codes, videos, and audio recordings based on a user's request (Banh & Strobel, 2023). Driven by advances in AI learning methods, generative AI models are trained to understand complex data distributions, enabling them to produce results that closely resemble human-generated outputs. Unlike previous applications of AI, which were often specialized for specific tasks, this AI is more general-purpose, highly versatile, and can be used across various fields (Alavi et al., 2024). J. de la Torre-López et al. (2023) argue that the application of AI has proven effective in automating many tasks that are time-consuming and repetitive, such as conducting literature reviews. AI can effectively organize and categorize large amounts of structured and unstructured data, thus making the search for needed knowledge more efficient and accurate. By using machine learning, AI systems can continuously improve KM by adapting to changes in the organization's knowledge base and learning from new data. Natural language processing systems can help discover knowledge by analyzing text documents, e-mails, and reports to extract valuable insights. By incorporating AI into KM strategies, organizations can create more flexible and adaptive knowledge ecosystems that respond more quickly and accurately to their business needs. As AI automates repetitive daily tasks, organizational members will need to learn to work with intelligent systems. AI literacy is essential so that all employees interacting with AI systems can work effectively and develop their skills (Bersin & Zao-Sanders, 2020). A systematic literature review identified how AI can be integrated into KM practices and the results it can deliver to business organizations (Table 1).

Table 1. **Use of AI in KM processes**

KM process stage	**Use of AI**	**Expected result**
Discovery	• Transforming existing knowledge into new knowledge • Generating ideas • Forecasting and recommendations • Content creation	Promoting creativity and innovation, facilitating learning
Storage	• Optimization of the search process • Classification and organization of knowledge • Systematization of knowledge • Identification of related topics	Easier access to the necessary knowledge, increased productivity, and a reduced risk of knowledge loss due to employees leaving the organization or changing roles
Sharing	• Using AI-enabled collaboration platforms • Providing new employees with the necessary knowledge • Natural language processing capabilities	Improved collaboration between organizational teams. Overcoming time, space, language, and social barriers
Application	• Help from virtual AI assistants • Best practice suggestions based on data analysis • Providing the latest knowledge	More efficient decision-making, faster response to questions or problems, and more accurate and consistent application of knowledge for the benefit of the organization

Source: Compiled by the authors based on M. Alavi et al., 2024; H. Benbya et al., 2023; P. Bhattacharya et al., 2019; E. Brynjolfsson et al., 2023; T. Davenport, 2019; A. Esteva et al., 2021; S. Feuerriegel et al., 2024; M. Jarrahi et al., 2023; A. Maedche et al., 2019; C. O'Dell & T. Davenport, 2019; J. Paschen et al., 2020.

The theoretical framework of the study combines the KM perspective with the perspective of AI as an enabling and transformative technology. To further explain how AI can contribute to the creation and transformation of organizational knowledge, the study also draws on the SECI model (Nonaka & Takeuchi, 1995; Nonaka et al., 2000). The SECI model provides a complementary theoretical lens for examining how tacit and explicit knowledge is created, transformed, and combined through socialization, externalization, combination, and internalization. In this study, the SECI model is used to interpret how AI-supported activities may facilitate particular forms of knowledge conversion, while the broader KM perspective provides a framework for examining AI applications across knowledge creation, storage, retrieval, sharing, and application. Together, these perspectives enable a more comprehensive analysis of how AI integration reshapes organizational KM processes.

Research Methodology

The theoretical part states that KM processes are changing due to AI, and that traditional models of knowledge creation, storage, sharing, and use are being transformed; therefore, empirical research is required to determine how AI technologies affect these processes. The aim of this study is to explore the potential applications of AI in knowledge management processes within Lithuanian business organizations. To achieve the goal, the following research questions were formulated:

Q1: *What factors drive business organizations to integrate AI into KM processes?*

Q2: *How is AI applied in the processes of knowledge creation, storage, sharing, and use in Lithuanian business organizations?*

Q3: *How does the interaction between humans and AI manifest itself in the organizational context of KM?*

Considering the relevance and novelty of the topic, the expert interview genre was chosen to achieve the research objective, which will help obtain a deep, contextual, and practical understanding of the phenomenon under study, as well as the existing experience of applying AI tools to KM processes in Lithuanian business organizations. In the course of the research, semi-structured expert interviews were conducted with Lithuanian AI technology experts to assess the experience of Lithuanian business organizations and the applicability of AI in KM.

The advantages of this interview method are that experts not only have special professional or technical knowledge but are also familiar with organizational procedures and their field of activity, and their status allows them to speak on behalf of a certain professional field or organization, whereas the interviews themselves are attractive due to the value of the information collected (Gaižauskaitė & Valavičienė, 2016). The expert interview method is suitable when specialized knowledge and contextual insights are required to examine poorly understood or newly emerging research topics. An expert is a person with specific insights and knowledge derived from their professional position and experience (level of expertise) (Flick, 2014, p. 227). When selecting study participants, a criterion-based approach was applied: individuals with deep, extensive, and knowledge-based competencies in this field were invited to participate, enabling them to reasonably assess the phenomena under study and provide insights grounded not only in theoretical knowledge but also in practical experience. Experts who were known to work with and be familiar with AI technologies were invited to participate in the study. 13 experts agreed to participate in the study and were given codes (I1, I2, I3, I4, I5, I6, I7, I8, I9, I10, I11, I12, and I13). The study involved 13 experts, selected through purposive sampling based on their professional experience in knowledge management, AI applications, and digital transformation. The study participants represented different business organizations and professional positions, including management, IT, knowledge management, and other functions related to the application of digital technologies. The experts' professional experience and practical exposure to AI and KM solutions enabled them to collect data from different perspectives on the opportunities and challenges of integrating AI into organizational KM processes. To ensure the participants' confidentiality, their individual characteristics and the names of their organizations are not included in the article.

The interview questionnaire was prepared based on the analysis of scientific literature conducted (Table 1), incorporating theoretical information on the principles of AI and its implementation in business organizations. The questionnaire consisted of 17 questions, divided into 7 blocks. Questions began with the informants' work experience, followed by general questions about AI to prompt reflection on their experiences. Later on, a more detailed approach to this topic was taken, asking questions about the use of AI in AI processes: questions in the third block were about the use of AI for knowledge creation, whereas questions in the fourth block concerned knowledge storage, while questions in the fifth block dealt with knowledge sharing, questions in the sixth block were devoted to the use of AI for knowledge application, and questions in the seventh block focused on the interaction of AI and humans. The interview texts were transcribed, and content analysis was performed with the objective to identify meaningful content units as inductive codes and group them into subcategories and categories. The interview data were analyzed in several stages. First, the transcripts were reviewed to identify significant statements and recurring themes. These statements were then coded and grouped into subcategories and broader categories based on their thematic relevance, research questions, and theoretical assumptions. Finally, the relationships among the categories were interpreted, and the findings were integrated into the study's results and conclusions.

When conducting scientific research, special attention is paid to research ethics. All participants were informed of the study's purpose and procedures in advance. To ensure their comfort, impartiality, and voluntary participation, all participants were informed that the research data would be anonymized. The informant's personal information is not disclosed; instead, only summarized and anonymized data are provided. The principle of confidentiality was observed by explaining to the participants how the information obtained during the interview would be used and properly protected. The principles of reliability and honesty were consistently observed throughout the study to ensure the research quality and to uphold responsibility for the results.

Research Results

The importance of KM for business organizations. Almost all informants confirmed that KM is indeed important for business organizations today. Three main reasons emerged from the answers: rapidly changing circumstances, the need to capture all organizational knowledge, and the creation of added value. The informants emphasized that it is important for organizations to adapt to the rapidly changing business environment. Some experts focused on KM as an opportunity to collect and systematize existing organizational knowledge. Data dispersion and a possible risk of knowledge loss if it is not properly managed were mentioned as well. Several experts also highlighted the unspoken knowledge held in people's minds (I5, I8, I11) and the need to document it. In the absence of KM, some processes may stagnate, as there is no necessary access to important knowledge. Some experts emphasized the usability of knowledge in business decisions (I4), highlighted that KM facilitates the creation and maintenance of added value in the organization's activities (I7), and noted that KM contributes to achieving the organization's goals (I12). An interesting aspect is not only the benefit from the current perspective, but also its sustainability for the future. KM helps collect and preserve existing knowledge for the sake of using it to inform certain business decisions that can help achieve goals and create value, which is crucial in a changing environment.

According to the experts, business organizations' decisions to adopt AI are driven by interrelated factors: technological readiness, operational efficiency, problem-solving, and competitive and strategic pressures. It is worth noting that technological advancements and the visible benefits are encouraging organizations to pay increasing attention to integrating AI into their operational processes. Experts mentioned several factors, the most common of which are AI's technological capabilities (I1, I2, I4, I6, I8, I10, I13), speed (I4, I7, I11), and cost savings (I2, I4, I7). The technological aspect primarily focuses on more efficient (I1, I2, I13) and larger-scale (I4, I10) data processing, enabling the organization to create valuable knowledge. Some experts suggest that, before making a decision, an organization should identify the problem it wants to solve with AI (I6, I10, I12). On the other hand, some experts noted that business organizations often implement AI technologies simply to keep up with the market trends (I2, I3, I5, I12).

The findings suggest that AI adoption is not driven solely by perceived efficiency gains or clearly identified organizational needs. Several experts pointed to competitive pressure and fear of falling behind as important drivers, indicating an emerging FOMO effect among managers. AI adoption may therefore be motivated not only by its actual organizational value but also by the perception that competitors are already adopting the technology. The interviews also revealed several contextual barriers to AI adoption that may be particularly relevant to Lithuanian business organizations, including limited access to specialized AI expertise, resource constraints, organizational risk aversion, and uneven levels of digital maturity.

The applicability of AI to the creation of new knowledge in the organization. The study highlighted various ways of using AI for knowledge creation. Some experts mentioned generating new ideas (I4, I5, I8, I12). AI supports brainstorming (I5, I8) and speculative modeling, encouraging creative exploration and enabling organizations to move from initial ideas to practical application, for example, when developing a business plan (I12). Some experts highlighted AI's ability to create contexts (I2, I5), as well as quickly transform abstract concepts (I8) into structured formats (I1) and generalizations (I7), thereby making this knowledge easier to utilize. AI can also identify relationships across various data domains, enabling deeper insights previously inaccessible due to limited human capabilities (I7, I10). Natural language processing capabilities help document unspoken knowledge. Several experts (I1, I2, I5, I7, I11) identified the analytical features of AI, specifically, the creation of insights that can inform business decisions (Table 3).

Table 2. **Use of AI for knowledge creation**

Expert-identified dimension	Expert-identified uses of AI
Transforming and contextualizing information	AI transforms unstructured, abstract, or fragmented information into contextualized, clarified, and more usable forms of knowledge.
Identifying patterns and connections	AI identifies patterns, relationships, and conceptual connections within large, diverse datasets, revealing connections that may not be readily apparent to humans.
Interpreting and analyzing information	AI processes and interprets textual, verbal, and other forms of data to generate analyses, insights, assessments, and recommendations that support knowledge development.
Generating and combining knowledge and new ideas	AI supports the creation of new ideas and knowledge by combining existing knowledge with new information and stimulating ideation and brainstorming.
Simulating and exploring possibilities	AI enables the exploration and testing of possible scenarios, supporting knowledge creation through experimentation and anticipation of potential outcomes.

Compiled by authors on aggregated expert responses.

When discussing the accuracy and relevance of AI-generated insights for a business organization with the experts, two dominant categories of responses emerged: the need for human supervision (I1, I2, I3, I9, I10, I11) and the need for model training (I1, I2, I8, I10, I11, I12). Human supervision is necessary not only for transparency (I9) and ensuring validity (I3, I13), but also because humans are characterized by their critical thinking (I12), which can be a crucial factor in certain situations. From a technological perspective, it is crucial to properly prepare the model so that it utilizes high-quality data (I10), operates transparently (I8), provides clear feedback (I2), and is continually improved (I1). Less frequently mentioned aspects are the use of another model for verification (I2, I7) and comparison with human insights (I1, I10). Finally, direct references to the sources from which the information was taken can provide validity to the insights generated (I8, I12). The findings suggest that AI contributes to knowledge creation by transforming and contextualizing heterogeneous information, identifying previously hidden patterns and connections, generating insights and recommendations, and facilitating the combination of existing and new knowledge into novel ideas and solutions. Thus, summarizing all the points listed above, ensuring the accuracy and relevance of AI-generated insights in business organizations requires a combination of human oversight and advanced technological methodologies.

The applicability of AI to the storage of new knowledge in an organization. It was emphasized that this technology can collect information from various sources (I5) and systematically record it (I2, I3). When AI generates concise summaries from large datasets, long documents, or transcribed meetings (I2, I7, I9, I12), it plays a crucial role. By categorizing (I4) and labeling (I2, I13), AI identifies key information and organizes it into structured formats (I1, I5, I11). Such transformation into organized tables or summaries simplifies the accessibility and ease of use of the stored knowledge.

Table 3. **Use of AI for knowledge storage**

Expert-identified dimension	**Expert-identified uses of AI**
Organizing and structuring knowledge	AI helps organize and structure information into coherent and systematically recorded knowledge that can be more easily stored and accessed.
Classifying and categorizing knowledge	AI supports the classification, labeling, and categorization of information, facilitating its organization and subsequent retrieval.
Condensing and summarizing knowledge	AI transforms larger volumes of information into concise summaries, reducing information volume while preserving the key content for future use.
Formatting and documenting knowledge	AI converts, formats, and documents information in standardized forms, while supporting its incorporation into organizational knowledge repositories.

Compiled by authors on aggregated expert responses.

The findings show that AI contributes to knowledge storage not merely by retaining information, but also by transforming unstructured information into organized, classified, summarized, and standardized forms that facilitate its subsequent retrieval and reuse.

The applicability of AI to knowledge retrieval. Stored knowledge needs to be discoverable, and experts believe that AI can improve knowledge retrieval capabilities through advanced search methods. One of the methods highlighted is semantic search, which allows users to find information not only by keywords but also by context, thereby improving the relevance of results and the search speed (I5, I7). Retrieval-Augmented Generation search engines take it a step further, by integrating external data sources and searching for specific document sections to accurately answer complex queries (I1, I7, I10). Finally, chatbot systems utilizing GPT models offer an additional level of utility by simultaneously accessing and extracting data from multiple sources, and directing users to the precise documents that answer their queries (I3, I5, I11) (See Table 4). This can be an interactive way to encourage greater employee engagement and learning:

"*<…> we built a test where we simply brought all our internal docs into it in a simple way.*" (I3).

These innovations make AI an invaluable tool for accurate and efficient knowledge retrieval.

Table 4. **Use of AI for knowledge retrieval**

Expert-identified dimension	**Expert-identified uses of AI**
Semantic and context-based knowledge retrieval	AI enables users to retrieve knowledge based on meaning and context rather than relying solely on exact keywords, thus making the search process more intuitive and efficient.
AI-enhanced document and information retrieval	AI facilitates the retrieval of relevant documents and supplementary information and can connect users directly to the sources needed for further exploration.

Expert-identified dimension	Expert-identified uses of AI
Conversational and interactive knowledge retrieval	AI transforms knowledge retrieval into a more interactive, conversational, and user-oriented process, enabling users to formulate queries and explore information through dialogue.
Integrated and cross-source knowledge retrieval	AI enables the integration and synthesis of information from multiple sources, supporting more comprehensive knowledge retrieval.

Compiled by authors on aggregated expert responses.

Integration of AI systems into existing databases or knowledge repositories can pose challenges. According to the experts' responses, three main categories of challenges are identified: infrastructure, data preparation, and usage procedures. The lack of a contextualization infrastructure (I1) and the need for structural foundations such as security (I10) and compatibility (I9) are key barriers. When it comes to data preparation, data are often inconsistent, come from different sources and formats (I4), and archival records pose unique digitization challenges (I10). According to I10, it is important to improve data quality, and I6 complements this idea by stating that:

"*<…>preparing data, cleaning the data, categorizing the data, and otherwise preparing the data for artificial intelligence is 80 percent of the success.*"

To ensure effective integration of AI systems, it is also necessary to strike a balance between traditional processes and AI-based methods (I3) and to understand how data should be stored and utilized (I4). The findings indicate that AI transforms knowledge retrieval from conventional keyword-based searching towards semantic, contextual, conversational, and cross-source retrieval, enabling users to locate and access relevant knowledge more efficiently.

The applicability of AI to knowledge sharing in a business organization. Expert assessments have revealed that AI in knowledge-sharing processes not only increases the transfer and accessibility of information but also makes knowledge sharing more efficient, creates a psychologically safer communication environment, improves the understandability of knowledge, and strengthens organizational cooperation. Some experts note that AI can enhance this process by providing better access to organizational knowledge, making it available to all members of the organization (I1, I2, I6). Tools such as AI-based chatbots enable employees to efficiently query knowledge bases and support collaboration across teams. The potential of AI to combine knowledge from different disciplines and thereby discover new opportunities for cooperation was also mentioned (I2, I5). According to other experts, AI can accelerate communication and cooperation within teams (I3, I7) and even eliminate language barriers (I8). No less important is psychological safety, as AI creates a medium for asking and sharing without feeling like 'you are bothering someone' or that 'you are being insecure' (I3, I5, I8). Collaboration is also greatly facilitated by providing clarity:

"*<...>that knowledge is systematized and presented to each employee in a language they understand.*" (I3).

Communication becomes much simpler when knowledge can be conveyed in a way that everyone understands (I5, I7, I11). Finally, a standard knowledge base enables better knowledge discovery across team members (I4, I9).

Two key themes emerged during the interviews: organizations should integrate AI into the onboarding process and also focus on developing the employees' digital maturity. Virtual assistants or chatbots can be an effective aid in the hiring process, answering frequently asked questions and providing an interactive, informative introduction to the workplace (I3, I8, I12, I11). Some experts emphasized that, in order to master AI effectively, it is crucial to enhance the employees' digital literacy through training and adaptation plans (I6, I9). Moreover, it is necessary to ensure that all employees understand the organization's workflow and the tools used (I10). In this way, a favorable and practical environment is created that enables new employees to engage with AI-based knowledge systems.

Table 5. **Use of AI for knowledge sharing**

Expert-identified dimension	**Expert-identified uses of AI**
Enhancing knowledge accessibility and sharing	AI expands access to organizational knowledge and facilitates knowledge sharing across employees, teams, and stakeholders.
Improving the efficiency of knowledge sharing	AI reduces the time required to locate, process, and communicate knowledge, enabling more efficient use of organizational resources.
Creating psychologically safer knowledge-sharing environments	AI can reduce concerns about personal judgment and criticism, creating safer conditions for individuals to ask questions, to seek assistance, and to share knowledge.
Improving knowledge clarity and communication	AI helps structure, simplify, contextualize, and present knowledge in ways that make it easier to understand and communicate.
Integrating organizational knowledge and strengthening collaboration	AI supports the integration and centralization of organizational knowledge while facilitating connections and collaboration across teams and professional domains.

Compiled by authors on aggregated expert responses.

The use of AI in the practical application of knowledge. The experts emphasized that AI enables the application of knowledge by automating organizational activities and decision-making, generating predictive, decision-oriented insights, providing personalized assistance and mentoring, and translating organizational knowledge into practical business solutions. Experts distinguish between helping make automated decisions (I1, I10) and fully automating an organizational department (I7). In forecasting, AI uses models that predict long-term trends by collecting data from various sources (I5) and considering multiple variables (I10).

The experts have identified AI as an assistant or mentor (I2, I3, I4, I8, I9, I12) and emphasized its continuous operation (I3). Such readily available assistance can facilitate the learning process (I9) and help to complete tasks faster (I8) and more accurately (I4, I8). The ability of AI to translate knowledge into business solutions is evident in its application in customer service (I3). Additionally, its role in mediating between knowledge and end users, as well as in driving business growth and efficiency (I3, I12), is highlighted. By effectively integrating AI, organizations can ensure that knowledge is not only accessible but is also applied to support decisions.

Table 6. **Use of AI for knowledge application**

Expert-identified dimension	Expert-identified uses of AI
Automating knowledge application and decision-making	AI enables the application of organizational knowledge by automating routine activities and processes, as well as selected decision-making tasks.
Generating predictive and data-driven insights	AI integrates and analyzes data to generate forecasts, identify patterns, and produce actionable insights that support organizational decisions.
Providing intelligent assistance and personalized support	AI provides individualized assistance, guidance, learning, and mentoring, helping employees apply knowledge to specific tasks and situations.
Translating knowledge into business solutions	AI facilitates the practical application of organizational knowledge by translating it into business solutions and supporting interactions with customers.

Compiled by authors on aggregated expert responses.

According to the experts, the effectiveness of AI technologies in business organizations is primarily assessed by financial efficiency, time costs, employee satisfaction, and strategic impact. From a financial perspective, the success of AI can be assessed by calculating the costs (I2, I4), return on investment (I6, I13), contribution to profitability (I3), and revenue growth (I1, I5, I7, I10). Some experts also mentioned efficiency (I6, I12), which is manifested in a reduced task completion time (I7), as artificial intelligence can significantly speed up processes, for example, by reducing task completion time from several tens of hours to several minutes (I4). The experts noted that AI-enabled risk management (I1) and error reduction (I9) can also positively impact a business organization's financial indicators. At the strategic level, the impact of AI can be assessed by its compatibility with business goals and its ability to inform long-term decisions (I1, I4). In addition, the non-financial indicator mentioned by some experts – notably, employee satisfaction (I3, I9) – provides valuable insights into the broader benefits of implementing AI for the organization. By combining financial, time, satisfaction, and strategic indicators, organizations can comprehensively assess the impact of AI technologies on their business success.

The role of humans in interpreting insights generated by AI. The experts' responses revealed that the role of humans in interpreting and reviewing insights generated by AI is significant and encompasses several different functions. The findings highlight human oversight as a critical component of AI-enabled knowledge management. The experts identified three interconnected human roles: a decision-maker and interpreter, a validator and quality assurer, and a governor of AI use. Humans can act as the final decision-maker, by combining AI recommendations with their own critical judgment before making important decisions (I1, I5, I6). Some experts note that humans can perform the function of an accuracy filter, by checking facts (I8) and repeatedly reviewing AI results. It is essential to manage critically important issues:

"*<…> only with human participation will we be able to largely protect ourselves from those initial gaps, inaccuracies and possibly even catastrophic consequences.*" (I10).

Humans can also play a management role, by setting the boundaries for AI application within the organization (I3, I6) and determining how to unify diverse employee perspectives so that to facilitate AI implementation (I2). These roles highlight the essential collaboration between humans and AI, by underscoring the importance of careful supervision and integration (Table 8).

The experts' responses revealed that the ethical issues related to AI use in organizational KM are highly multifaceted. The experts emphasized the need to ensure transparency in data use (I1, I4), to comply with the General Data Protection Regulation (I1, I7), and to apply cybersecurity practices (I10, I12, I13) so that to avoid potential data misuse (I6). Some experts distinguished bias (I1, I2, I10, I11) and possible discriminatory practices (I4, I6, I7, I8). Interestingly, I4 and I10 observed that this bias can arise from how a person trains an AI model. Another important topic touched upon during the interviews is environmental and social responsibility. The energy consumption and footprint of AI systems raise ethical concerns regarding the technology's environmental impact (I2, I10). In terms of accountability, the lack of responsibility and transparency in decision-making (I3, I4) poses significant challenges, as do the risks of plagiarism and intellectual property misuse (I3). Finally, questions about the reliability of this tool arise from AI hallucinations, where systems generate false or misleading information, necessitating human oversight and quality control (I5, I7, I11, I13). AI tools enable people to overcome skill barriers, by allowing them to engage in new activities, such as creating works of art or utilizing specialized knowledge without prior experience (I6, I10), and the discovery of new opportunities:

"*<…>discovering new directions, angles, points of view, I think that is very positive.*" (I2).

By combining and generalizing knowledge more quickly (I4, I7) and automating tasks such as data analysis or coding, AI enables people to be more productive and find time for creative activities (I7, I11, I13). This also allows people to focus on value-added tasks that promote emotional satisfaction (I7, I5). Ultimately, AI serves as a catalyst, integrating productivity and imagination into modern work processes. This symbiosis emphasizes that AI does not replace human creativity, but, rather, gives it new meaning.

The experts identified key dimensions of ethical challenges associated with AI use in organizational knowledge management: data privacy, security, and regulatory compliance; fairness and non-discrimination; environmental and social responsibility; accountability and intellectual property; and the reliability and integrity of AI-generated knowledge. The responses reveal that ethical concerns extend beyond the technical performance of AI and encompass broader questions of how organizational knowledge is collected, processed, shared, and used. In particular, concerns about data misuse, bias, discrimination, and reliability highlight the potential risks to the quality, trustworthiness, and legitimacy of AI-enabled knowledge processes, while concerns about accountability and intellectual property emphasize the need to clearly define human responsibility for AI-supported activities and outputs. The environmental and employment-related concerns further demonstrate that the implications of AI use extend beyond individual organizations to wider social and environmental contexts. Overall, the findings suggest that the effective integration of AI into knowledge management requires not only technological capabilities but also transparency, responsible data governance, human oversight, and clear organizational standards for its responsible use.

Overall, the experts demonstrated a relatively high degree of agreement regarding the potential of AI to support KM. However, differences emerged in their assessments of risks, organizational readiness, and the conditions required for successful AI-KM integration.

Discussion and Conclusions

Knowledge is a valuable organizational resource, and it is important to manage it in order to adapt to rapidly changing circumstances by collecting and effectively using what the organization already knows and by discovering new value-creating perspectives. The study confirms theoretical insights that a KM system integrates knowledge, people, processes, and technology, while helping to ensure that knowledge resources are created and used effectively, thereby increasing an organization's competitive advantage (Khadivar et al., 2025; Nveke & Adalusi, 2025; Taherdoost & Madanchian, 2023; Borges et al., 2021).

As in previous studies, the role of AI in the knowledge creation process is associated with the identification of relationships and regularities (O'Dell & Davenport, 2019), natural language processing and data structuring (Benbya et al., 2023), prediction through the prism of analytics and recommendations (Jarrahi et al., 2023), and the generation of new ideas (Alavi, 2024). In the context of knowledge storage, AI's contributions to data classification, organization, and document generation from data have been confirmed (Paschen et al., 2020; Alavi et al., 2024), and empirical results further demonstrate its ability to generate summaries. In the knowledge-sharing process, AI is significant in creating shared knowledge bases and ensuring access for all members of the organization, thereby reducing knowledge fragmentation (Alavi et al., 2024), as well as in developing AI-based learning opportunities for different employee groups (Benbya et al., 2023).

Empirical research reveals new aspects, such as more efficient time allocation, greater psychological safety, and clearer communication. In the context of knowledge application, AI is associated with task automation (Brynjolfsson et al., 2023) and the use of real-time AI assistants that can act as mentors or consultants (Davenport, 2019; Maedche et al., 2019). The study extends existing understanding by demonstrating AI's ability not only to apply knowledge but also to translate predictions into business decisions, while emphasizing that critical human thinking remains a prerequisite for these processes (Bersin & Zao-Sanders, 2020).

The study demonstrates that AI is embedded across the entire KM lifecycle, encompassing knowledge creation, storage, retrieval, sharing, and application. Across these processes, AI performs different but interconnected functions: it transforms and generates knowledge, structures and organizes information, enables semantic and contextual retrieval, facilitates knowledge accessibility and sharing, and supports the transformation of knowledge into insights, decisions, and practical solutions. Thus, AI should not be viewed as a tool supporting a single KM activity, but as a cross-cutting capability that reshapes the KM process. The findings further indicate that AI's contribution is determined by the interaction between its technological capabilities and the specific requirements of KM processes. Semantic processing, natural language processing, data analytics, pattern recognition, generative capabilities, automation, and personalization enable a range of knowledge-related activities. Consequently, the value of AI in KM emerges not from the technological capability itself, but from how these capabilities are embedded in and applied to knowledge processes.

Importantly, the findings highlight the continuing importance of human oversight. Although AI can accelerate knowledge processing, identify patterns, generate insights, support decision-making, and automate certain activities, human judgment remains necessary to validate, interpret, contextualize, and responsibly apply AI-generated knowledge. Human oversight, therefore, is the essential clause that shapes the quality and organizational value of AI-enabled knowledge management. The findings suggest that AI-enabled KM can be conceptualized as a human–AI interaction in which AI capabilities augment knowledge processes while human judgment provides contextual interpretation, validation, and responsibility. This interaction can contribute to organizational outcomes, including greater efficiency, improved decision-making, enhanced knowledge accessibility, stronger collaboration, innovation, and organizational learning and adaptability. This perspective extends the understanding of AI in KM from a technological support tool towards an organizational capability that transforms the ways how knowledge is created, organized, accessed, shared, and applied.

The study also highlights significant challenges in applying AI to KM. Among the most important of these, experts identify insufficient technical and AI-use competencies among employees, data quality problems, information privacy and security risks, algorithmic bias, and issues of transparency and trust in AI results. This allows us to state that the integration of AI into KM is not only a technological but also an organizational change that requires appropriate competencies, management rules, and accountability mechanisms.

The results show that AI can create the prerequisites for transforming employee activities by automating routine tasks and providing more opportunities to focus on more complex, creative, and higher-value activities. However, it depends on how organizations define the role of AI, allocate responsibility between their employees and the technology applied, and ensure human assessment and control over AI-generated results.

From a practical point of view, the study shows that, for Lithuanian business organizations implementing AI into KM, it is appropriate to first assess existing KM processes, data quality, and technological infrastructure, employee competencies, and organizational readiness. The implementation of AI should focus not only on automating individual tasks but also on solving clearly defined KM problems. At the same time, it is necessary to establish the principles of data use, verification of AI-generated results, privacy, security, and accountability. The findings suggest that business organizations should prioritize AI applications that would strengthen the already existing knowledge conversion processes. For example, AI can support externalization by transforming the employees' experiential knowledge into documented procedures, combination by integrating dispersed organizational information, and internalization by providing personalized access to organizational knowledge. However, socialization should not be reduced to AI-mediated interaction, as tacit knowledge remains strongly dependent on human experience and interpersonal exchange.

Author contributions

Indrė Stasiūnaitė: conceptualization, data curation, formal analysis, investigation, methodology, validation, visualization, writing – original draft.

Daiva Siudikienė: conceptualization, methodology, supervision, validation, visualization, writing – original draft, writing – review and editing.

References

Addis, M. (2016). Tacit and explicit knowledge in construction management. *Construction management and economics*, *34*(7-8), 439–445. https://doi.org/10.1080/01446193.2016.1180416

Alavi, M., & Leidner, D. E. (2001). Knowledge management and knowledge management systems: Conceptual foundations and research issues. *MIS Quarterly*, *25*(1), 107–136. https://doi.org/10.2307/3250961

Alavi, M., Leidner, D., & Mousavi, R. (2024). Knowledge Management Perspective of Generative Artificial Intelligence (GenAI). *Journal of the Association for Information Systems*, *25*(1), 1–12. https://doi.org/10.17705/1jais.00859

Aldoseri, A., Al-Khalifa, K. N., & Hamouda, A. M. (2024). AI-Powered Innovation in Digital Transformation: Key Pillars and Industry Impact. *Sustainability*, *16*(5), Article 1790. https://doi.org/10.3390/su16051790

Balasubramanian, N., Ye, Y., & Xu, M. (2022). Substituting human decision-making with machine learning: Implications for organizational learning. *Academy of Management Review*, *47*(3), 448–465. https://doi.org/10.5465/amr.2019.0470

Bankins, S. (2021). The ethical use of artificial intelligence in human resource management: A decision-making framework. *Ethics and Information Technology*, *23*(4), 841–854. https://doi.org/10.1007/s10676-021-09619-6

Banh, L., & Strobel, G. (2023). Generative artificial intelligence. *Electronic Markets*, *33*(1), Article 63. https://doi.org/10.1007/s12525-023-00680-1

Benbya, H., Strich, F., & Tamm, T. (2023). Navigating Generative Artificial Intelligence Promises and Perils For Knowledge And Creative Work. *Journal of the Association of Information Systems*, *25*(1), 23–36. https://aisel.aisnet.org/jais/vol25/iss1/13

Bersin, J., & Zao-Sanders, M. (2020, February 12). Boost your team's data literacy. *Harvard Business Review*. https://hbr.org/2020/02/boost-your-teams-data-literacy

Bhattacharya, P., Ghosh, K., Ghosh, S., Pal, A., Mehta, P., Bhattacharya, A., & Majumder, P. (2019). Artificial intelligence for legal assistance. *Proceedings of the 11th annual meeting of the forum for information retrieval evaluation*, 4–6. https://doi.org/10.1145/3368567.3368587

Borges, A. F., Laurindo, F. J., Spínola, M. M., Gonçalves, R. F., & Mattos, C. A. (2021). The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions. *International Journal of Information Management*, *57*, Article 102225. https://doi.org/10.1016/j.ijinfomgt.2020.102225

Borges, R., Bernardi, M., & Petrin, R. (2019). Cross-country findings on tacit knowledge sharing: evidence from the Brazilian and Indonesian IT workers. *Journal of Knowledge Management*, *23*(4), 742–762. https://doi.org/10.1108/JKM-04-2018-0234

Brynjolfsson, E., Li, D., & Raymond, L. R. (2023). *Generative AI at Work* (Working Paper 31161). National Bureau of Economic Research. http://www.nber.org/papers/w31161

Canhoto, A. I., & Clear, F. (2020). Artificial intelligence and machine learning as business tools: A framework for diagnosing value destruction potential. *Business Horizons*, *63*(2), 183–193. https://doi.org/10.1016/j.bushor.2019.11.003

Chatterjee, S., Ghosh, S. K., & Chaudhuri, R. (2020). Knowledge management in improving business process: an interpretative framework for successful implementation of AI–CRM–KM system in organizations. *Business Process Management Journal*, *26*(6), 1261–1281. https://doi.org/10.1108/BPMJ-05-2019-0183

Dalkir, K. (2013). *Knowledge Management in Theory and Practice.* Routledge.

Davenport, T. (2019, October 10). Managing support knowledge with AI: Talla helps Toast. *Forbes*. https://www.forbes.com/sites/tomdavenport/2019/10/10/managing-support-knowledge-with-ai-talla-helps-toast/

De la Torre-López, J., Ramírez, A., & Romero, J. R. (2023). Artificial intelligence to automate the systematic review of scientific literature. *Computing*, *105*(10), 2171–2194. https://doi.org/10.1007/s00607-023-01181-x

Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial Intelligence and Business Value: A Literature Review. *Information Systems Frontier*, *24*, 1709–1734. https://doi.org/10.1007/s10796-021-10186-w

Epetimehin, F. M., & Ekundayo, O. (2011). Organizational knowledge management: survival strategy for Nigeria insurance industry. *Journal of Management and Corporate Governance*, *3*, 53–64. https://www.cenresinjournals.com/wp-content/uploads/2020/03/page-53-64-514-1.pdf

Esteva, A., Chou, K., Yeung, S., Naik, N., Madani, A., Mottaghi, A., & Socher, R. (2021). Deep learning-enabled medical computer vision. *NPJ Digital Medicine*, *4*(1), Article 5. https://doi.org/10.1038/s41746-020-00376-2

Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2024). Generative AI. *Business & Information Systems Engineering*, *66*(1), 111–126. https://doi.org/10.1007/s12599-023-00834-7

Flick, U. (2014). *An Introduction to Qualitative Research* (5th ed.). Sage Publications.

Füller, J., Hutter, K., Wahl, J., Bilgram, V., & Tekic, Z. (2022). How AI revolutionizes innovation management – Perceptions and implementation preferences of AI-based innovators. *Technological Forecasting and Social Change*, *178*, Article 121598. https://doi.org/10.1016/j.techfore.2022.121598

Gaižauskaitė, I., ir Valavičienė, N., (2016). *Socialinių tyrimų metodai: kokybinis interviu.* Mykolo Riomerio universitetas.

Haenlein, M., & Kaplan, A. (2019). A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence. *California Management Review*, *61*(4), 5–14. https://doi.org/10.1177/0008125619864925

Haefner, N., Wincent, J., Parida, V., & Gassmann, O. (2021). Artificial intelligence and innovation management: A review, framework, and research agenda. *Technological Forecasting and Social Change*, *162*, Article 120392. https://doi.org/10.1016/j.techfore.2020.120392

Jarrahi, M. H., Askay, D., Eshraghi, A., & Smith, P. (2023). Artificial intelligence and knowledge management: A partnership between human and AI. *Business Horizons*, *66*(1), 87–99. https://doi.org/10.1016/j.bushor.2022.03.002

Javaid, M., Haleem, A., Singh, R. P., & Suman, R. (2022). Artificial intelligence applications for industry 4.0: A literature-based study. *Journal of Industrial Integration and Management*, *7*(1), 83–111. https://doi.org/10.1142/S2424862221300040

King, W. R. (Ed.). (2009). *Knowledge Management and Organizational Learning*. Springer US.

Khadivar, A., Abbasi, F., & Akbarian, S. (2025). A Model For Optimization of Knowledge Management Outsourcing Decision Using Genetic Algorithm. *Strategic Management of Organizational Knowledge*, *8*(2), 67–85. https://doi.org/10.47176/SMOK.2025.1846

Kolyasnikov, M. S., & Kelchevskaya, N. R. (2020). Knowledge management strategies in companies: Trends and the impact of industry 4.0. *Upravlenec*, *11*(4), 82–96. https://doi.org/10.29141/2218-5003-2020-11-4-7

Leoni, L., Ardolino, M., El Baz, J., Gueli, G., & Bacchetti, A. (2022). The mediating role of knowledge management processes in the effective use of artificial intelligence in manufacturing firms. *International Journal of Operations & Production Management*, *42*(13), 411–437. https://doi.org/10.1108/IJOPM-05-2022-0282

Maedche, A., Legner, C., Benlian, A., Berger, B., Gimpel, H., Hess, T., & Söllner, M. (2019). AI-based digital assistants: Opportunities, threats, and research perspectives. *Business & Information Systems Engineering*, *61*, 535–544. https://doi.org/10.1007/s12599-019-00600-8

Majumder, S., & Dey, N. (2022). *AI-empowered Knowledge Management*. Springer Singapore.

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, *58*(3), Article 103434. https://doi.org/10.1016/j.im.2021.103434

Muthuveloo, R., Shanmugam, N., & Teoh, A. P. (2017). The impact of tacit knowledge management on organizational performance: Evidence from Malaysia. *Asia Pacific Management Review*, *22*(4), 192–201. https://doi.org/10.1016/j.apmrv.2017.07.010

Nonaka, I. (1994). A Dynamic Theory of Organizational Knowledge Creation. *Organization Science*, *5*(1), 14–37. https://www.jstor.org/stable/2635068

Nonaka, I., & Takeuchi, H. (1995). *The Knowledge-Creating Company: How Japanese Companies Create the Dynamics of Innovation.* Oxford University Press.

Nonaka, I., Toyama, R., & Konno, N. (2000). SECI, Ba and leadership: A unified model of dynamic knowledge creation. *Long Range Planning*, *33*(1), 5–34. https://doi.org/10.1016/S0024-6301(99)00115-6

O'Dell, C., & Davenport, T. (2019). Application of AI for knowledge management. *CIO Review*. https:// knowledgemanagement.cioreview.com/cxoinsight/ application-of-aifor-knowledge-management-nid-30328- cid-132.html

Omotayo, F. O. (2015). Knowledge management as an important tool in organisational management: A review of literature. *Library Philosophy and Practice (e-journal).* http://digitalcommons.unl.edu/libphilprac/1238

Paschen, J., Kietzmann, J., & Kietzmann, T. C. (2019). Artificial intelligence (AI) and its implications for market knowledge in B2B marketing. *Journal of Business & Industrial Marketing*, *34*(7), 1410–1419. https://doi.org/10.1108/JBIM-10-2018-0295

Paschen, J., Wilson, M., & Ferreira, J. J. (2020). Collaborative intelligence: How human and artificial intelligence create value along the B2B sales funnel. *Business Horizons*, *63*(3), 403–414. https://doi.org/10.1016/j.bushor.2020.01.003

Raudeliūnienė, J., & Račinskaja, I. (2014). Assessment of the knowledge acquisition process in Lithuanian insurance sector. *Business: Theory and Practice*, *15*(2), 149–159. https://doi.org/10.3846/btp.2014.15

Rezaei, M., Pironti, M., & Quaglia, R. (2025). AI in knowledge sharing, which ethical challenges are raised in decision-making processes for organisations?. *Management Decision*, *63*(10), 3369–3388. https://doi.org/10.1108/MD-10-2023-2023

Sowa, K., Przegalinska, A., & Ciechanowski, L. (2021). Cobots in knowledge work: Human–AI collaboration in managerial professions. *Journal of Business Research*, *125*, 135–142. https://doi.org/10.1016/j.jbusres.2020.11.038

Storey, V. C. (2025). Knowledge Management in a World of Generative AI: Impact and Implications. *ACM Transactions on Management Information Systems*, *16*(3), 1–14. https://doi.org/10.1145/3719209

Taherdoost, H., & Madanchian, M. (2023). Artificial Intelligence and Knowledge Management: Impacts, Benefits, and Implementation. *Computers*, *12*(4), Article 72. https://doi.org/10.3390/computers12040072

Taylor, P. (2023). Data Growth Worldwide 2010-2025. *Statista.* https://www.statista.com/statistics/871513/worldwide-data-created/

Vining, R., McDonald, N., McKenna, L., Ward, M. E., Doyle, B., Liang, J., Hernandez, J., Guilfoyle, J., Shuhaiber, A., Geary, U., Fogarty, M., & Brennan, R. (2022). Developing a Framework for Trustworthy AI-Supported Knowledge Management in the Governance of Risk and Change. In M. Kurosu, S. Yamamoto, H. Mori, M. M. Soares, E. Rosenzweig, A. Marcus, P.-L. P. Rau, D. Harris, & W.-C. Li (Eds.), *HCI International 2022 - Late Breaking Papers. Design, User Experience and Interaction. HCII 2022. Lecture Notes in Computer Science, vol. 13516* (pp. 318–333). Springer, Cham. https://doi.org/10.1007/978-3-031-17615-9_22

Yang, J. (2007). The Impact of Knowledge Sharing on Organizational Learning and Effectiveness. *Journal of Knowledge Management*, *11*(2), 83–90. https://doi.org/10.1108/13673270710738933

Yi, J. (2009). A measure of knowledge sharing behavior: scale development and validation. *Knowledge Management Research & Practice*, *7*(1), 65–81. https://doi.org/10.1057/kmrp.2008.36