An Analysis of Knowledge Management Changes Through Artificial Intelligence with Probst's Model

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Abstract: In recent years, the integration of Artificial Intelligence (AI) into Knowledge Management (KM) has led to transformational changes. These changes have significantly enhanced traditional KM processes. To identify how AI technologies improve and reshape knowledge processes, this study conducted a systematic literature review. The review identified AI technologies suitable for each of Probst's building blocks, which outline the eight central KM processes. The research reveals a wide range of AI technologies, including machine learning, natural language processing and chatbots such as ChatGPT. These technologies can be applied in different domains and introduce innovative approaches to improve KM processes. Based on the AI technologies analysed, this study proposes a four-stage model to support the documentation and application of best practices and lessons learned. The model is designed to enhance the knowledge development process and aims to document and secure key project developments in the long term. A further objective was to analyse which KM process is most affected by chatbots. The findings indicate that chatbots have the potential to transform the use of knowledge in organisations. They act as facilitators by breaking down existing barriers, foster an open culture of knowledge sharing, streamline workflows and increase the accessibility of knowledge. The study also examines the broader changes that AI will bring to KM and forecasts the sixth generation of KM. It draws on Bencsik's (2021) evolutionary and revolutionary perspectives that specifically forecast this next generation. The study shows that AI not only enhances existing KM processes but also has the potential to fundamentally disrupt traditional methods and approaches. These findings underline the need for future research to explore the effective integration and scalability of AI technologies in real-world KM environments. This will help ensure that their long term impact and potential benefits are fully understood across different industries and organisational contexts.

Keywords: Knowledge management, Artificial intelligence, Probst's Building Block Model, Innovation, AI technologies for knowledge management

1. Introduction

The origins of knowledge management (KM) can be traced back to Michael Polanyi's (1966) work, "The Tacit Dimension". Initially, Polanyi's work had no significant impact on the discipline, but it has since become a cornerstone of KM. The foundations of artificial intelligence (AI) were laid earlier by Alan Turing in 1950 through his article "Computing Machinery and Intelligence", which introduced the "Turing Test" to assess machine intelligence. This test shaped the core principles and objectives of AI, profoundly influencing the field to this day. These historical milestones laid the groundwork for extensive literature on KM and AI. Their development has fostered a strong symbiosis between the two fields, which are now more interconnected than ever. The primary goals of KM are to capture, utilise and develop knowledge. Effective KM provides organisations with a sustainable competitive advantage (Davenport, 1998). This can lead to higher quality, increased creativity and improved efficiency. Knowledge is divided into explicit (documented and codified) and tacit (based on personal experiences and hard to articulate) forms (Nonaka and Takeuchi, 1995). While knowledge management systems (KMS) generally focus on explicit knowledge, effectively transforming tacit knowledge into a shareable format is a significant challenge that limits their overall effectiveness. The key challenge is to capture and structure tacit knowledge to make it shareable (Nonaka and Takeuchi, 1995).

In today's dynamic business environment, the development and implementation of effective KMS are crucial to ensure adaptability and competitiveness (Bencsik, 2021). The integration of AI with KM has recently emerged as a key driver of transformation, which enables machines to learn, apply and develop knowledge to improve accessibility for employees. AI and KM complement each other: KM aids to understand and structure knowledge, while AI enhances efficiency in the expansion, use and development of knowledge (Vajpayee and Ramachandran, 2019). This intersection enables organisations to drive innovation and streamline processes by leveraging the decision-making and automation capabilities of AI.

Building on these foundations, existing research has explored the role of AI in specific KM processes. However, it does not comprehensively cover the full scope of KM processes. Mohammad et al. (2022) focus on the relationship between AI technologies and KM processes. They identify AI technologies applicable to six KM processes and establish a significant link between knowledge development and data mining. Their study underscores the challenge of fully integrating AI into KM. Bencsik (2021) extends this perspective through an analysis of the KM processes represented in Probst's building block model (Probst, Raub and Romhardt, 2012).

The focus is on the prediction of the success of innovation and the assurance of strategic feasibility through informed management decisions. The study provides valuable insights into the potential applications of AI in different KM processes. Furthermore, Bencsik (2021) lays the groundwork for broader changes in KM through AI and proposes the future role of AI in the sixth generation of KM. Bencsik (2021) highlights a research gap in this area, which emphasises the need for detailed exploration of KM's future possibilities.

Bencsik (2021) categorises the evolution of KM into five generations. Each generation reflects shifts in focus and methodology. The *first generation* centred on the use of IT for knowledge creation and management, though it proved inadequate for managing tacit knowledge. The *second generation* recognised diverse types of knowledge, including knowledge-based, experience-based and problem-solving approaches. The challenge was the codification of tacit knowledge for wider distribution. The *third generation* viewed KM as a network to mobilise knowledge and enhance performance through maintenance and networking. The *fourth generation* positioned knowledge as a capital factor, aims to quantify and utilise knowledge resources effectively. The *fifth generation* explored the interplay between corporate competitiveness and innovation, focusing on the valuation and quantification of human capital.

These generations represent the natural evolution driven by expert thinking, organisational practices and technological advances. Building on this framework, Bencsik (2021) proposes two potential future directions for the sixth generation of KM. The first is an *evolutionary* approach, which returns to the initial stages of KM but at a higher level, where IT regains importance and AI overshadows previous focuses. This scenario mirrors the first generation but incorporates advanced IT capabilities like AI to drive KM evolution on an expanded technological scale. The second approach is *revolutionary* in its aim to fully utilise the capabilities of AI to bring the entire KM process to a new level of organisational efficiency. In this approach, AI-based solutions are integrated into the KM processes, to enable faster, more efficient and successful interventions or tasks.

This structured overview not only highlights the historical evolution of KM, but is also essential for the anticipation of the characteristics and innovations of the next, sixth generation. It shapes our understanding of how KM may evolve with advances in AI and organisational needs. Therefore, this study investigates changes in KM through AI based on Probst's building block model, which outlines the entire KM process (Probst, Raub and Romhardt, 2012). As outlined by Brocke et al. (2009), a systematic literature review was conducted to identify new AI technologies that improve KM processes. This research includes four key contributions. First, it identifies and examines AI technologies suitable for each KM process, presented in a comprehensive tabular format. Second, it proposes a four-stage model to support the creation of best practices and lessons learned for the knowledge development process. Third, it provides a predictive analysis of the anticipated sixth generation of KM. Fourth, it analyses the KM building block most affected by chatbots like ChatGPT.

2. Background: Probst's Building Block Model

The Probst building block model is essential for understanding KM processes, as illustrated in Figure 1. This model comprises eight blocks in a cyclical sequence that links the strategic and operational aspects of KM (Probst, Raub and Romhardt, 2012). The outer cycle includes strategic blocks essential to secure the organisation's long-term core competencies, while the inner cycle includes operational blocks that drive these strategic objectives. Each block addresses specific problem areas that may disrupt knowledge flow. The building blocks are described as follows according to Probst, Raub and Romhardt, 2012.

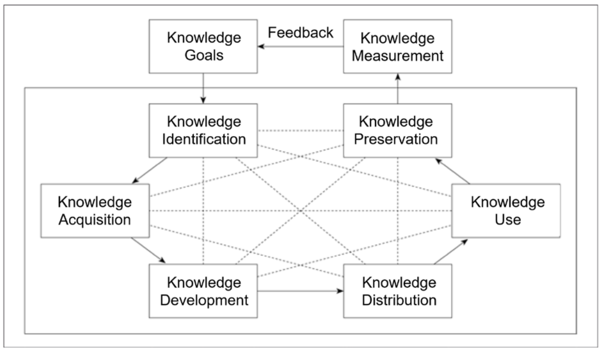

Figure 1: Probst's building block model (Source: Based on Probst, Raub and Romhardt, 2012, p. 34)

Defining *knowledge goals* provides the direction for KM activities across three organisational levels. Normative goals foster a knowledge-conscious culture. Strategic goals define core organisational knowledge and future competencies. Operational goals ensure KM implementation at every organisational level. Effective knowledge identification is achieved by building structures that maintain transparency, reduce inefficiencies, prevent redundancies and aid employees in information retrieval. Knowledge acquisition adds value through external sources, such as hiring specialists, acquiring companies, or purchasing software and repositories to enhance internal resources. Knowledge development aims to create new skills, ideas and processes that foster innovation and employee creativity. Knowledge distribution emphasises that effective transfer extends beyond the mere exchange of information. It targets organisational knowledge to specific employee groups and between individuals, teams or workgroups. The value of KM becomes tangible in knowledge use, as knowledge only generates value when actively applied. Employees accept and apply knowledge based on evident benefits. Knowledge preservation maintains accessible and relevant skills through systematic storage and updates. Finally, knowledge measurement evaluates the effectiveness of KM initiatives, ensures that knowledge objectives are aligned with organisational outcomes and that KM activities are implemented effectively.

3. Methodology

This study follows the systematic literature review approach outlined by Brocke et al. (2009). Therefore, keyword lists for “Knowledge Management” and “Artificial Intelligence” were developed, with additional terms derived from foundational literature to refine the search. The keyword lists are illustrated in Table 1.

Table 1: Keyword lists for literature searches (Source: Table created by author)

Keyword list 1	"Knowledge Management" AND ("Artificial Intelligence" OR "Artificial Neural Network*" OR "Deep Learning" OR "Machine Learning" OR "Natural Language Processing")
Keyword list 2	"Knowledge Management" AND ("Chatbot*" OR "ChatGPT" OR "Large Language Model*")
The asterisk (*) in keyword list 2 acts as a wildcard to capture both singular and plural forms of key terms.	

The literature search was conducted in eight databases: *ACM Digital Library, IATED Digital Library, PubMed, Web of Science, ERIC, SpringerLink, ScienceDirect* and *IEEE Xplore*. This was supplemented by forward and backward searches to include related work (Brocke et al., 2009). The inclusion criteria for this study encompasses peer-reviewed publications from journals, conference proceedings and books published in the last five years. These publications must specifically address the intersection of KM and AI applications. Initially, only these inclusion criteria were applied and studies that did not meet these criteria were excluded. The search was conducted from October to November 2023 and initially yielded 745 hits. This number was reduced to 670 after the removal of duplicates. Based on the inclusion criteria, 69 articles were identified. The forward and backward search identified a further 6 articles. A total of 75 articles were identified for in-depth analysis. As a result, 15 articles were selected for inclusion in this study. Figure 2 illustrates the multi-stage systematic literature review process adopted for this study.

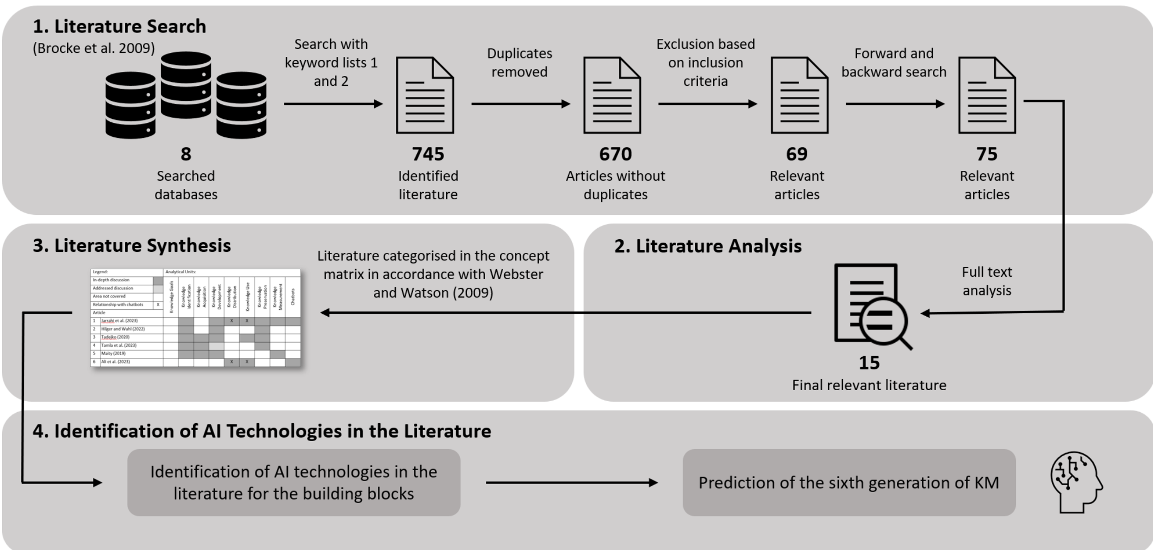

Figure 2: Overview of the literature review (Source: Figure created by author)

4. Results

This section presents the results of the literature review. The primary focus is on the analysis and synthesis of the literature.

4.1 Literature Analysis and Synthesis

The synthesis of the literature follows the methodology proposed by Webster and Watson (2002). It focuses on the identification of thematic patterns and theoretical perspectives to understand the interaction between KM and AI. The concept matrix in Table 2 is segmented in accordance with Probst's building block model. It uses colour coding to indicate the depth of discussion on AI technologies within KM processes. The matrix also positions chatbots alongside KM building blocks to emphasise the direct relationship with these technologies. An additional marker, represented by an "X", illustrates this link. For example, an "X" for knowledge development indicates that chatbots are discussed in the literature as supportive AI technologies for knowledge development. These colour differentiations are described in the legend.

Table 2: Concept matrix of the analysed literature (Source: Table created by author based on Webster and Watson, 2002, p. 17)

Legend:	
In-depth discussion	
Addressed discussion	
Area not covered	
Relationship with chatbots	X

	Article	Knowledge Goals	Knowledge Identification	Knowledge Acquisition	Knowledge Development	Knowledge Distribution	Knowledge Use	Knowledge Preservation	Knowledge Measurement	Chatbots
1	Jarrahi et al. (2023)					X	X			
2	Hilger and Wahl (2022)									
3	Tadejko (2020)									
4	Tamla et al. (2023)									
5	Maity (2019)									
6	Ali et al. (2023)					X	X			
7	Abubakar et al. (2019)									
8	Korzynski et al. (2023)			X	X	X	X			
9	Owoc, Sawicka and Weichbroth (2021)								X	
10	Bilgram and Laarmann (2023)				X		X			
11	Majumder and Dey (2022)									
12	Masood and Hashmi (2019)									
13	Botega and da Silva (2020)									
14	Bencsik (2021)									
15	Paschen, Kietzmann and Kietzmann (2019)									

The analysis in Table 2 demonstrates a strong emphasis on certain KM processes, such as *knowledge identification* and *development*, where AI technologies play a significant role. This shows that AI technologies for these processes are widely recognised and discussed. The consistent presence of chatbots across five KM processes (marked with an "X") underscores their growing importance and potential to improve KM processes. However, it is evident from Tables 2 that no AI technologies are in-depth discussed in the literature related to *knowledge goals*. This absence is noteworthy. Probst, Raub and Romhardt (2012) emphasise that these goals need to work synergistically across all corporate levels. This synergy is crucial to effectively contribute to corporate goals. It remains a challenge to integrate AI in the formulation of knowledge goals. The current capabilities of AI are exceeded by the complex nature of precise and specific knowledge goal formulation. This indicates potential areas for future research.

4.2 AI Technologies Within the KM Processes

To provide a clearer overview of the interaction between AI technologies and KM processes, Table 3 categorises these technologies identified in the reviewed literature. This table adopts a simplified presentation style where each KM process is analysed for its connection with specific AI technologies. Instead of overburdening the table with direct citations, article numbers are used that correspond to those in the concept matrix in Table 2.

Table 3: Presentation of AI technologies across all building blocks (Source: Table created by author)

AI Technologies	Knowledge Goals	Knowledge Identification	Knowledge Acquisition	Knowledge Development	Knowledge Distribution	Knowledge Use	Knowledge Preservation	Knowledge Measurement
AI-based KMS			5	13				
AI-based virtual trainers				1, 5, 9				5
Artificial neural networks (ANNs)		7						7, 14
Data mining				11			9	
Deep learning							1	
Expert systems							14	
Image processing		3		3			3	
Intelligent agents		5	5					
Intelligent search with NLP					12			
Chatbots			8	8, 10	1, 6, 8	1, 6, 8, 10		9
Machine Learning (ML)		3	3	3				3
Named entity recognition (NER)		4					4	
Natural language processing (NLP)		2, 12	3, 4, 14, 15	2, 3, 15		3	2, 3, 9, 12	
Optical character recognition (OCR)		12			12		12	

Note: The numbers in the cells refer to article indices that discuss the AI technologies in the context of the KM process. These indices correspond to the detailed list provided in the concept matrix in Table 2.

The analysis of Table 3 highlights the diverse use of AI technologies across KM processes. Notably, NLP and chatbots are predominantly used in five different KM processes. This underlines a significant reliance on these technologies to improve the efficiency of KM.

4.3 Application of AI Technologies in KM

After the identification of AI technologies for seven KM process in Table 3, this section presents selected applications of these technologies. This approach provides a foundation for understanding the potential impact of AI in KM and supports the forecast of the next generation of KM.

4.3.1 Search enhancement with NLP

NLP technologies enable systems to understand and analyse the meaning and context of text inputs from users. The integration of NLP with knowledge graphs (KG) enhances the capabilities of intelligent search and retrieval functions, which leads to more powerful search functions (Hilger and Wahl, 2022). These advanced NLP search capabilities address a common problem: employees are often faced with overwhelming results when searching relational databases such as NoSQL with a single keyword, which requires extensive filtering. The integration of NLP-based intelligent search into existing KMS can significantly improve the user experience by allowing search queries to be formulated in natural language (Masood and Hashimi, 2019). It enables employees to navigate knowledge repositories and extract relevant results from both explicit and implicit contexts.

In the context of *knowledge identification*, we highlight the importance of text analysis tools based on NLP. These tools are useful for the identification and reinforcement of weak points in organisations and the discovery of unknown patterns in large amounts of information (Hilger and Wahl, 2022; Masood and Hashimi, 2019). For organisations that aim to fully identify their knowledge resources, these technologies are essential. Named entity recognition (NER) greatly enhances the effectiveness of text analysis tools. NER identifies and contextualises specific entities in text, making overlooked information accessible (Hilger and Wahl, 2022).

4.3.2 Transformation of unstructured data into searchable information

Organisations often face the challenge of managing large volumes of unstructured data such as scanned documents, PDFs or images that are not searchable. Optical character recognition (OCR) is recommended to solve this problem. This technology extracts text from scanned data and stores it in a searchable digital form (Masood and Hashimi, 2019). After the extraction process, the unstructured data can be transformed into a searchable document by using the text to create a search index. Tools such as Azure Search Index can then be used to index and structure the content of this data, in preparation for more efficient search queries. In addition to OCR, image processing is a crucial technology for structuring unstructured data such as images. These AI technologies enable effective organisation of images through tagging and categorising, which facilitates long-term storage and retrieval of images (Tadejko, 2020). Important information is extracted from images and made usable through features such as object, scene, face and text recognition. This ensures that visual knowledge is not only stored but also accessible for future use and decision-making processes.

4.3.3 Cloud-Based AI technologies

Cloud-based AI services from providers such as Amazon AWS, Microsoft Azure, Google Cloud and IBM Watson offer advanced ML and NLP tools (Tadejko, 2020; Tamla et al., 2023). For instance, Amazon Comprehend uses NLP to analyse document content without pre-processing. This makes it valuable for assessing large textual datasets such as social media responses and customer service transcripts through sentiment analysis (Tadejko, 2020). IBM Watson NLU is designed to classify data, extract insights, perform syntax analysis and discover relationships between entities. These capabilities support the recognition and interpretation of clues in textual data to develop knowledge within organisations (Tadejko, 2020). Access to these cloud-based solutions unlocks powerful computational capabilities, which enable organisations to develop and apply complex AI models across various business processes.

4.3.4 AI-based training systems for personalised employee development

AI-based training systems support personalised employee development by analysing initial skills, cognitive levels, job requirements and organisational needs. These systems learn from behavioural data to refine employee profiles and create tailored learning strategies (Maity, 2019). With the use of NLP, virtual trainers can extract content from company training materials and adapt it to individual learning preferences, enabling customised training. Furthermore, AI-based trainers can act as personal mentors, identifying skill gaps and providing targeted support in interactive learning environments. This reduces human interventions and bias, while facilitating efficient, learner-centred training (Maity, 2019). Additionally, these systems support training needs analysis and apply algorithms to provide timely repetition of knowledge at moments when users are most likely to forget (Owoc, Sawicka and Weichbroth, 2021).

From another perspective, AI-based virtual trainers have the potential to analyse and measure employee performance against pre-defined parameters. This supports the *knowledge measurement* process to assess the effectiveness of KM initiatives. The application of AI-based virtual trainers could revolutionise individual learning through mass personalisation and individual knowledge development.

4.3.5 Enhancement of creativity and innovation

Creativity is essential for innovation, problem solving and progress. While Probst, Raub and Romhardt (2012) have traditionally viewed creativity as spontaneous and uncontrollable, AI technologies demonstrate that creativity can be enhanced with technological support. Generative AI models have made significant progress in the development of knowledge. ChatGPT for example, utilise large, diverse datasets to generate coherent, context-aware responses (Korzynski et al., 2023). This opens up innovative avenues for idea generation. ChatGPT can be used at various stages of the innovation process, including idea generation, brainstorming and the design process. The text-to-code generation feature allows the creation of code, images, user journeys and prototypes using natural language, which supports creativity and the development of ideas (Bilgram and Laarmann, 2023). This capability also enables less technically skilled users to create early digital prototypes that can be converted into program code. Another example is a prototype presented by Botega and da Silva (2020), which uses AI to support KM in the selection of methods that foster creativity and innovation in the design process. To overcome creative blocks and promote the development of creative solutions, this AI-based system stores, retrieves and applies knowledge about creativity and innovation methods.

4.3.6 The role of chatbots in modern KM

In the rapidly evolving AI landscape, chatbots in particular play an important role in modern KM. These technologies not only streamline information retrieval, but also foster a more open and collaborative knowledge culture within organisations. Chatbots provide an informal and accessible way for employees to request information without the fear of being perceived as incompetent by other employees (Jarrahi et al., 2023). ChatGPT, for example, offers a simple conversational mode that provides personalised answers to open-ended questions and adapts to the user's language. This user-centred and user-friendly adaptation facilitates and secures organisational knowledge retrieval (Korzynski et al., 2023). Chatbots broaden the knowledge spectrum of users by providing explicit knowledge through general query capabilities (Ali et al., 2023). ChatGPT can be used for a variety of NLP tasks, such as the creation and translation of scripts and documents (Ali et al., 2023). Additionally, ChatGPT can analyse and summarise both unstructured and structured data, making it easier and quicker for decision-makers to find the information they need (Korzynski et al., 2023).

4.4 Four-Stage Model to Support the Creation of Best Practices and Lessons Learned

Probst, Raub and Romhardt (2012) emphasise the importance to document team experiences during projects. This can be valuable for teams that face similar challenges. However, experiences are often not systematically documented at the end of projects.

Given that no specific AI technologies were identified in the literature for this area, this study proposes a four-stage concept. The concept is based on existing knowledge to help organisations systematically document lessons learned and best practices. Figure 3 shows the four phases of this concept.

Figure 3: Four-stage concept for best practices and lessons learned (Source: Figure created by author)

In the *preparation phase*, AI technologies such as ML, intelligent agents and NLP are recommended. These technologies enable the effective capture and analysis of extensive data from various sources. This includes project documentation, emails, meeting minutes and performance reports. Studies by Hilger and Wahl (2022), Maity (2019) and Masood and Hashimi (2019) demonstrate that these AI technologies are particularly well-suited to the extraction and consolidation of relevant information from large datasets. This capability is crucial in the *preparation phase* as it provides a solid foundation for the subsequent phases.

In the *identification phase*, AI technologies such as ML and NLP are recommended to analyse the data collected in the first phase and identify crucial patterns and insights. ML excels in the recognition of recurring problems and trends, while NLP specialises in the extraction of key themes from text-based data. These technologies provide deeper insights beyond what human analysts could capture. This makes them essential to identify effective strategies, patterns, relationships and potential challenges. Research studies by Hilger and Wahl (2022) and Masood and Hashmi (2019) emphasise the effectiveness of ML and NLP to uncover complex data patterns.

In the *report generation phase*, natural language generation (NLG) is recommended to translate insights from analysis and pattern recognition into automated, easily understandable reports. NLG can convert complex insights, data and patterns from projects into text form. These reports can be customised to the specific needs of the organisation. NLG translates machine actions into language that is comprehensible for humans, which is crucial to effectively communicate analysis results (Paschen, Kietzmann and Kietzmann, 2019).

In the *storage phase*, the implementation of a knowledge database is recommended. This database serves to store all lessons learned and systematically categorise them. Equipped with an intelligent search function, the knowledge base provides users with quick access to relevant information. Hilger and Wahl (2022) emphasise the benefits of intelligent search functions.

Alternatively, the proposed concept to document lessons learned and best practices can be implemented effectively in a chatbot. The conversational mode can increase user-friendliness and enhance employees' willingness to interact with the system (Jarrahi et al., 2023). Interestingly, ChatGPT already provides the capability to develop custom chatbots. This makes it a valuable resource to implement this concept. However, the use of ChatGPT must comply with the data protection requirements and regulations of the organisation.

4.5 Changes in KM Through AI: The Sixth Generation of KM

The examples in Section 4.3 illustrate various AI technologies and their applications within KM processes, emphasising the diversity and rapid development of AI in this field. These advancements illustrate the dual potential of AI: it can support individual KM processes and create synergies as part of a comprehensive system to improve overall efficiency. AI technologies offer tailored solutions that streamline traditional KM approaches and enhance process effectiveness.

A critical review of the literature reveals that most studies concentrate on specific KM aspects rather than the entire process. However, this review confirms the versatile applicability of AI technologies across seven KM building blocks, thereby broadening the understanding of its potential in KM. The comprehensive integration of AI could unlock new perspectives and possibilities. The current analysis highlights the deployment of NLP and chatbots across five building blocks, which serves to illustrate their flexibility, central role and transformative impact in modern KM. This trend highlights the need for organisations to invest in these technologies and adapt their strategies accordingly.

As introduced in the initial chapter, Bencsik's (2021) study provides a foundation to explore the changes in KM due to AI. Bencsik's analysis of the historical evolution of KM over five generations provides a contextual framework to forecast the next generation of KM. To address the research gap presented in the introduction (Chapter 1), the sixth generation of KM required an examination of both *evolutionary* and *revolutionary* approaches. At first glance, the integration of AI into existing KM systems appears to be *evolutionary*, as it often supports established KM processes. However, a more detailed examination reveals that AI has the potential to achieve a *revolutionary* level of advancement. The capabilities presented in Section 4.3 – including generative models and technologies such as ChatGPT – demonstrate that AI can drive KM beyond traditional support functions to generate and process knowledge in unprecedented ways. AI technologies that go beyond pure support functions – such as the automatic generation of knowledge from large databases and the development of self-learning, adaptive systems – allow for a fundamental redesign of KM processes. Therefore, AI opens up a wide range of innovative applications. These range from the enhancement of the interaction and learning experience to the promotion of creativity and the support of complex decision-making processes. Such technologies extend far beyond mere integration into existing systems and revolutionise the way knowledge is created, distributed, used and preserved.

This study suggests that the sixth generation of KM, as envisioned by Bencsik (2021), may indeed follow a revolutionary path. The integration of AI into KM represents a strategic reorientation towards the development of integrated and intelligent KM.

4.6 Impact of Chatbots on KM Building Blocks

This study highlights the use of chatbots in five KM processes, as detailed in Table 2. Chatbots contribute to improvements in efficiency and in the promotion of innovation in organisations. The focus of this section is to identify which KM building block is most affected by chatbots. This can be achieved through the analysis of the concept matrix presented in Table 2. The concept matrix analysis reveals that chatbots significantly impact the *knowledge use* process, with four visual “X” marks. The area of *knowledge distribution* also shows notable integration, with three marks. There are two marks for *knowledge development* and one mark each for *knowledge acquisition* and *measurement*. This indicates a smaller but present influence.

In summary, the concept matrix confirms the transformative role of chatbots, particularly in the process of *knowledge use*. Their broad applicability underscores their potential to enhance various KM processes, as discussed in Subsections 4.3.5 and 4.3.6. This study highlights the importance of the integration of chatbots into KM processes in order to realise their full potential for efficiency improvement and innovation.

5. Conclusion

The integration of AI in KM enables organisations to access the required knowledge for more efficient decision-making. AI has the potential to significantly increase efficiency while augmenting human tasks. The sixth generation of KM appears to be a *revolutionary* approach to the transformative impact of AI technologies. It is characterised by the deep applicability and the extension of AI in KM beyond the pure support functions. This integration not only redefines traditional KM processes, but also significantly enhances the use of knowledge in ways never before imagined. This systematic review aims to be a valuable resource for scholars and practitioners. It provides insights into the opportunities associated with AI technologies and their symbiotic relationship with KM processes. The result showed that the most frequent AI technologies include NLP and chatbots. These technologies proved crucial in five identified building blocks in the literature. The results also indicated a significant relationship between *knowledge use* and chatbots. This improvement leads to a more dynamic and efficient use of knowledge.

This research has successfully achieved its intended objectives to explore the integration of AI technologies in KM processes. However, several limitations must be acknowledged and addressed. The focus on the eight specific databases may have inadvertently excluded potentially valuable publications. Additionally, the selection of search terms may have influenced the study's scope. Future studies could refine these parameters for broader inclusivity and precision. Furthermore, the focus on literature from 2019 to 2023 may have overlooked earlier foundational research in AI and KM.

This study identifies avenues for future research to improve our understanding and application of AI in KM. There is a notable gap in the use of AI to define and formulate *knowledge goals*. This suggests the need for further research into how AI could support or augment the human judgement required to set organisational goals. Additionally, future research should focus to evaluate the efficiency of specific AI technologies in real-world KM contexts. The effective exploitation of the transformative potential of AI will be crucial. Organisations seek to revolutionise knowledge processes and take advantage of ongoing technological advances.

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