A Systematic Literature Review of the Use Cases of Generative Artificial Intelligence in Organisational Knowledge Management

Markus Makkonen[1,*,†], Krista Sorri[1,†] and Jussi Myllärniemi[1,†]

[1] *Tampere University, Korkeakoulunkatu 1, FI-33720 Tampere, Finland*

Abstract

Organisational knowledge management can be considered a highly socio-technical phenomenon, and during the past few decades, it has undergone drastic changes, initially driven by digitalisation and digital transformation and more recently by artificial intelligence (AI) in general and generative artificial intelligence (GenAI) in particular. The use of GenAI in organisational knowledge management has the potential to provide many benefits but also many challenges for the organisations using it, making it critical to better understand its concrete use cases in organisations. In this study, we aim to promote this understanding by conducting a systematic literature review of the concrete use cases of GenAI in organisational knowledge management and their associated benefits and challenges by focusing on two particular knowledge management sub-processes: knowledge capture and knowledge access/retrieval. By screening 674 papers published by mid-2025, we find 29 publications that fulfil our screening criteria and are included in our review. Most of these focus on the use of GenAI in both knowledge capture and knowledge access/retrieval or only in knowledge access/retrieval, with fewer publications focusing on the use of GenAI only in knowledge capture. Most of the publications also approach the use cases and their associated benefits and challenges from a relatively narrow technical perspective, thus raising the call for future studies adopting a broader socio-technical perspective.

Keywords

generative artificial intelligence, organisational knowledge management, use cases, benefits, challenges, systematic literature review

1. Introduction

Organisational knowledge management can be considered a phenomenon that is highly socio-technical, as successful knowledge management in organisations requires the alignment of both various technical factors (e.g., technology, processes, and tasks) and various social factors (e.g., people, structures, and culture) associated with it [1–3]. Thus, it is not surprising that socio-technicality in general [1, 2, 4], and the social-technical systems (STS) theory in particular [3],

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* Corresponding author.

† These authors contributed equally.

markus.makkonen@tuni.fi (M. Makkonen); krista.sorri@tuni.fi (K.Sorri); jussi.myllarniemi@tuni.fi (J. Myllärniemi)

0000-0002-1553-211X (M. Makkonen); 0000-0003-0062-8677 (K.Sorri); 0000-0002-2846-0426 (J. Myllärniemi)

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have commonly been applied as a theoretical lens to study organisational knowledge management and its success in organisations. One well-known example of this is the integrated socio-technical knowledge management model by Handzic [2], which suggests that various socio-technical knowledge enablers (e.g., organisational leadership, organisational culture, knowledge measurement, and information technology) facilitate the knowledge management processes of organisations and are, therefore, critical for the management of various knowledge stocks in organisations (covering both explicit and tacit knowledge) and for the overall fostering of organisational knowledge.

However, during the past few decades, organisational knowledge management has undergone drastic changes, initially driven by digitalisation and digital transformation [5–6] and more recently by artificial intelligence (AI) in general [7–8] and generative artificial intelligence (GenAI) in particular [9]. For example, in their recent editorial for the Journal of the Association for Information Systems, which is one of the flagship journals in information systems (IS), Alavi et al. [9] suggested that the use of GenAI has the potential to have a significant impact on all four organisational knowledge management processes identified in the classic framework by Alavi and Leidner [10] (i.e., knowledge creation, knowledge storage/retrieval, knowledge transfer, and knowledge application), thus potentially providing many benefits but also many challenges for the organisations using it. The actualisation of these potential benefits and challenges is influenced by the concrete use cases of GenAI in organisations, which we define as concrete deployments of GenAI in real-world organisational environments for a particular purpose [11]. These use cases typically emerge and evolve through the continuous and reciprocal interaction between the technical and social components of a particular socio-technical system [12], with the fit, harmony, and joint optimisation of these two interdependent components influencing how well that system helps to achieve both its more specific instrumental objectives (e.g., improving the performance of the various organisational knowledge management processes) and its more general humanistic objectives (e.g., improving job satisfaction and the quality of work life) [13]. That is why, in order to comprehensively understand the potential benefits and challenges of using GenAI in organisational knowledge management, we must first understand its concrete use cases in organisations.

Regrettably, our current understanding of the concrete use cases of GenAI in organisational knowledge management remains very limited. For example, although a few prior literature review studies [14–18] have focused on the use of GenAI in organisational knowledge management in general, none of them has focused specifically on the concrete use cases of GenAI in organisational knowledge management or their associated benefits and challenges. To address this gap, this study conducts a systematic literature review focusing on these use cases in the case of the *knowledge storage/retrieval* process of the classic framework by Alavi and Leidner [10], and more specifically in the case of two of its sub-processes: *knowledge capture* and *knowledge access/retrieval*. Of these, the knowledge capture sub-process focuses more on the storage aspect of Alavi's and Leidner's knowledge storage/retrieval process in terms of identifying, evaluating, selecting, and codifying knowledge so that it can be stored (e.g., transforming tacit knowledge into explicit knowledge) [9–10, 19–20]. Typically, it focuses on existing knowledge instead of new knowledge, thus separating it from Alavi's and Leidner's knowledge creation process [20]. In contrast, the knowledge access/retrieval sub-process focuses more on the retrieval aspect of Alavi's and Leidner's knowledge storage/retrieval process in terms of making the stored knowledge available to users and acquiring it for them to use [9–10]. In prior

literature, such as [21], the terms "knowledge access" and "knowledge retrieval" have typically been used somewhat interchangeably, which is why we also use the term "knowledge access/retrieval" for this sub-process.

Both these sub-processes can be considered highly technology-intensive, which is why information technology (IT) in general [10] and both AI and GenAI in particular [9, 22–23] have been suggested to possess significant potential to impact them, thus making them an ideal focus for our conducted systematic literature review on the concrete use cases of GenAI in organisational knowledge management and their associated benefits and challenges. However, despite being highly technology-intensive, both these sub-processes can also be considered highly socio-technical in terms of that the associated benefits and challenges are not determined only by technology but influenced by the interaction of both the technical and the social components of a socio-technical system [13]. For example, instead of paying attention only to the technical quality of the captured knowledge or to the technical performance of the system when accessing/retrieving this knowledge, it is also critical to pay attention to whether this knowledge is actually useful for a particular task performed by a particular user in a particular context. Thus, in summary, this systematic literature review aims to answer the following two research questions: (1) *what are the most common concrete use cases of GenAI in the knowledge capture and knowledge access/retrieval sub-processes of organisational knowledge management* and (2) *what kind of benefits and challenges are associated with these use cases*?

2. Methodology

To answer the aforementioned two research questions, we conducted a systematic literature review by following the Preferred Reporting Items for Systematic reviews, and Meta-Analyses (PRISMA) guidelines [24]. By a systematic literature review, in this study, we refer to an evidence-based research methodology in which the prior, relevant, and high-quality literature on a selected topic is synthesised [25–26]. We selected Google Scholar (https://scholar.google.com) as the search engine for the conducted systematic literature review. When using it, citations and patents were excluded because we wanted to focus only on academic journal and conference publications.

After assessing nine alternative search strings (e.g., we did not first include "large language models" and "LLM" in the search string, but later decided to do this in order to not exclude relevant publications), the following search string was selected to be used to conduct the systematic literature review: *("generative artificial intelligence" OR "generative AI" OR GenAI OR "large language models" OR LLM) AND ("knowledge capture" OR "knowledge access" OR "knowledge retrieval") AND "use case" AND (benefit OR challenge)*. The search string was derived directly from the keywords of the two research questions of the paper without much variation in the used search words and search phrases. This allowed us to maintain the scope of the conducted systematic literature review as focused as possible, which was required due to the high number of resulting publications. However, we acknowledge the trade-off of this approach in terms of potentially excluding some relevant publications that should have been included, and this limitation and its implications is discussed in more detail in Section 5.

The search was conducted on 15 May 2025 and resulted in a total of 674 publications. The metadata of these publications (e.g., the titles and authors of the publications, the publication times, and the links to the publications) was systematically extracted by using Google Scholar

Scraper [27]. This scraper was selected from one of the most well-known commercial platforms (Apify) to ensure the quality of this process. For example, the used scraper extracted the metadata via the Google Scholar API, which makes the process replicable with no risk of hallucinations, which would be the case if using many modern tools relying on the use of large language models (LLMs). This metadata was then uploaded to Covidence (https://www.covidence.org), which is a web-based tool for conducting systematic literature reviews. Covidence identified five duplicates and excluded them. After this, a screening process consisting of two screening rounds was conducted.

In the first screening round, the titles and abstracts of the remaining 669 publications were independently reviewed by two researchers each, resulting in the exclusion of 511 publications. In the second screening round, the full texts of the remaining 158 publications were similarly independently reviewed by two researchers each, resulting in the exclusion of 129 publications. The inclusion and exclusion criteria used in both screening rounds were the same, so we included academic journal and conference publications, but excluded books, book chapters, theses (bachelor's, master's, and doctoral), reports, preprints, other systematic literature reviews, and publications for which the full text was not available or which were out of scope in terms of not focusing on one or more concrete use cases of GenAI in the knowledge capture or knowledge access/retrieval sub-processes of organisational knowledge management. Here, the assessment of the out-of-scope criterion was based on the definitions for the concrete use cases as well as the knowledge capture or knowledge access/retrieval sub-processes presented in the introduction. No quality assessment of the publications in terms of, for example, journal or conference rankings was used as the inclusion or exclusion criteria, as we did not want to determine the quality of the publication based on the journal or conference in which it was published. In both screening rounds, if the two researchers disagreed on including or excluding a particular publication, a third researcher was used to determine its inclusion or exclusion. As a result of the screening process, 29 publications were included in the review. Finally, these publications were each re-read by one of the three researchers, who each independently coded them in terms of four code categories: (1) the concrete use case of GenAI in organisational knowledge management presented in the publication, (2) the knowledge (sub)-process(es) associated with this use case, (3) the benefit(s) associated with this use case, and (4) the challenge(s) associated with this use case. The coded information was then extracted and consolidated into a table managed in Microsoft Excel, in which each column corresponded to one of the four code categories. An abbreviated version of this table (to make it more suitable for publication) is presented in Appendix B, and it was used for answering the two research questions presented in the introduction. The entire PRISMA process is illustrated in Figure 1.

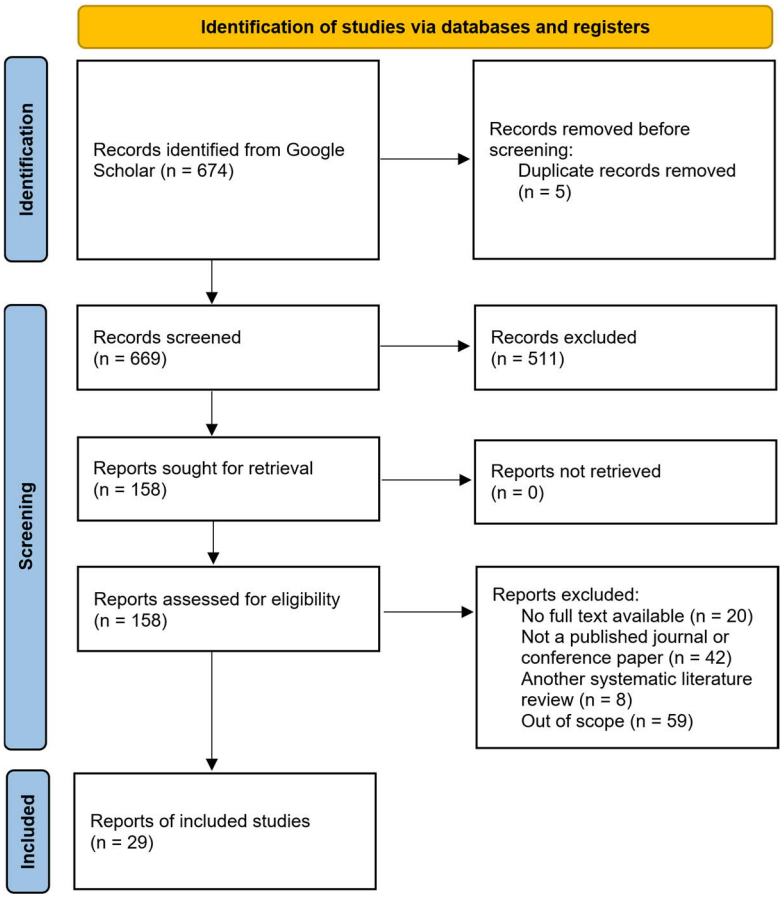


Figure 1: Illustration of the PRISMA process.

3. Results

The full bibliographical information of the included 29 publications (which are referred to as [A1–A29] in the paper) is reported in Appendix A. In turn, the summary of the included 29 publications in terms of the presented concrete use case of GenAI in organisational knowledge management, whether the use case was associated with the knowledge capture (KC) and/or knowledge access/retrieval (KA/R) sub-process, as well as the benefits (B) and challenges (C) associated with the use case is reported in Appendix B. Of the publications, 17 (59%) were journal publications and 12 (41%) were conference publications. In terms of context, 12 (41%) of the publications focused on IT and data, four (14%) on manufacturing, three (10%) on education, two (7%) on health and medicine, two (7%) on media, two (7%) on telecommunications, one (3%) in government, one (3%) in law, one (3%) in energy, and one (3%) in transportation. The presented use cases were very varied, with most of the publications approaching them from a relatively narrow technical perspective and only a few adopting a broader socio-technical perspective. Some of the best examples of the latter publications are [A7], [A16], [A22], and [A26].

In terms of organisational knowledge management sub-processes, 14 (48%) of the publications focused on the use of GenAI in both knowledge capture and knowledge access/retrieval, two (7%) only in knowledge capture, and 13 (45%) only in knowledge access/retrieval. Thus, in total, 16 (55%) of the publications focused on the use of GenAI in knowledge capture, whereas

27 (93%) of the publications focused on the use of GenAI in knowledge access/retrieval, making knowledge access/retrieval a clearly far more common organisational knowledge management sub-process to be targeted with GenAI in comparison to knowledge capture.

In terms of the benefits and challenges associated with the use cases, most publications mentioned both multiple benefits and multiple challenges, with only eight (28%) publications mentioning no challenges and two publications (7%) mentioning no benefits. The most commonly mentioned benefits were improvements in various personal-level and organisational-level outcomes (e.g., performance, productivity, efficiency, effectiveness, quality, accuracy, truthfulness, engagement, personalisation, adaptability, accessibility, creativity, and learning), increased work automation, decreased manual work, as well as the availability of features and functionalities that were not previously available. In turn, the most commonly mentioned challenges were the risks of hallucinations and biases, privacy and security risks, high computational requirements, high requirements for the amount and quality of data, integration with prior systems, the need for solution-specific fine-tuning, the need to have a human in the loop (especially if there is more complexity or exceptions involved), the lack of explainability, and fitting the technical solutions with the user and organisational needs. These benefits and challenges suggest some interesting paradoxical tensions. For example, whereas the use of GenAI in organisational knowledge management may introduce improvements in the accuracy, truthfulness, and accessibility of knowledge, it may also simultaneously introduce the risks of hallucinations and biases, which may require retaining a human in the loop to mitigate them.

4. Discussion and conclusion

In this study, we conducted a systematic literature review of the concrete use cases of GenAI in organisational knowledge management and their associated benefits and challenges by focusing on these in the case of the knowledge capture and knowledge access/retrieval sub-processes that belong to the broader knowledge storage/retrieval process identified the classic framework by Alavi and Leidner [10]. Our aim was to answer two research questions: (1) what are the most common concrete use cases of GenAI in the knowledge capture and knowledge access/retrieval sub-processes of organisational knowledge management and (2) what kind of benefits and challenges are associated with these use cases?

In terms of the first research question, we found a wide variety in the use cases of GenAI in organisational knowledge management, with most of the use cases focusing on either both knowledge capture and knowledge access/retrieval or only knowledge access/retrieval, but very few use cases focusing on only knowledge capture. We also found that in most of the reviewed publications, the use cases and their associated benefits and challenges were approached from a relatively narrow technical perspective instead of a broader socio-technical perspective that would focus on both the technical and the social components of a socio-technical system. This can be considered a clear gap in the current research on the use of GenAI in organisational knowledge management and raises the call for future research with a broader socio-technical instead of a narrow technical focus. Addressing this call would aid future research to better align with the key message of Sommerville [28] in his keynote at the inaugural STPIS workshop in 2015, which was that designing software and systems, especially for widespread adoption, is not about the technology but about the interaction of the technical and social components of a socio-technical system. Similarly, addressing this call would aid especially future information

systems (IS) research to better align with its characteristic axis of cohesion, which is suggested to be the socio-technical perspective [13]. Some examples of the ways for future research to achieve alignment in practice could be to transition from the traditional systems and software engineering approaches to the more holistic socio-technical systems engineering (STSE) approach proposed by Baxter and Sommerville [29] or to apply the work systems perspective (WSP) based socio-technical thinking advocated by Alter [30].

In terms of the second research question, we found the most commonly mentioned benefits associated with the use of GenAI in organisational knowledge management to be the improvements in various personal-level and organisational-level outcomes (e.g., performance, productivity, efficiency, effectiveness, quality, accuracy, truthfulness, engagement, personalisation, adaptability, accessibility, creativity, and learning), increased work automation, decreased manual work, as well as the availability of features and functionalities that were not previously available. In contrast, we found the most commonly mentioned challenges associated with the use of GenAI in organisational knowledge management to be the risks of hallucinations and biases, privacy and security risks, high computational requirements, high requirements for the amount and quality of data, integration with prior systems, the need for solution-specific fine-tuning, the need to have a human in the loop, the lack of explainability, and fitting the technical solutions with the user and organisational needs. As already mentioned above, these benefits and challenges suggest some interesting paradoxical tensions. For example, whereas the use of GenAI in organisational knowledge management may introduce improvements in the accuracy, truthfulness, and accessibility of knowledge, it may also simultaneously introduce the risks of hallucinations and biases, which may require retaining a human in the loop to mitigate them. Many of these benefits and challenges have also been highlighted in the prior literature review studies on the topic. For example, the studies by Pimentel and Véliz Palomino [14], AlMuzaini et al. [15], Nguyen et al. [16], as well as Strelau and Żukowska [17] all mention improvements in performance, productivity, efficiency, effectiveness, and competitive advantage as one of the main benefits, whereas the study by Strelau [18] mentions the risk of hallucinations and biases as one of the main challenges of using GenAI in organisational knowledge management. However, compared to these prior studies, which examined the benefits and challenges at a relatively general level, our study examines them at a much more specific level by focusing on the concrete use cases of GenAI in organisational knowledge management.

Our conducted systematic literature review study makes contributions to both research and practice. In terms of research, our study differs from the prior literature review studies on the use of GenAI in organisational knowledge management by focusing on the concrete use cases and their associated benefits and challenges. As discussed above, this enabled us to identify a clear gap in the prior literature by finding that the use cases and their associated benefits and challenges have so far been approached from a relatively narrow technical perspective instead of a broader socio-technical perspective that would focus on both the technical and the social components of a socio-technical system. In turn, in terms of practice, our study and the concrete use cases presented in it provide the organisations that are considering taking GenAI into use in organisational knowledge management with valuable reference cases that are difficult to find in both academic and industry literature due to the relative novelty of this technology and the real-world solutions based on it. The organisations can use these reference cases as inspiration for the design, development, and implementation of their own solutions by learning through

examples what kind of benefits they can potentially gain from them and what kind of challenges they must overcome in order to gain those.

5. Limitations and future research

We see this study has four main limitations that also act as the most potential paths for future research. First, in terms of organisational knowledge management processes, the conducted systematic literature review focused only on the two sub-processes (i.e., knowledge capture and knowledge access/retrieval) of the knowledge storage/retrieval process. Future research could extend this scope by focusing also on the other sub-processes of the knowledge storage/retrieval process (i.e., knowledge storage) or on other organisational knowledge management processes, such as the knowledge creation process, the knowledge transfer process, and the knowledge application process [10].

Second, in terms of the search engines used for conducting the systematic literature review, the present study used only Google Scholar instead of its other commonly used alternatives, such as Scopus or Web of Science. The advantage of Google Scholar is that it provides comprehensive coverage of multidisciplinary publications from a vast geographical area and is publisher-independent [31–33]. Recent scientometric studies have even shown Google Scholar to offer the most comprehensive coverage compared to the other commonly used alternatives [33], which can be considered good enough for it to be used alone as a search engine for conducting systematic literature reviews [34]. However, the disadvantage of Google Scholar is that its search algorithms are not transparent and may result in less static and more dynamic search results, meaning that the conducted systematic literature review may not be replicable by other researchers. We consider this limitation acceptable due to the preliminary nature of our study, but future research should address this limitation by utilising not only Google Scholar but also its other commonly used alternatives.

Third, as already mentioned in Section 2, the search string used for conducting the systematic literature review in the present study was derived directly from the keywords of the two research questions of the paper without much variation in the used search words and search phrases. This approach allowed to maintain the scope of the conducted systematic literature review as focused as possible, which was required due to the high number of resulting publications. However, the trade-off of this approach is that it may have resulted in excluding some relevant publications that should have been included, such as publications that refer to use cases with less technical terms like “applications”, “implementations”, “solutions”, “trials”, and “pilots”. We once again consider this limitation acceptable due to the preliminary nature of our study, but future research should address this limitation by revising the search string through introducing more variation in the used search words and search phrases.

Fourth, in terms of the reviewed literature, the conducted systematic literature review focused only on academic journal and conference publications, and future research could extend this scope by focusing also on other kinds of academic publications and on so-called grey literature, which can potentially provide access to even more recent use cases of GenAI in organisational knowledge management.

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Declaration on Generative AI

During the preparation of this work, the authors used Microsoft Copilot to check grammar and spelling. After using it, the authors have reviewed and edited the content as needed and take full responsibility for the content of this paper.

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A. Included publications

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B. Extracted Information from the Included Publications

Reference and use case	KC	KA /R	Benefits (B)/Challenges (C)
[A1] An approach to address the challenges posed by the rapid increase in data volumes by leveraging LLMs within GTR and GTR-T frameworks for structured and unstructured knowledge retrieval		X	**B:** adaptability to unstructured and structured data with minor refinement, accuracy and truthfulness, leveraging GenAI and in-context learning to enhance human–text interaction **C:** none mentioned
[A2] An approach that integrates multi-agent systems with GenAI to enhance information retrieval and response generation	X	X	**B:** facilitating the dynamic adaptation and enhancement of technology management processes, offering strategic insights that support informed decision-making, fostering innovation, sustaining a competitive edge in a rapidly evolving market **C:** establishing robust data connections that align with the specific requirements of technology management, ensuring access to pertinent and current information
[A3] An RAG-based automated AI assistant that can help resolve maintenance and product breakdown issues	X	X	**B:** reducing human workload in service call centres **C:** understanding only Chinese characters
[A4] A GenAINet framework in which distributed GenAI agents communicate knowledge (facts, experiences, and methods) to accomplish arbitrary tasks	X	X	**B:** improving query accuracy while reducing communication costs, completing tasks independently through collaborative reasoning without predefined communication protocols **C:** making the framework scalable in wireless networks, using too much energy
[A5] A modularised application with either a proprietary or an open-source LLM for automated document writing and a secure, self-hosted search index for knowledge retrieval	X	X	**B:** document generation quality comparable to fully online RAG pipelines, accommodation of different cost, scale, and data security preferences with different application versions **C:** none mentioned

[A6] An innovative open-source software framework designed to create AI-powered learning assistants tailored for integration into learning management systems		X	**B:** enhancing teaching methodologies, enhancing student engagement, providing personalised learning experiences, encouraging collaboration and innovation among educators, researchers, and developers, fostering a community dedicated to advancing the role of AI in education **C:** none mentioned
[A7] A system based on LLMs using RAG approaches to provide an interactive conversational interface for users interacting with lecture materials	X	X	**B:** creation of new lecture materials, support within lectures, support for students, improving or supplementing personal teaching materials **C:** system malfunctions, missing features, constraints of the system's knowledge bank, response time
[A8] Developing a context modelling method utilising LLMs and applying it in SME–agricultural cooperative which collaborates with a large number of different national and international organisations		X	**B:** enhanced organisational productivity by providing a ground for personalised digital workspaces, efficient information handling, improved knowledge management **C:** none mentioned
[A9] An intelligent enhancement model for agile concept design targeting iterative products applied in a requirement collection for further development of a mini excavator	X	X	**B:** making the design validation process more closely aligned with real-world usage scenarios, improving the feasibility and market adaptability of the design solutions **C:** acquisition and integration of multi-source heterogeneous data
[A10] Three different scenarios of integrating RAG architecture with data spaces and respective integration challenges		X	**B:** none mentioned **C:** giving LLM-generated responses with data space knowledge to users outside the data space infrastructure might be concerning, policy negotiation for DS-RAG could turn out to be complicated in practice
[A11] A coaching assistant for network operator processes based on a RAG system	X	X	**B:** local embedding models for retrieval combined with LLMs for answer generation effectively support individualised employee coaching **C:** none mentioned
[A12] Demonstrating the capability of LLMs to effectively extract data from unstructured sources		X	**B:** automating the extraction of entities from unstructured data sources, automating the data integration of entities from multiple data sources **C:** none mentioned

[A13] An innovative question answering approach designed to automate support for stakeholders (e.g., requirements engineers) during natural language requirements analysis		X	**B:** collaborative AI agents for requirements analysis, systematic question generation for enhanced detection, real-time integration of external knowledge in RAG **C:** practical and adaptable design for wider adoption
[A14] Using ChatGPT in medical schools and the performance of LLMs on medical knowledge and reasoning tasks representative of basic medical education	X		**B:** fostering critical thinking, promoting creativity, offering novel learning opportunities **C:** algorithms lack human cognition or intuition and operate within predefined bounds by basing their outputs on patterns identified from the prompt and the training data
[A15] A conceptual approach for providing a view of LLMs and their influence on the telecom industry		X	**B:** none mentioned **C:** amount of data, privacy, real-time context, behavioural alignment
[A16] A customised LLM agent that uses elements of prompt engineering, heuristic reasoning, and retrieval-augmented generation to solve tasks associated with predefined safety concepts in interaction with a system model graph		X	**B:** avoiding chain-of-thought processes derail in which the results no longer comply with a set of required rules or miss their goals, promoting the accuracy of retrieved external information via tools when the number of possible options increases **C:** none mentioned
[A17] An LLM-based Q&A system to facilitate needs-driven and self-directed learning regarding guidelines for healthcare professionals	X	X	**B:** facilitating knowledge access and preservation for health professionals and patients by giving much-needed guidance at the point of care in remote and low-resource areas **C:** improving prompting and embedding techniques, hallucinations and propagating biases and errors
[A18] Using a general-purpose LLM to distil question–answer pairs from raw sources followed by LLM fine-tuning	X	X	**B:** recalling knowledge from training, extracting insights through ontological knowledge graphs **C:** knowledge recall in which generative approaches can be combined with retrieval augmentation
[A19] An innovative application of LLMs integrated with the LangChain technology framework aimed at revolutionising customer service in the telecom sector	X	X	**B:** improved acceptance of knowledge recommendations, enhanced efficiency of customer service operations, elevated customer experience **C:** data privacy and security risks, integration with existing systems

[A20] An innovative approach using an LLM-based system for identifying technological trends in big data applications within the transportation sector	X	X	**B:** enabling informed decision-making by uncovering prevalent patterns and spotlighting the most commonly used technologies **C:** hallucinations in the outputs and the need for validation
[A21] The application of LLMs to the practical task of automating insight generation in the advertising technology sector, which is a traditionally labour-intensive area demanding substantial human effort	X	X	**B:** more efficient data analysis, processing of complex datasets, and generating actionable insights aligned with the business context **C:** careful integration into systems that combine computational power with human expertise
[A22] A conceptual framework for how design theories can be leveraged to enhance human-GenAI collaboration in creative endeavours by overcoming the fixation effect		X	**B:** shedding light on the fixation effect, defixation techniques, and the ways to enhance human-GenAI collaborations in creative endeavours **C:** questionable applicability to other GenAI tools than ChatGPT
[A23] A user-centric XAI dashboard that uses an LLM-based natural language chat to empower users, demystify AI, and promote understanding and transparency		X	**B:** making XAI more accessible to users with no previous expertise in XAI or machine learning **C:** keeping up with the rapid development of LLMs, potential biases
[A24] An interactive system built on the concept of self-consistency that helps users to assess the reliability of the responses generated by LLMs		X	**B:** helping to detect hallucinations **C:** consistency does not guarantee truthfulness, no integration of multiple language models, multiple responses, or additional sources
[A25] An AI-driven chatbot based on LLMs and RAG that provides legal assistance to citizens and helps them to understand contract law without the need for prior legal knowledge or a lawyer		X	**B:** democratisation of justice, reducing the risk of misinformation, adaptability to different countries **C:** cannot replace human expertise in more complex legal cases, no automated legal updates, no integration of multimodality, limited explainability due to the lack of explicit legal references, limited adaptability to different countries
[A26] A reference framework based on LLMs for extracting procedural specifications from unstructured technical sources and converting them into structured instructions	X	X	**B:** integrating human expertise with advanced automation technologies to reduce errors and promote process adaptability **C:** none mentioned

[A27] A study on how LLM-based AI agents and agentic workflows can help in streamlining pharma analyses, optimising clinical trial designs, and advancing precision medicine	X	X	**B:** streamlining complex processes, enhancing decision-making, speeding up research **C:** integration with prior systems, data quality and privacy, maintaining reproducibility, building trust among users and stakeholders
[A28] A method for enhancing fact-check report summarisation based on language models and entity graphs annotated with argumentation elements detected automatically by using a pre-trained language model		X	**B:** adapting the size of a fact-check report according to the preferences of fact-check consumers **C:** more annotated examples needed, need to consider fine-tuning the language model
[A29] A two-module framework for automatically generating abstracted clinical summaries from patient-doctor conversation transcripts based on fine-tuned pre-trained language models	X		**B:** automation of clinical summarisation, superior performance due to the two-module architecture **C:** performance dependent on the quality and diversity of training data, use of simulated patient-doctor conversations as evaluation data, risk of hallucinations and biases, requirement of substantial computational resources

KC = knowledge capture, KA/R = knowledge access/retrieval, B = benefits, C = challenges