Transforming Knowledge Management Using Generative AI: From Theory to Practice

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Abstract: Generative AI is revolutionizing the way people and companies create, capture and access knowledge. This study is driven by problems and new opportunities related to knowledge work. We identify, organize, and prioritize generative AI use cases for knowledge management. Our analysis of business needs and in-depth interaction with companies is the main data source used to create insights into this study. In addition to the use cases, the research highlights the challenges of using generative AI for knowledge management and existing research tasks. Creating a reusable toolkit for Generative AI-enhanced knowledge management is proposed as the next step of applied research to address the identified use cases and challenges.

1 INTRODUCTION

Businesses have long recognized the importance of leveraging internal knowledge for success, and this has led to significant investment in this area in the past few decades. While precise and quick access to business knowledge has been a priority, knowledge management (KM) remains a labor-intensive and complex challenge. Despite several tools and technological advancements, companies still struggle to locate the right information at the right time. They often need to sift through various fragmented internal knowledge sources, including document management systems, databases, note-taking tools, internal repositories, file-sharing platforms, and emails (Khan et al., 2024). Knowledge workers spend too much time on information searches or duplicate efforts by recreating existing information. This situation leads to inefficiencies, increased operational costs, and delayed project timelines.

While the sudden rise of generative AI (GenAI) was unprecedented and left many surprised, its potential to transform the field of KM was seen in the very beginning through capturing, creating, accessing, and streamlining knowledge governance processes (Murphy, 2023). Nowadays, GenAI's role in KM is also explored from an academic point of view (Alavi et al., 2024; Benbya et al., 2024; Pimentel & Veliz, 2024).

The rapid progress in NLP (NLP), particularly through Large Language Models (LLMs), provides businesses with innovative methods to interact with vast amounts of structured and unstructured data. GenAI models enable users to engage with data through conversational interfaces, asking long-tail queries in natural language and receiving precise answers from large document sets. This has steered the current research to existing KM problems and new opportunities related to the way businesses create, capture, and access knowledge. GenAI showed potential to increase the productivity of knowledge work in various areas. For example, according to the US National Bureau of Economic Research, GenAI systems can increase productivity by 14% on average (as measured by issues resolved per hour), and by 34% for novice and low-skilled workers (Brynjolfsson et al, 2023).

Despite GenAI's immense potential, businesses face significant challenges in adopting GenAI for KM. These challenges are caused by a lack of knowledge and technical skills in the rapidly moving field of GenAI. While businesses recognize the potential of GenAI to empower employees and

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enhance customer experience, the diverse range of GenAI solutions and the complexity of AI integration based on business size and type present significant challenges. Businesses struggle to leverage AI effectively due to concerns over data privacy, confidentiality, operations transparency, and the accuracy of GenAI solutions. While several existing GenAI solutions, such as Microsoft Co-pilot, attempt to address the challenge of precise knowledge access across scattered business documents, they often fall short in providing a tailored, customized, and holistic approach that meets modern businesses' unique and rapidly evolving needs. These solutions typically offer broad functionalities but lack the specificity required to handle the nuanced and domain-specific KM needs of businesses.

In addition to these issues, businesses also face difficulties in developing and deploying complex GenAI solutions due to a lack of expertise and uncertainty about the appropriate level of AI integration. While they see the substantial potential of GenAI, they are often indecisive and/or lack the necessary resources to implement these technologies effectively. This gap results in underutilized data, inefficiencies, and missed opportunities for leveraging information to drive business growth and innovation

Despite the growing potential of GenAI for business, its right application remains a challenge. The use of GenAI can even reduce productivity if applied incorrectly or to inappropriate tasks (Dell'Acqua et al, 2023). To obtain benefits from the application of GenAI and mitigate the respective risks, businesses must navigate a complex landscape of technologies and best practices for their implementation. The selection, integration, and deployment of specific GenAI technologies vary based on use cases, industry, the company’s AI readiness, integration levels, company-specific knowledge access needs, and several other critical issues.

To develop a GenAI-enhanced KM solution, we performed a structured study in this paper, which analyzes the KM requirements of businesses and identifies the most relevant use cases. Subsequently, we investigate the development of a GenAI-KM toolkit that can be used to address these use-cases. We performed this study in collaboration with several companies and research institutes using a co-creation approach in which the companies underwent a detailed need analysis process. The research questions investigated in this study are as follows:

RQ1. How GenAI can transform KM? What are the GenAI use cases for KM?
RQ2. What are the challenges of using GenAI for KM, and how can they be addressed?
RQ3. What are the research tasks associated with applying GenAI for KM?
RQ4. How to develop GenAI-enhanced KM solutions?

The remainder of this paper is structured as follows: Section 2 explores how GenAI can transform KM by identifying, organising and prioritising corresponding use cases. This section combines theory-enhanced with industry-focused perspectives, data collection, analysis, and synthesis process are disclosed in the methodology part of section 2. Section 3 explores the challenges of using GenAI in KM and, specifically, in tackling the identified use cases. Section 4 outlines key research topics that must be addressed for effective implementation. Section 5 discusses a reusable GenAI toolkit as a potential practical solution. Section 6 concludes the paper with future work.

2 GENAI-BASED USE CASES FOR KNOWLEDGE MANAGEMENT

2.1 Research Methodology

To define, organize, and prioritize GenAI use cases for KM, we followed 3 steps (see Fig. 1).

Step 1: The research presented in this study is driven by our experience in AI and KM by observing the needs and requirements of companies. The AI needs analysis and consultancy offered by Haaga-Helia University of Applied Sciences to 60+ companies as part of the Finnish AI Region (FAIR) EDIH project[1] shed light on the existing opportunities of GenAI for businesses and also revealed several challenges that companies face in adopting GenAI solutions. Then it became clear that addressing these challenges necessitates a comprehensive study both from academic and industry perspectives.

Step 2: We identified and organized GenAI use cases based on the literature review. The result was an organized list of generic GenAI use cases (knowledge services). Since a dialogue with businesses is needed to define the specific use cases, the generic use cases were associated with specific

[1] https://www.fairedih.fi

use cases from various application areas (sales and marketing, customer service, etc.).

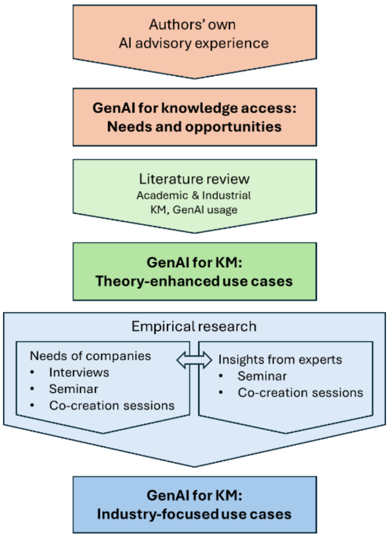

Figure 1: Methodology adopted to identify, organize, and prioritize the GenAI use cases for KM.

Step 3: The third step aimed to elaborate the original description of GenAI use cases for KM via empirical analysis of companies' needs and prioritize them. The main questions in this step included: "*What are the most needed GenAI-based knowledge services, and how to formulate them in a business-understandable way*?". Interaction with companies using different data collection and co-creation methods was the main approach here. Experts (e.g. from consulting) were also involved here to extend the list of generic use cases and define the most/least popular ones.

2.2 Theory-Enhanced List of Use Cases

The description of GenAI's role in knowledge management was inspired and based on the work of Alavi et al (2024), where the authors examined how GenAI impacts the processes of knowledge creation, storage, transfer, and application, highlighting both the opportunities and challenges this technology presents. Various academic papers, research reports and business articles, such as (Murphy, 2023), were used to synthesize the list of use cases.

Since the aim was to specify KM-related business needs in a way that would help to design and develop GenAI-based solutions, we decided to formulate the role of GenAI in KM in the form of knowledge services (Maier et al., 2009) arranged around knowledge processes. Such a service-based approach helps business users easily understand the functionality of KM solutions and gives IT specialists an understanding of what information systems should do. We named these GenAI-based services as generic ones to differentiate them from specific ones in various domains (content synthesis services vs. customer proposal generation). Such generic services allow us to see similarities across application domains and create reusable solutions that can be used in various application areas. These knowledge services correspond to activities, behaviors, or means supporting knowledge conveyance and transformation processes in ISO 30401:2018 (Kudryavtsev, Sadykova, 2019; Carlucci et al, 2022). The theory-enhanced GenAI-based services (use cases) for the main knowledge processes:

Knowledge Creation Services (Use Cases)

1. **Idea Generation Service:** An AI service that generates new ideas, concepts, or solutions based on the analysis of existing data, trends, and patterns. It aids in sparking creativity and innovation.
2. **Content Synthesis Service:** This service automates the synthesis of new knowledge content by integrating and reinterpreting existing information, research findings, and data analyses, generating comprehensive reports, articles, or research papers.
3. **Learning and Reflection aid Service:** This service provides contextual examples and in-depth explanations that help in understanding complex concepts, fostering a deeper level of creativity and innovation.

Knowledge Capture and Organization Services (Use Cases)

1. **Knowledge Capture Service:** This service helps knowledge workers to externalize their knowledge in the most convenient and easy way (e.g. by making notes, voice recording, or screencast) and convert this information into a suitable format for further processing (e.g. by transcribing audio into text).
2. **Automated Categorization and Tagging Service:** This service uses AI to organize, tag, and categorize knowledge resources efficiently, enhancing the structure of knowledge repositories and making it easier to store vast amounts of information in a searchable and accessible manner.
3. **Knowledge Curation Service:** Proactively manages the knowledge base by identifying and archiving content that has become obsolete or less relevant, ensuring the repository stays current and valuable. Simultaneously, it highlights areas in need of fresh insights or updates, guiding the

continuous growth and evolution of organizational knowledge.

Knowledge Access Services (Use Cases)

1. **Conversational Interface (Chatbot):** This service focuses on interacting with users through a conversational interface, employing NLP to understand and respond to queries in a natural, engaging manner. It's designed to facilitate easy access to information by answering questions, providing explanations, and guiding users through complex datasets or knowledge repositories, making the process more intuitive and user-friendly
2. **Advanced/Enhanced Search Service:** This service enhances traditional search functionalities by incorporating sophisticated NLP algorithms. It allows users to input search queries in their own words, including complex questions and conversational phrases, and employs AI to interpret these queries accurately. The service searches through extensive databases and knowledge repositories to find precise, relevant answers and information, significantly improving the efficiency and effectiveness of knowledge retrieval.
3. **Personalized Knowledge Feed Service (Tailoring knowledge):** Delivers customized knowledge recommendations to users based on their roles, interests, and past interactions, ensuring they receive the most relevant and timely information.
4. **Expert Search and Recommendation:** Utilizes AI to quickly identify and recommend experts within the organization based on specific queries or project needs. By analyzing employees' contributions, skills, and historical project involvement, this service facilitates efficient collaboration and knowledge sharing among team members.

Domain-specific examples complemented the synthesized list of generic GenAI-based services (use cases), as they were necessary for communicating with companies. This level of generalisation is much more apparent to them.

2.3 Data Collection, Analysis and Co-Creation

The main focus of the research was on step 3, especially the analysis of business needs. 20+ companies from different sectors participated in interviews. In addition to interviews, we organized an awareness-raising seminar in May 2024 in Helsinki, Finland – "Generative AI-Enhanced Knowledge Management in Business". Within this seminar, we presented our vision of GenAI use cases for KM and collected feedback from participants (representatives of various companies), including their own use cases. The panel discussion was a part of this seminar and included AI and KM experts from the industry. This discussion helped to extend the list of GenAI use cases for KM and organize them. The summary of the panel discussion was published in the article (Khan, Kudryavtsev, 2024). 20+ onsite participants and 20+ online participants attended the seminar.

The most detailed analysis, description, and prioritization of the use cases were done together with 6 Finnish companies that participated in co-creation sessions: Company 1: ~60 persons, electric/automation/energy; Company 2: ~120 persons, demolition & hazard. material removal; Company 3: ~10 persons, IT/software development/automation; Company 4: ~360 persons, metal manufacturing; Company 5: ~740 persons, IT/Accounting/HR; Company 6: ~10 persons, healthcare.

They facilitated in-depth need analysis by providing detailed information about their processes, challenges, and expectations.

Simultaneously, we contacted research organizations specialising in KM, GenAI, NLP, and other relevant fields to incorporate cutting-edge insights and methodologies into the analysis of use cases and corresponding challenges. The University of Helsinki and Tampere University expressed strong interest in the study and contributed their in-depth expertise in LLMs and KM. Co-creation with these academic partners provided additional perspective during the formulation of use cases.

2.4 Industry-Focused Prioritized List of Use-Cases

The results of the elaboration and prioritization of use cases are presented in Table 1.

The three most needed generic use cases were defined:

1. AI assistance for talking to the company's data and systems ("ChatGPT" for the company's own documents/data) *to support the knowledge access process;*

2. Report and document creation assistance (project reports, business proposals/offers) *to support the knowledge creation process.*

3. Speech-to-structured document conversion *to support the knowledge capture process.*

These generic use cases generalize company-specific use cases.

Table 1: The industry-focused prioritized list of the most needed GenAI use cases for KM.

Knowledge process	Generic use cases	Company-specific use cases
Knowledge access	1. AI assistance for talking to the company's data and systems ("ChatGPT" for the company's own documents/data)	• Flexible chatbot-type search functionality for a collection of company-specific manuals and documentation • Conversational agent for dental video learning content • GenAI-based assistant on top of the existing scheduling/optimization software (platform).
Knowledge creation	2. Report and document creation assistance (project reports, business proposals/offers)	• Sales order generation assistant • Reports generation assistant • Customer proposal/quotation generation assistant, including the proposal generation assistant for renewable energy systems • Write summary reports from project data (could be of multiple types, e.g., incidents or overall view) • Generate easy-to-read summaries of projects for customers (instead of complex tables and diagrams) • Verbal interpretation of financial reports using a wide range of language models
Knowledge capture	3. Speech to structured documents conversion	• Automated incident reporting and analysis for safety and operational transparency to generate reports based on predefined templates and even interact with systems via text or phone calls to create reports • Extraction of Finnish transcripts from video learning content and their precise translations into English and Scandinavian languages • Generate diaries from speech without typing

3 THE CHALLENGES OF USING GENAI FOR KM AND HOW TO TACKLE THEM

To understand the challenges of implementing the identified use cases, we have combined a literature review with an empirical qualitative approach – the panel discussion with AI and KM experts (Khan, Kudryavtsev, 2024). We learned that companies face various challenges when transitioning to generative AI-based systems for KM. These are both technical and related to practical and management work. GenAI systems, which rely on probabilistic models rather than rule-based processes, differ fundamentally from traditional knowledge systems, leading to potential compatibility issues during integration. LLMs' ability to process and understand vast amounts of information makes them suitable for tasks closely aligned with knowledge management principles, but these models are also less predictable. One of the primary challenges lies in aligning these dynamic AI-driven models with existing knowledge infrastructure, which is often structured and based on pre-defined rules. This paradigm shift requires organisations to rethink their entire KM infrastructure, which can involve costly overhauls of content management systems and staff retraining. Generative AI solutions also differ from traditional AI models (e.g., classification, regression, or clustering), where inputs and outputs remain well-defined, and models can be trained and owned in-house.

There are many competing technologies for implementing GenAI in organizations; however, as the technology is still emerging, the situation is different from mature technologies. The selection, integration, and implementation of the specific GenAI technologies is not straightforward and depends on the use cases, industry, company's AI readiness, and level of integration. Specialized expertise in GenAI is needed to navigate this multitude of opportunities. At the moment GenAI relies heavily on foundation models from a few major technology providers (e.g., OpenAI, Google, and Microsoft) that own the most capable models. These models must be accessed via cloud service (API) and are closed source. While open-source models are also available, they remain less capable and weaker for tasks that require state-of-the-art reasoning skills and large contextual information capacity. Companies must balance between capability, usage costs, latency, geographical availability, and data storage constraints. Particularly, SMEs have limited IT resources and AI implementation maturity, which creates a dependency on technology providers. While large organizations may have the resources to integrate GenAI into their KM systems effectively, SMEs may struggle with the costs associated with cloud-based AI services from major providers (Ghimire et al., 2024). These businesses must weigh the trade-offs between GenAI's powerful capabilities and the high costs, potential latency issues, and geographical restrictions associated with cloud-based models (Kaczorowska-Spychalska et al., 2024).

The main technical challenges are related to change management and integrating the new AI system with existing systems. This process can be complex and requires a strategic overhaul of current content management practices. The amount of content generation sources and channels is growing, and there is a need to deliver relevant content to various users at the right time and place. Companies might need to rebuild their content management systems to provide consistent and relevant content for various audiences. This rebuild is necessary to ensure that the content is up-to-date and valuable for different user groups. One of the primary challenges is the need to align the new AI capabilities with the established workflows and data structures in data infrastructure. Traditional KM systems are often designed around structured data and rule-based processes, whereas Generative AI relies on unstructured data and probabilistic models, which can lead to compatibility issues during integration. Organizations must adapt or overhaul their existing systems to ensure seamless interaction between these different paradigms. This requires extensive retraining of staff, who may be unfamiliar with the dynamic nature of AI-driven systems, resulting in potential resistance to adoption (Wu et al. 2024).

Users need to trust the responses generated by chatbots or other GenAI tools when making critical decisions. Organizations, therefore, need to implement strong validation processes and techniques such as retrieval-augmented generation (RAG) which are gaining popularity to ensure that responses are grounded in verified, organizational-specific knowledge sources (Earley, 2023). Businesses must navigate complexities related to data privacy, intellectual property, and ethical AI use when establishing governance frameworks for generative AI (Ghosh & Lakshmi, 2023). It is crucial to define clear policies regarding data access, ensuring that only authorized personnel can use AI tools and handle sensitive organizational knowledge (Ferrari, et al, 2023). A significant challenge lies in balancing innovation with compliance, as organizations must align their AI usage with global regulations like the GDPR or AI Act, particularly regarding data processing and consent management (Michael et al, 2024). Moreover, implementing robust audit trails and transparency protocols to monitor AI-generated content is essential to ensure traceability and accountability, minimizing the risks of biased or misleading outputs (Pimentel & Veliz, 2024). Continuous oversight is necessary to prevent "model drift," where AI systems gradually produce less accurate or aligned outputs over time, potentially leading to business risks (Reuel & Undheim, 2024). Finally, organisations must prioritise educating employees on the ethical implications of AI use, fostering a culture that promotes responsible AI utilization and ongoing governance adjustments to address evolving legal and technological landscapes (Earley, 2023).

The main problems with GenAI, particularly LLMs, are related to hallucination, bias, and limited real-world understanding (Naveed et al., 2023).

Ensuring the privacy of a company's information is the first and foremost concern highlighted by the companies. This requires secure mechanisms and regulatory sandboxes, as emphasized by the AI Act (European Commission, 2024) and compliance with GDPR.

Scalable methods for acquiring, transforming, and integrating diverse kinds of input data are required. Hence, incremental updates are required that can either periodically be performed in a batch-like manner or in a more dynamic, streaming-like fashion. (Hofer et al., 2024)

GenAI-based KM requires high-quality data. The difficulty of this task grows with the rising number and heterogeneity of data sources, especially if one relies on automatic data acquisition and data integration. This requires data cleaning at major steps in the construction pipeline so that the degree of dirty or wrong information entering the system is limited (Hofer et al., 2024).

Domain-specific knowledge models such as knowledge graphs (KG) hold good potential to address the limitations of LLMs (Deloitte 2023). Integrating KGs as a potential component may require constructing KGs from diverse data. LLMs are being increasingly used to construct KGs. While automated pipelines for KG construction have shown impressive performance, they are still prone to LLM's inherent limitation of hallucination and biases. At the same time, LLMs have also been found to show inferior performance for domain-specific knowledge (Ghanem et al., 2024), for instance, generating KG for a disease dataset, as they have been trained on generic datasets. These limitations can result in the omission of crucial entities and relationships, potentially leading to misinformation. Quality control measures must be used to ensure the reliability of the knowledge represented in KGs.

Feedback from domain experts is crucial to ensure the accuracy and dependability of the causal relationships within the data (Zhou et al., 2024). Cleaned and verified data can be then used in building a knowledge graph.

4 KEY RESEARCH AREAS FOR DEVELOPING A GENAI-KM SOLUTION

We identify several research topics that need to be investigated to meet the business KM requirements through a holistic GenAI-KM solution. These topics are important to explore innovative approaches, design scalable solutions, and overcome the technical and practical challenges associated with implementing GenAI in KM.

Identification of knowledge Tasks: Identifying the specific knowledge tasks that can benefit from GenAI is essential for maximizing its value in business applications. It is important to investigate where GenAI can automate or enhance these processes in a meaningful way, tailored to individual business needs.

Developing Efficient Data Pipelines for LLM Integration: The effectiveness of LLMs depends on the quality and consistency of the data they process. Building processes for the collection, preparation, and continual updating of company's structured and unstructured data will ensure that LLMs remain accurate and relevant.

Creating and Integrating Domain-Specific Knowledge Graphs with LLMs: Domain-specific KGs provide a powerful way to integrate external business knowledge into LLMs. KGs enable LLMs to respond more effectively to complex queries by discovering both semantic and syntactic relationships among data points. This integration allows businesses to leverage GenAI not only for data processing but also for discovering relationships and generating insights that would be difficult to achieve with traditional methods.

Designing Domain-Specific Architectures and Data Pipelines for LLMs: Domain-specific architectures and data pipelines ensure that LLMs are optimized for particular business environments. Efficient designs allow for the processing of domain-relevant data which may lead to faster and more accurate knowledge management solutions. By focusing on tailored architectures, businesses can ensure that their GenAI implementations meet their unique operational needs.

Ensuring System Scalability, Explainability, Traceability, and Accuracy: To maintain trust and effectiveness, GenAI systems must be scalable, explainable, and accurate. Developing methods to ensure that these systems can grow alongside the business while remaining transparent and traceable, is crucial.

Regulatory and Ethical Compliance of KG-LLM Systems: As businesses adopt GenAI systems, compliance with regulatory frameworks and ethical standards becomes a key consideration. Ensuring that GenAI integrations align with data privacy laws, security standards, and ethical guidelines is important for maintaining trust and preventing misuse. It is important to find the right balance between innovation and responsibility to ensure that GenAI solutions are used in an ethical and legally compliant manner.

5 MAKING GENAI-ENHANCED KM A REALITY

Through our rigorous analysis of modern KM requirements by the businesses and the underlying challenges, we propose developing a GenAI-enhanced toolkit to improve the three knowledge processes: how companies create, synthesize, and access critical business knowledge.

This toolkit can provide several smart services for both internal business processes and the enhancement of the customer experience. It can enable companies and technology providers to develop easy-to-deploy knowledge management solutions using business data. The toolkit's main, user-friendly components include:

- o Software components: customized products, code library,
- o Method components: guidelines, process models, templates,
- o Content components: reusable knowledge models.

From the technology perspective, we are considering advanced RAG combined with a knowledge graph (GraphRAG). However, we plan to assess the need for these technologies for the selected industrial use cases (see section 2.3). Since the integration of advanced technologies should be justified for each case, therefore, the toolkit will also include a decision-making guide. This guide will help companies select when they should utilize certain technology, e.g., when to use simple RAG and when to utilize GraphRAG.

Since the companies involved in this study showed strong interest in such a toolkit, this toolkit can be tested and evaluated within the target companies. For this purpose, a working demo/prototype of GenAI tools can be created and deployed. The recommendations on how to transform them into companies' own production-grade AI services can be provided.

Developing this toolkit involves understanding and documenting the specific KM requirements of businesses to ensure the effective integration of GenAI solutions. It also requires gathering stakeholder insights to identify where GenAI could enhance knowledge processes. Building on this, an evaluation of existing GenAI technologies must be done to assess their applicability and effectiveness for identified use cases. This is also important to select the technologies that best address the KM challenges, ensuring scalability, accuracy, and adaptability.

6 CONCLUSIONS

In this study, we highlight the transformative potential of GenAI in addressing longstanding challenges in KM. We highlight the key knowledge processes: knowledge capture, access, and synthesis, that could be enhanced through GenAI and could lead to significant improvements in productivity and decision-making. In addition, this study highlighted the challenges involved in adopting GenAI, including integrating GenAI with existing KM systems, ensuring data privacy and accuracy, and overcoming technical and resource limitations. The co-creation approach with companies allowed us to identify specific business needs, highlighting the requirement of a GenAI-KM toolkit which could be used to develop company-specific use cases. This toolkit holds the promise of streamlining KM systems by offering scalable and customizable solutions for diverse business contexts.

A key insight from this research is the importance of a domain-specific approach when integrating GenAI into KM systems. Generic solutions, while useful, often fall short of addressing the unique needs of businesses. By focusing on domain-specific knowledge graphs and adaptable data pipelines, the proposed toolkit can effectively overcome the limitations of current GenAI solutions.

Future work will focus on developing the GenAI-KM toolkit, extending its application to more diverse sectors, and ensuring its scalability and other features, such as explainability and traceability, to ensure trustworthiness. Additionally, research will explore methods to enhance the toolkit's compliance with regulatory frameworks to ensure data privacy and security.

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