Chapter 1:

Prompt Engineering Literature from the Knowledge Management Perspective: A Bibliometric Analysis

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Abstract

Prompt engineering, which defines the framework of interaction with artificial intelligence (AI), is emerging as a new competency within knowledge management (KM) processes. The rapid increase in the use of AI in daily life makes the role of prompt engineering increasingly significant in KM, tacit-explicit knowledge transformation, decision support, and digital transformation processes. The aim of this study is to present the current state of the prompt engineering literature from a KM perspective and to identify gaps and future research directions in the field. In this context, a search was conducted in the Scopus database using the keywords "knowledge management" and "prompt engineering" and 213 publications were analyzed. The analysis examined such aspects as the concentration of publications across fields, their distribution by year, major trends, emerging themes, and similar aspects. The results indicate that the prompt engineering literature remains largely focused on computer science, while publications in the fields of business, management, and accounting are limited; moreover, they reveal significant opportunities for future research in areas such as ethics, practical applications, and organizational integration. This study is expected to provide a foundation for research on the use of prompt engineering in knowledge management and to serve as a basis for further studies in this domain.

Keywords: knowledge management, artificial intelligence, retrieval-augmented generation, VOSviewer, large language models

1. Introduction

Knowledge management (KM) plays a critical role in organizations' strategic decision-making processes and in gaining competitive advantage. With the acceleration of digitalization, KM processes have become increasingly complex, making the development of new competencies essential. In particular, the proliferation of big data, analytics, and artificial intelligence (AI)-supported systems has led to the emergence of diverse skills within KM. These developments enable the reshaping of knowledge-based decision processes and allow organizations to implement digital transformation strategies more effectively. Therefore, it is crucial to benefit effectively from these new developments both in KM processes—covering knowledge creation, knowledge storage, knowledge sharing, and knowledge usage—and in tacit-explicit knowledge conversion processes—covering socialization, externalization, combination, and internalization (Önaçan, 2015, pp. 269-271). In this context, the competencies emerging alongside new technologies have become key factors shaping the future of KM.

In recent years, a new technology that has come to the forefront is AI. The rapid development and wide use of AI have had clear effects on KM and knowledge conversion processes. In this development, prompt engineering has appeared as a new skill. It helps produce more accurate and context-based results from AI systems, which makes decision support and digital transformation stronger. Therefore, prompt engineering is not only a technical tool but also a strategic skill in the KM field, opening new paths for research and practice.

Since prompt engineering is a relatively new concept that defines the framework of interaction with AI, its impact on KM is becoming increasingly evident. In the literature, studies that directly address this interaction are limited. Therefore, systematically examining the role of prompt engineering in KM, tacit-explicit knowledge conversion, decision support, and digital transformation processes is an important need from

both academic and practical perspectives. This need (or gap) opens new research avenues for scholars interested in the subject. The motivation of this study is to highlight this need and to reveal the intersection points between KM and prompt engineering. The aim of this study is to present the current state of the prompt engineering literature from a KM perspective and to identify gaps and future research directions in the field. In the subsequent sections, the conceptual framework, methodology, findings and discussions are presented, and the study concludes with results and recommendations.

2. Conceptual Framework

In this section, the theoretical foundation of the study is established. For this purpose, topics such as knowledge management, artificial intelligence, the role of AI in knowledge management, prompt engineering, prompt design, and the contributions of prompt engineering to knowledge management are presented.

2.1. Knowledge Management

One of the most critical building blocks of the information age is the process of transforming raw data into strategic value. Today, the management of knowledge, recognized as a strategic power, is of great importance. The traditional understanding of KM, which emphasized the preservation and conscious transmission of knowledge across generations, has today been replaced by a modern KM approach that uses advanced information technologies to create, store, share, and use knowledge to generate organizational value, marking a transition into an era based on cloud computing, big data, and AI integration. In this context, KM is defined by Önaçan (2022, p. 136) as the processes involving employees, business processes, organizational structure, knowledge assets/content, and technology, which aim to achieve decision superiority, competitive advantage, and positive business outcomes by collecting, organizing, recording, and transforming into useful knowledge the registered or unregistered organizational data and personal knowledge and experience-based accumulations obtained from both internal and external sources of

the organization, while ensuring that the right people can access this knowledge at the right time, in the right way, and from anywhere.

2.1.1. Knowledge Management Processes

KM is not a static state; it is a cyclical and dynamic set of processes. Although KM processes have been addressed with minor variations in the literature, they generally consist of four stages: knowledge creation, knowledge storage, knowledge sharing, and knowledge usage. Knowledge creation is the transformation of data and information obtained from internal and external sources into new knowledge by combining them with existing experiences and values. Knowledge storage is the organization and preservation of knowledge in accordance with objectives for future use. Knowledge sharing is the formatting, transfer, and dissemination of created knowledge by making it accessible. Knowledge usage is the effective application of knowledge in activities such as strategy, decision-making, process improvement, and problem-solving (Önaçan, 2015, pp. 269-270).

2.1.2. SECI Model

In the literature, the SECI model, which has gained significant importance, has also been referred to as the "knowledge conversion process", "modes of knowledge creation", "forms of knowledge generation" or "tacit-explicit knowledge conversion process" and its name derives from the initials of socialization, externalization, combination, and internalization. The SECI model, developed by Nonaka and Takeuchi (1995), explains the conversion between tacit and explicit knowledge. Explicit knowledge can be coded and transferred, whereas tacit knowledge is based on individual experience and intuition. The model assumes that these two types of knowledge continuously convert into each other and spread in a spiral from the individual to the organization. This process is illustrated in Figure 1 and briefly explained below.

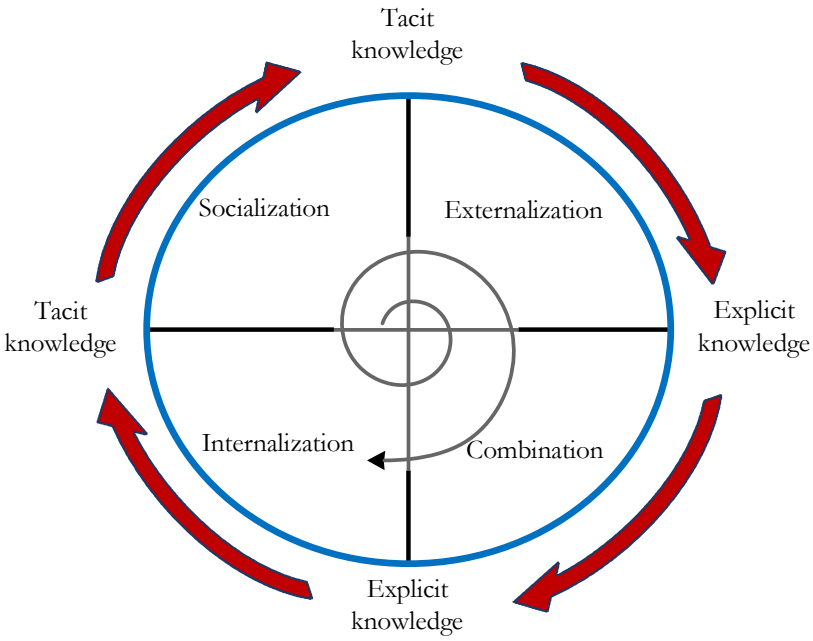


Figure 1. Tacit-explicit knowledge conversion process
Source: Adapted from Nonaka and Takeuchi (1995, p. 62)

Socialization refers to the conversion from tacit knowledge to tacit knowledge. Experience sharing and the master-apprentice relationship can be given as examples of this process. Externalization refers to the conversion from tacit knowledge to explicit knowledge. The articulation of ideas into reports, concepts, or guidelines can be given as examples of this process. Combination refers to the conversion from explicit knowledge to explicit knowledge. The synthesis of different reports and databases to create a new organizational document can be given as an example of this process. Internalization refers to the conversion from explicit knowledge to tacit knowledge. Employees reading organizational documents to develop their own mental practices and skills can be given as an example of this process. The continuous operation of this cycle is important for keeping organizational memory alive (Barreto & Abarca, 2025).

2.1.3. Benefits and Challenges of Knowledge Management

In a period when knowledge is recognized as a critical strategic resource, managing knowledge becomes inevitable. The management of knowledge provides significant benefits for organizations. Effective KM offers multidimensional benefits such as faster processes, reduced costs, increased employee motivation, the development of a learning culture, enhanced customer satisfaction, improved financial performance, and strengthened innovative capacity (Cantner et al., 2009; Figurska, 2014; North et al., 2004; Önaçan, 2015, pp. 20-21). In this respect, KM is considered one of the fundamental tools for achieving decision superiority and competitive advantage. However, KM is not an easy process and contains various challenges. Strategic misalignments, lack of qualified personnel, weak knowledge-sharing culture, organizational coordination problems, data and system errors, technological integration difficulties, security risks, and budget constraints are significant obstacles to this process (Kogi, 2025; Önaçan, 2015; Ramdani et al., 2026; Santhose & Lawrence, 2023). Therefore, while KM offers important opportunities to organizations, it is also a costly process that requires careful planning and strong support mechanisms.

2.1.4. The Role of Artificial Intelligence in Knowledge Management

AI, particularly through generative models and multimodal systems, creates a profound transformation in KM processes. Large language models (LLMs) (such as GPT-4, Claude, Gemini) and visual generation systems (such as DALL·E, Stable Diffusion, MidJourney) provide new opportunities in KM and knowledge conversion processes. Today, knowledge production is no longer solely human-centered but is increasingly shaped by hybrid processes involving human-machine interaction. This situation generates both significant opportunities and

new risks in terms of knowledge access, creation, accuracy, and organizational governance.

In the literature, the effects of AI on KM are discussed in terms of both benefits and risks (Aluçlu, 2024; Kayalı, 2026; Nakash & Bolisani, 2025; Yang, 2024; Zbuchea et al., 2019). The benefits include easier access to knowledge, more effective use of systematically documented knowledge, making tacit knowledge visible and shareable, accelerating knowledge sharing and collaboration, strengthening organizational learning and decision-making processes, transforming knowledge into a contextual and dynamic structure that increases organizational flexibility, achieving competitive advantage and agility, supporting a culture of continuous improvement, and introducing new contributions to the knowledge creation process through generative AI. On the other hand, risks such as the creation of false knowledge, cultural resistance, data privacy issues, excessive dependence on automation, difficulties in control, and epistemic uncertainty are noteworthy. Therefore, while AI is a powerful transformative actor in KM, it also necessitates the redesign of ethical and organizational control mechanisms.

2.2. Artificial Intelligence and Prompt Engineering

This section addresses AI, prompt engineering, and the ways in which prompt engineering contributes to KM.

2.2.1. Artificial Intelligence

AI is defined in various ways across different disciplines. According to McCarthy's classical definition, AI is the science and engineering of making intelligent machines, especially intelligent computer programs (Arslan, 2020, p. 76). According to the High-Level Expert Group on Artificial Intelligence (2019, p. 1), "AI refers to systems that display intelligent behavior by analyzing their environment and taking actions - with some degree of autonomy- to achieve specific goals".

The primary goal of AI is to develop machines capable of simulating complex functions unique to human intelligence, such as language processing, visual perception, problem-solving, learning, and decision-making. These systems mostly utilize machine learning methods to perform these functions, executing them in autonomous or semi-autonomous ways (Mutlu, 2024, p. 426). Its functional capabilities include perception, reasoning, learning, decision-making, and adaptation; while its technical capabilities encompass knowledge representation, problem-solving, learning algorithms, and generalization (Al-Khamees et al., 2026).

When examining the historical development, it is observed that the theoretical foundations were laid in the 1950s with Alan Turing's Computing Machinery and Intelligence article, and the field became an independent discipline with the 1956 Dartmouth Conference. In the 1970s-1980s, expert systems and symbolic AI came to the forefront; in the 1990s-2000s, machine learning gained importance with the rise of big data; and after 2010, deep learning based on multilayered artificial neural networks revolutionized fields such as natural language processing and computer vision. Today, generative AI (GenAI) is at the center of attention, while the future envisions the use of Artificial General Intelligence (AGI) (Lima, 2026).

GenAI refers to systems that learn patterns from large datasets and generate contextually appropriate outputs in response to user prompts. Built on deep learning and artificial neural networks, these models have the capacity to generate original content such as text, code, images, and audio. Their ability to produce coherent and contextual outputs based on learned patterns makes them transformative actors in KM processes (Feuerriegel et al., 2024, p. 111). AGI, which remains at the theoretical stage, refers to systems capable of learning and performing a wide range of tasks similar to human intelligence. While GenAI produces content from specific data types, AGI can generalize across contexts and has the potential to surpass human-level performance in diverse tasks. Although AGI, regarded in the literature as the ultimate goal of AI, has not yet been realized, large language models and multimodal systems are considered significant steps toward this direction (Bikkasani, 2025).

2.2.2. Machine Learning, Deep Learning and Artificial Neural Networks

Machine learning, deep learning, and artificial neural networks are complementary concepts. Machine learning enables inference from data, deep learning strengthens these inferences through multilayered algorithms, and artificial neural networks model this process with structures inspired by the human brain. To elaborate further, machine learning is an AI method that allows computers to learn from data without being explicitly programmed. The system extracts patterns from the provided data and generates predictions or decisions based on these patterns. It has subfields such as supervised, unsupervised, and reinforcement learning. This approach enhances the problem-solving capacity of AI while forming the foundation for more complex methods such as deep learning. Deep learning, a subset of machine learning, uses multilayered artificial neural networks to extract features from data. Compared to machine learning, it processes larger amounts of data in more complex ways, supporting the infrastructure of prompt engineering and LLMs (Akın & Şahin, 2024, p. 29). Artificial neural networks are mathematical models that form the basis of deep learning and are inspired by the functions of neurons in the human brain. Artificial neural networks consist of interconnected simple processing units. These units are likened to neurons in the human brain. The inputs to a neuron are first multiplied by the "weights" of the connections and then summed. The resulting sum is processed through an activation function. The activation function passes this value through a specific threshold to produce an "output". Thus, the network selects which information is important and transfers it to the next layer. Artificial neural networks process data in layers; each layer transforms the information further, ultimately producing a meaningful result (Öztürk & Şahin, 2018, pp. 27-33).

2.2.3. Large Language Models, Transformer Architecture and Natural Language Processing

Large Language Models (LLMs) are deep learning-based AI systems trained on datasets composed of extensive text corpora. LLMs are built on massive neural networks with billions of parameters and trained using vast text corpora. The learning process fundamentally relies on next-token prediction. The model, when given a context, determines the word (or token) most likely to follow by using statistical pattern recognition (Bender et al., 2021). These models learn the statistical patterns of language and perform tasks such as text generation, summarization, question answering, and information retrieval (Mienye et al., 2025). LLMs employ the transformer architecture for language modeling. The transformer uses the self-attention mechanism to establish relationships among all words in a sentence simultaneously, enabling the learning of long-range dependencies and parallel data processing. This technical infrastructure preserves context, enhances semantic accuracy, and allows LLMs to operate effectively in alignment with prompt engineering (Vaswani et al., 2017). LLMs utilize Natural Language Processing (NLP) methods to understand and generate human language. NLP is divided into two main components: Natural Language Understanding (NLU), which extracts meaning from text, and Natural Language Generation (NLG), which produces contextually appropriate responses (Jurafsky & Martin, 2026). By scaling these processes with large datasets and transformer architecture, LLMs provide a more powerful language processing capacity. This enables well-designed prompts to leverage NLU and NLG capabilities more efficiently, thereby enhancing the effectiveness of prompt engineering (Kumar, 2024).

AI uses LLMs and NLP techniques to understand human language. These LLMs process text primarily through tokenization and vector-based representation methods. In the tokenization process, text is divided into words or subunits, and each token is converted into numerical vectors that the model can learn from. AI interprets the context and meaning of text through these vectors; for example, attention mechanisms calculated based on the content of words and sentences establish relationships across

contexts. The attention mechanism enables the model to decide which tokens to focus on more, thereby concentrating on the most relevant information in the context. During this process, large datasets are used in model training, and token-based and vector-based representations are constructed on these datasets (Jurafsky & Martin, 2026; Vaswani et al., 2017). Additionally, prompts guide the model to provide specific information or answers within a given context. Through these representations, AI grasps the context and intent of the question and predicts an appropriate answer. By performing semantic similarity and meaning-level computations, it evaluates the alignment between actual and predicted answers (Reimers & Gurevych, 2019). Furthermore, threshold values and attention mechanisms enhance the contextual alignment, semantic coherence, and quality of the response to a question (Vaswani et al., 2017). Thus, AI can comprehend human language not only at a superficial level but also in terms of deeper meanings.

2.2.4. Issues Related to Artificial Intelligence

AI technologies provide significant contributions in many fields today, yet they also bring various risks. Ray (2026) categorizes these risks under hallucination, bias, privacy, security, ethics, and sustainability. Additionally, Seghid et al. (2026) highlight adversarial attacks, disinformation, socioeconomic inequalities, and environmental impacts; Pervez et al. (2026) emphasize transparency, accountability, and social impacts; while Mathews et al. (2026) underline intellectual property, legal responsibility, and regulatory gaps. These multidimensional issues necessitate the development of policies and regulations for the safe and responsible use of AI.

2.2.5. The Concept of Prompt Engineering

Interaction with AI systems occurs through prompting and prompt engineering (Schulhoff et al., 2025, p. 1). In general terms, prompt engineering refers to the process of designing, optimizing, and applying inputs (prompts) to obtain desired outputs from AI models (Şimşek, 2024). This discipline enables users to communicate effectively with AI

systems, thereby enhancing model performance and making it possible to achieve desired results (Tan et al., 2024). In other words, prompt engineering, in relation to context engineering, defines how communication with the model is established within the contextual knowledge space -specifically how inputs are expressed- and focuses on user-centered interaction design.

2.2.6. Problems Related to Prompts

Prompt design plays a critical role in ensuring the accuracy and reliability of outputs obtained from AI. The literature emphasizes that prompts can lead to various problems. Prompts written in natural language may contain ambiguity and polysemy, which increases the risk of producing incorrect outputs (Liu et al., 2023). Formal errors or missing context can result in inconsistent responses, while biases may reproduce and amplify social prejudices present in training data. In addition, malicious prompts can trigger the generation of harmful content (Fatawi et al., 2026). Excessively complex or lengthy prompts raise computational costs, leading to higher energy consumption and sustainability concerns. Therefore, prompt engineering is considered not only a technical process but also a research field that must be addressed from ethical and societal perspectives.

2.2.7. Prompt Design and Considerations

Prompt design refers to the systematic process of designing, optimizing, and applying inputs (prompts) to obtain desired outputs from AI models (Şimşek, 2024). This process is critical for obtaining reliable and goal-oriented responses from AI. The principle of "Garbage in, garbage out" meaning that the quality of inputs directly determines the quality of outputs, reflects the fundamental approach in this field (Şimşek, 2024; Sırvermez, 2024). Bsharat et al. (2023) emphasize that an effective prompt is not composed of random expressions but consists of five fundamental components brought together through a logical architecture:

Role: It is the artificial identity assigned to the model. For example, "Act as a senior KM expert" directs the model to generate responses from a specific expertise perspective.

Context: It defines the background of the task, the target audience, and environmental conditions. This makes the model's responses more accurate and relevant.

Task: It specifies exactly what is expected from the model. A clear and precise task definition ensures the model's focus.

Constraints: It establishes the boundaries, prohibitions, and rules of the response. For instance, "Use academic language, do not exceed 500 words" ensures the appropriateness of the output.

Output Format: It defines the structural form of the result. For example, "Provide the output in table format" ensures the model presents its response in a specific format.

Prompt type refers to the general category of interaction between the user and the model, while prompt technique denotes the specific methods used within these categories. In the literature, the most common types include new task prompts that do not require extensive training, reasoning and logic prompts, hallucination-reducing prompts, and code-generation prompts. Frequently used techniques within these types are zero-shot, few-shot, chain-of-thought, automatic chain-of-thought, self-consistency, ReAct, and tree of thoughts. These techniques play a critical role in making the outputs of prompt engineering more reliable, contextually appropriate, and efficient (Sırvermez, 2024; Tan et al., 2024). Properly structured prompts maximize the potential of AI models.

2.2.8. The Contribution of Prompt Engineering to Knowledge Management

The impact of AI on KM has been discussed above. Prompt engineering is also considered to have direct effects on KM. These can be listed as follows (Aljonied, 2026; Gibreel et al., 2026; Koutsiana et al., 2026; Wang et al., 2025): First, prompt engineering makes significant

contributions to knowledge creation. It enables more effective use of AI's NLP capacity; prompts determine the context and thereby generate accurate and goal-oriented knowledge. Role assignment ensures that content is tailored to decision-makers, and formats such as tables, bullet points, or risk matrices allow direct integration into decision support systems. Reliability is enhanced by adding references, dates, and criteria. Additionally, the generation of educational materials (e.g., quizzes, case analyses, role-playing) becomes possible. Advanced prompts can summarize and report large datasets, thereby generating new insights.

Secondly, prompt engineering facilitates knowledge sharing. Well-designed prompts enable users to obtain clearer and contextually appropriate results, producing outputs based on reliable sources. By adding criteria such as "from academic articles" or "post-2024 data", prompts can retrieve focused information; advanced prompts can condense hundreds of pages of data into concise summaries. Role assignment makes search results suitable for decision-makers, while the use of common terminology within an organization ensures knowledge standardization and consistency in communication.

Thirdly, prompt engineering makes knowledge storage organized and accessible. Through prompts, data can be generated in formats such as tables, JSON, or XML and stored in databases; metadata such as source, date, author, and topic can be automatically added to ensure organization. Tasks such as "separate by topic headings" systematize the storage process, large datasets are summarized for efficient space usage, and directives like "prepare for long-term archiving" support the archiving process.

Fourthly, prompt engineering makes the use of knowledge contextually appropriate, fast, and easily integrated into decision-support processes. Prompts ensure that outputs are tailored to the user; formats such as risk matrices, SWOT analyses, and scenario planning can be directly applied in decision-making processes. The same information can be transformed into reports, presentations, summaries, or educational

materials through different prompts. It also facilitates the generation of new analyses and insights from stored data.

Fifthly, it plays a critical role in the SECI model. Within socialization, prompt engineering facilitates the transfer of synthesized tacit knowledge acquired from different experts in AI to other individuals through well-designed prompts. It provides a common language and format, enables digital sharing, and enhances accessibility. Within externalization, it helps transform tacit knowledge into written form, organizes its transfer into a specific format, and enables its conversion into organizational knowledge. Within combination, information gathered from scattered sources can be transformed into coherent knowledge repositories through prompt engineering. For example, the prompt "Compare these three reports and present the common themes in a table" enables the synthesis of explicit knowledge. Within internalization, prompt engineering accelerates the transformation of explicit knowledge into tacit knowledge during the learning process. For instance, the prompt "Summarize this report as a training scenario and add application examples" helps employees develop their own mental practices from organizational documents.

3. Methodology

In this study, the literature was examined through bibliometric methods using the results of a search conducted in the Scopus database on June 29, 2026, with the keywords "knowledge management" and "prompt engineering" applied to titles, abstracts, and keywords. The following query was used in the search: TITLE-ABS-KEY("knowledge management") AND TITLE-ABS-KEY("prompt engineering"). Boolean operator "AND" was used to combine the keywords, and the search was restricted to the fields TITLE, ABSTRACT, and KEYWORDS. Additionally, a separate search was conducted with the query TITLE-ABS-KEY("knowledge management") AND TITLE-ABS-KEY("prompt engineering") AND TITLE-ABS-KEY("bibliometric") and no publications were found in Scopus. The search covered all years available in Scopus up to the aforementioned date. All records identified in the

search results were included in the study, except for two publications that did not have abstracts. Based on the purpose of the study, the research questions (RQs) were identified and presented with their respective RQ numbers (RQ#), along with the methods used to answer each RQ, in Table 1.

Table 1. Research questions (RQs)

RQ#	RQ	Method
RQ1	What is the distribution of publications by subject area?	DA (Scopus filters)
RQ2	What are the document types of the publications?	DA (Scopus filters)
RQ3	What is the distribution of publications by language?	DA (Scopus filters)
RQ4	What are the source types of the publications?	DA (Scopus filters)
RQ5	What is the open-access status of the publications?	DA (Scopus filters)
RQ6	What is the distribution of publications by country?	DA (Scopus filters)
RQ7	What is the level of Turkey's academic contribution in this field?	DA (Scopus filters)
RQ8	What is the distribution of publications by year?	DA (Scopus filters)
RQ9	What are the citation counts of the publications?	BA (VOSviewer; Citation, Documents)
RQ10	Which sources have the highest number of publications and citations?	BA (VOSviewer; Citation, Sources)
RQ11	What are the most frequently used keywords?	Co-occurrence Analysis (VOSviewer; Keywords) TA (Copilot, GEMINI)
RQ12	Which thematic areas stand out in the studies?	Text Analysis (VOSviewer; Title and Abstracts) TA (Copilot, GEMINI)

Different analytical techniques were applied in line with the research questions. RQ1-8 were examined through descriptive analysis (DA) using the filters of the Scopus database. The other research questions were subjected to bibliometric analysis (BA), co-occurrence analysis, and text analysis using VOSviewer. For RQ11 and RQ12, thematic analysis (TA) was conducted with the support of Copilot and GEMINI. The usability of GenAI in scientific research is nowadays widely acknowledged (Knöchel et al., 2025). During TA, terms in each category were first sub-categorized, then common axes among these categories were identified, theme names representing the clusters were created, and finally, the

clusters were interpreted. Support and suggestions for alternative perspectives was obtained for these processes from these mentioned AI tools. Finally, by the researcher, different suggestions and viewpoints were compared and evaluated, final decisions were made, and interpretations were provided.

Scopus, developed by Elsevier, is one of the largest abstract and citation databases, covering a wide range of publications in social sciences, business, engineering, and health sciences. Compared to other databases, it was chosen because it includes more journals and conference proceedings, provides up-to-date citation data, and is widely used in bibliometric analyses (Burnham, 2006).

After the dataset was created, VOSviewer software was used for certain analyses together with Scopus filters. Developed by Van Eck and Waltman (2010) and freely available, this software is a powerful tool for visualizing and clustering bibliometric networks. VOSviewer supports techniques such as citation analysis, co-authorship analysis, co-occurrence analysis, and keyword mapping. Thus, trends, relationships, and thematic areas in the literature can be presented more clearly.

As a methodology, BA is a systematic approach to revealing trends, patterns, and impacts in the scientific literature. It uncovers the structure of scientific studies by measuring and mapping data such as publications, citations, and keywords. Donthu et al. (2021) define this method as a powerful tool for evaluating the development of research fields with objective data and identifying future directions. In this study, BA was chosen not only to describe the current state but also because it is a strong method for revealing gaps in the literature and highlighting future research opportunities.

This methodological framework, while primarily based on the bibliometric analysis approach, enables the study to reveal both quantitative trends and qualitative thematic orientations. Thus, the current state of prompt engineering literature within the context of knowledge management is assessed in this study from a holistic perspective.

This study does not fall within the scope of research requiring ethics committee approval, such as those involving the collection of data from participants through surveys, interviews, focus groups, observations, experiments, or other qualitative and quantitative approaches; the experimental or scientific use of humans or animals (including materials/data); clinical studies conducted on humans; studies conducted on animals; or retrospective studies subject to personal data protection legislation. Therefore, ethics committee approval was not deemed necessary.

4. Findings and Discussions

The findings obtained within the scope of the study, together with the related discussions, are presented below in a way that addresses the research questions.

4.1. Distribution of Publications by Subject Area

When examining the distribution of 213 publications obtained from the Scopus database by subject area (Figure 2), the largest share is found in the field of Computer Science (181 publications, ~41%). This is followed by Engineering with 69 publications, Mathematics with 46, and Decision Sciences with 35. Social Sciences (26), Medicine (13), Business, Management and Accounting (10), Materials Science (8), and Physics and Astronomy (8) are represented at a more limited level. In addition, a small number of publications are also found in Arts and Humanities and other fields. Some publications are listed in more than one subject area in Scopus. Because of this, the total counts exceed 213 publications.

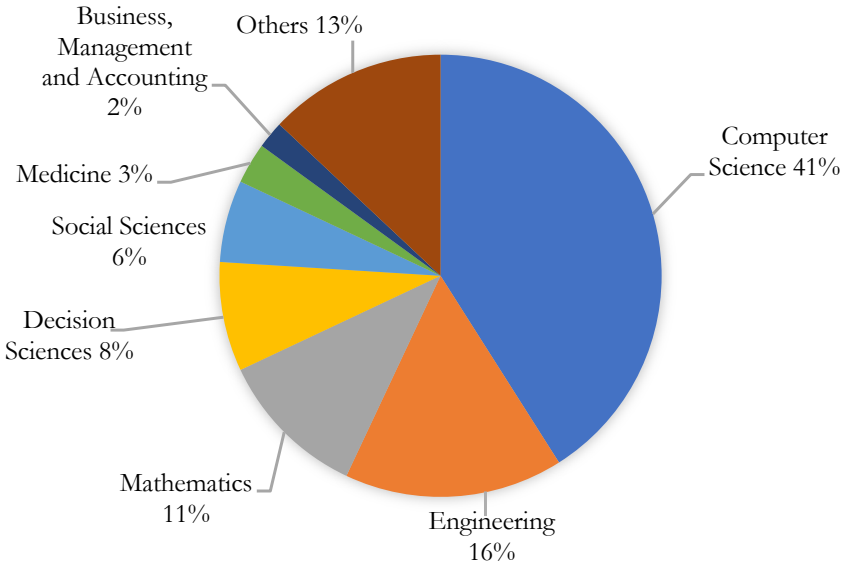


Figure 2. Distribution of publications by subject area

The findings indicate that, from the KM perspective, prompt engineering studies are largely concentrated in technical disciplines. The high proportion in computer science and engineering stems from the concept's direct association with AI systems and efforts to develop supporting infrastructures. This reveals that, at the outset, technical dimensions such as algorithm development, modeling, and system integration were prioritized. Publications in mathematics and decision sciences, on the other hand, reinforce the analytical dimension by focusing on criteria such as optimization, accuracy, and efficiency.

The low proportions in Social Sciences and Business, Management and Accounting indicate that prompt engineering has not yet been sufficiently examined in organizational contexts and KM processes. This gap offers new research opportunities, particularly in KM and knowledge conversion processes, decision support systems, and digital transformation.

The limited number of studies in fields such as medicine, materials science, and physics indicates that the concept has begun to be applied in different contexts. This diversity suggests that prompt engineering can be regarded not only as a technical tool but also as a method supporting KM

and knowledge conversion processes across different disciplines. However, the limited number of studies in these areas indicates that the field is still at an early stage and requires further research.

4.2. Document Types of the Publications

When examining the distribution of publications by document type (Figure 3), the largest share belongs to conference papers (151 publications; ~71%). This is followed by articles (50), books (5), book chapters (4), and reviews (3).

In the humanities, conferences function as testing grounds, journals provide scientific validation, and books offer synthesis and broader frameworks. In computer science, on the other hand, conference papers are often not merely preliminary steps but final peer-reviewed publications (CASRAI Editorial Board, 2026). Accordingly, when computer science and the humanities/social sciences are examined separately, publications in computer science consist of 141 conference papers, 31 articles, 4 books, 3 book chapters, and 2 reviews. In the humanities and social sciences (including 'Arts and Humanities', 'Social Sciences', 'Business, Management and Accounting', 'Economics, Econometrics and Finance', and Psychology), the publications comprise 27 conference papers, 7 articles, 3 book chapters, 2 books, and 1 review.

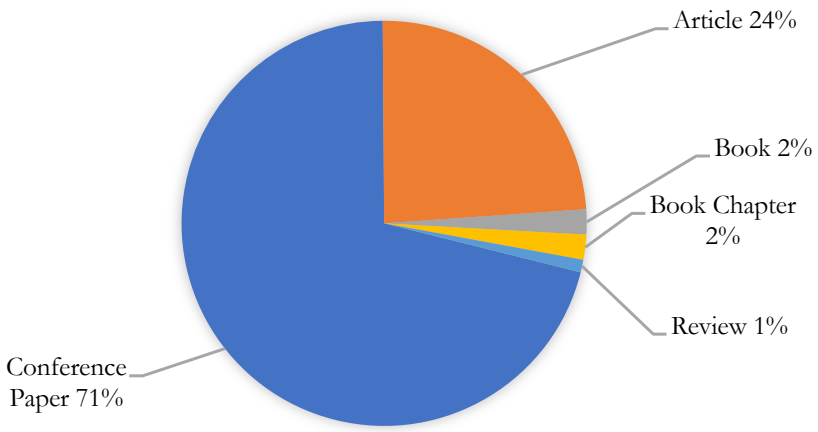


Figure 3. Distribution of publications according to document types

This distribution shows that the prompt engineering literature largely consists of conference-based outputs. Most publications are in the field of computer science and in the format of conference papers; this aligns with the fact that conferences in this field are regarded as final publications. In the humanities and social sciences, however, the number of publications is quite limited. The high proportion of conferences indicates that the concept has been rapidly discussed within academic communities, but has not yet sufficiently evolved into in-depth articles and books in the context of KM. This picture suggests that the theoretical framework of prompt engineering in the field of KM has not yet been fully established and is progressing mainly through applied examples. Overall, the development of the field in computer science progresses through product, technology, and skill development. This suggests that usable and mature outputs are produced first, and then other disciplines build theoretical and applied studies upon them. The scarcity of books and book chapters indicates the need for further work to develop the theoretical and methodological framework, while the limited number of review studies highlights the lack of systematic evaluations.

4.3. Distribution of Publications by Language

When examining the distribution of publications by language (Figure 4), 208 publications (98%) are in English, while only five are in Chinese. This distribution demonstrates that the literature is shaped almost entirely through English, with contributions in other languages remaining very limited.

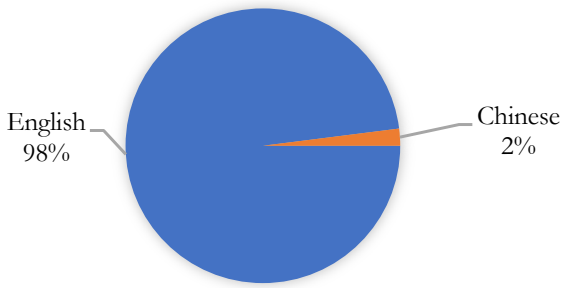


Figure 4. Distribution of publications by language

The language distribution reveals that prompt engineering is discussed globally in the context of KM primarily through English. The dominance of English demonstrates that studies on prompt engineering in KM reach international academic communities and possess global impact potential. However, the absence of publications in languages other than Chinese indicates that prompt engineering research in local KM contexts has not yet developed. This situation presents a significant opportunity for studies in Turkish and other regional languages. Research produced in local languages would better reflect the cultural and institutional differences of KM practices and reveal how the concept evolves in different contexts.

4.4. Source Types of the Publications

When examining the source types (Figure 5), the majority of publications consist of conference proceedings. Out of a total of 213 publications, 125 are conference proceedings, 60 are journals, 21 are book series, and seven are books. A book series is a multi-volume academic collection published at regular intervals on a specific theme or field, with volumes that complement each other.

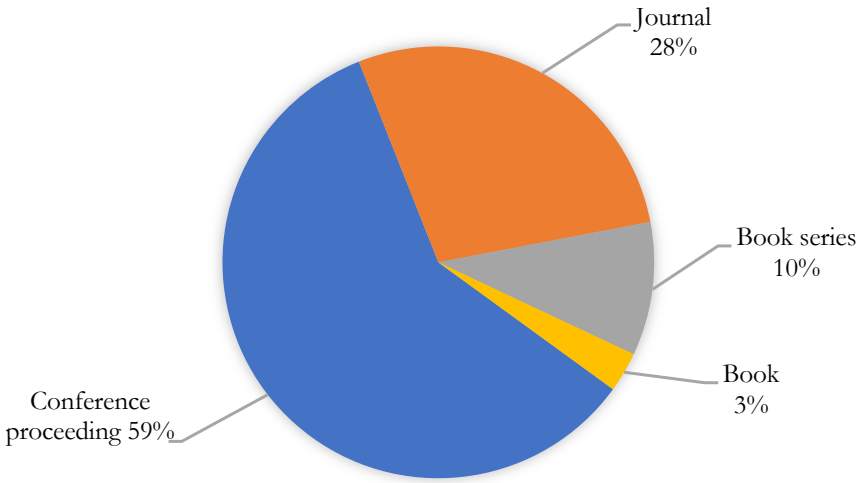


Figure 5. Source type of publications

This RQ is directly related to RQ2. In the answer to RQ2, conference papers, articles, books, book chapters, and reviews are generally published respectively in conference proceedings, journals, books, books, and journals. Therefore, the numbers of conference papers and conference proceedings would be expected to be close or even identical, but differences are observed here. This difference is considered to stem from the fact that some conference papers have been published in journals, books, or book series. The reason conference papers are published in journals, books, or book series may be that conference proceedings provide short-term visibility, whereas book series, books, or journals create a more lasting impact and are regarded as long-term reference sources.

4.5. Open-Access Status of the Publications

When the open-access status of the publications is examined, it becomes evident that Scopus records classify open access in a specific way: if a publication is assigned to any open-access model (Gold, Green, Hybrid Gold, or Bronze), it is also tagged as "All Open Access." Thus, the "All Open Access" category should be understood not as an independent model but as an overarching classification that includes the other types of open access. In some cases, a single publication is marked with more than one open-access model simultaneously. This explains why the sum of the subcategories is higher than the number reported under "All Open Access." As shown in Figure 6, among the publications with open-access information recorded in the database, 56 are Gold (54%), 33 are Green (32%), 9 are Hybrid Gold (8%), and 6 are Bronze (6%). The "All Open Access" category, representing publications with at least one open-access tag, contains 77 studies. In contrast, 136 publications have no open-access information entered into the database. This means that the majority of the publications (approximately 64%) lack open-access information.

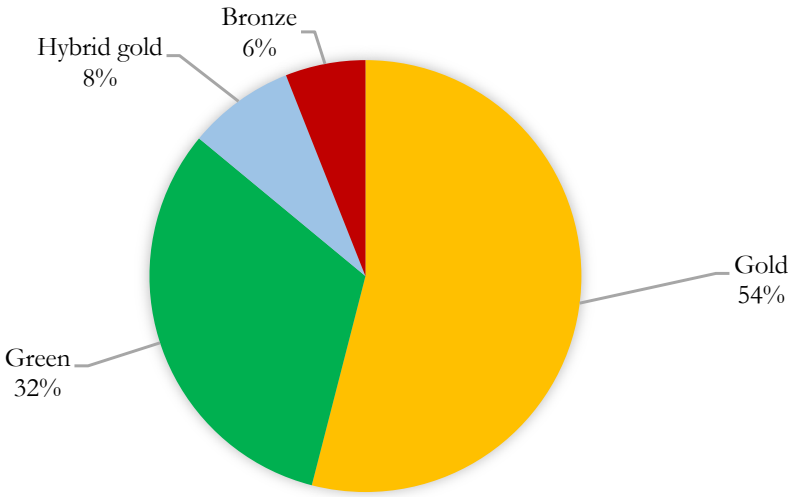


Figure 6. Open-access status of the publications

Gold open access makes publications available to everyone from the moment they are published and is usually supported by article processing charges (APCs) paid by the author or the institution. With a 54% share in the dataset, this model shows that it is accepted and becoming common in the literature. The Green model allows authors to share their work in institutional or subject-specific repositories; with a 32% share, it reflects a trend consistent with universities' open science policies. Hybrid Gold refers to publications in subscription-based journals that become open access through APC payments; its 8% share shows that it is less preferred. The Bronze model provides free access but does not specify reuse rights; with a 6% share, it is chosen at a lower level in the academic community. The "All Open Access" category is not an independent model but an overarching classification that includes Gold, Green, Hybrid, and Bronze types (open-access.network, 2025; Piwowar et al., 2018). Out of the 213 publications analyzed, 77 (36%) are in the All Open Access category. At the same time, 136 publications (64%) have no open access information recorded in the Scopus database. In Scopus, there is no specific data field indicating that a publication is not open access. A publication without open access information may either not be open access or may simply be a publication for which open access information has not yet been entered.

The UNESCO Recommendation on Open Science (UNESCO, 2021), the European Union's Horizon 2020 and Horizon Europe programs in which Turkey participates (OECD, 2025), TÜBİTAK's Open Science Policy (TÜBİTAK, 2019), and the National Artificial Intelligence Strategy (2021-2025) (T.C. Cumhurbaşkanlığı Dijital Dönüşüm Ofisi Başkanlığı [CBDDO] & T.C. Sanayi ve Teknoloji Bakanlığı [STB], 2021) together establish the legal and institutional framework that encourages researchers and institutions to publish in open access. Considering the binding provisions in these policy documents, it is expected—just as in other fields—that the literature on prompt engineering from a KM perspective will reach wider audiences and gain greater international visibility.

4.6. Distribution of Publications by Country

When examining the distribution by country (Figure 7), China holds the largest share with 87 publications (~35%). The United States follows with 32 publications, India with 18, Germany with 16, and Italy with 10. Countries with moderate contributions include Australia (8), the United Kingdom (7), France (5), Singapore (4), and Finland (4). Turkey, Switzerland, South Korea, and Greece each contribute 3 publications, representing ~1% of the total. Countries with lower contributions include Brazil, Ukraine, Taiwan, Spain, and Saudi Arabia (2 publications each), as well as Lebanon, Japan, Ireland, Denmark, Canada, and Bangladesh (1 publication each). The "Others" category covers 21 publications, accounting for ~8% of the total. It should be noted that some publications are affiliated with more than one country. As a result, the raw counts add up to more than the total number of publications. In addition, due to rounding, the sum of percentages may not equal 100.

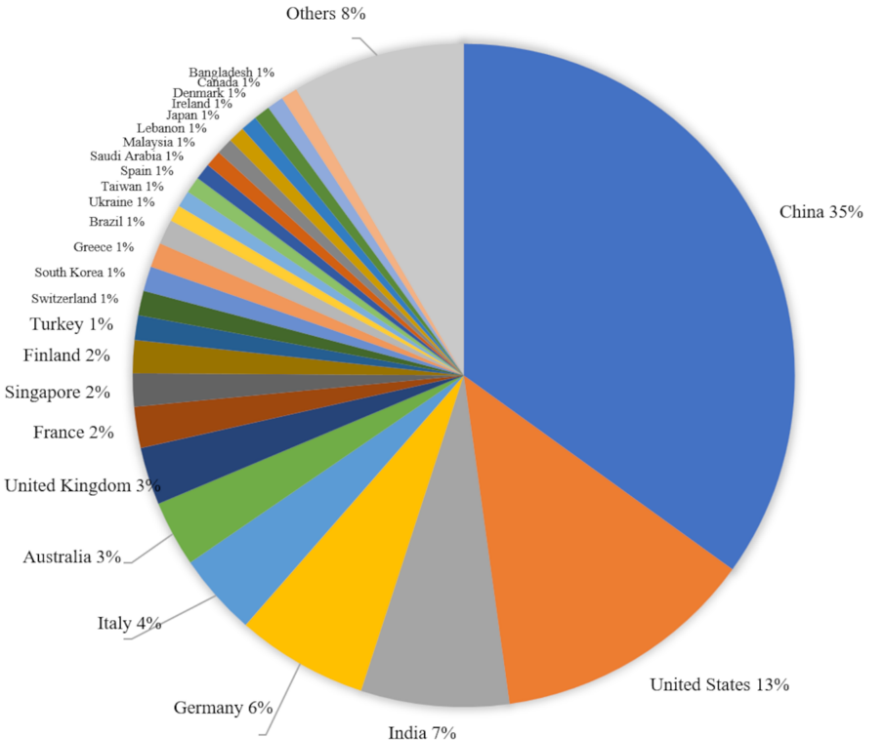


Figure 7. Distribution of publications by country

The country distribution indicates that, from a KM perspective, the prompt engineering literature is still concentrated in certain countries. This shows that while the field has begun to attract global interest, scientific output is not evenly distributed across countries. The fact that many countries are represented by only a small number of publications suggests that studies combining KM and prompt engineering are still in a developmental phase. It is anticipated that in the coming years, with the increase of research from diverse regions, both geographical diversity and the theoretical accumulation of KM perspectives in the literature will be strengthened.

4.7. Level of Turkey's Academic Contribution in This Field

From the perspective of KM, there are three studies on prompt engineering originating from Turkey. One of these is a journal article,

while the other two are conference papers. One conference paper was published in 2025, and the other two in 2026. All three publications are in English. Conference papers fall within the subject areas of computer science and decision sciences, while the article is classified as multidisciplinary.

Turkey's contribution to the prompt engineering literature remains limited. The small number of publications indicates that the field is still in its early stages, while the presence of studies across different types and disciplines demonstrates that the subject is not confined solely to its technical dimension. The growing interest in KM and AI (CBDDO & STB, 2021) may provide a foundation for strengthening academic contributions in the near future. In particular, the expansion of interdisciplinary research and the establishment of new programs and research centers at universities present significant opportunities to enhance Turkey's visibility in this field.

4.8. Distribution of Publications by Year

When examining the distribution of publications by year (Figure 8), it is observed that the first study in this field was conducted in 2023. In 2023, four publications were produced, followed by 20 in 2024. A remarkable increase occurred in 2025, with a total of 136 publications. In the first half of 2026, 53 publications were produced.

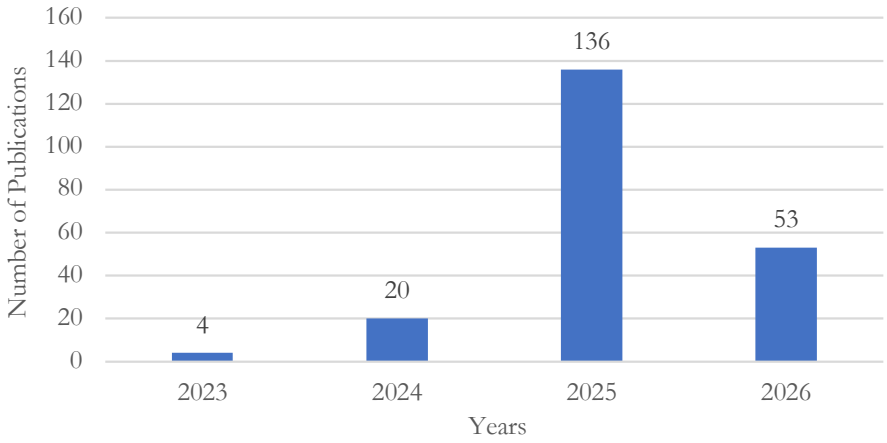


Figure 8. Distribution of publications by year

The data indicate that the field has rapidly attracted academic interest, with a significant increase observed in 2025. This surge suggests that the topic has been quickly accepted among researchers and studied intensively. Considering the upward trend in previous years, it is anticipated that the number of publications in 2026 may surpass that of 2025 by year's end. This trend demonstrates that the subject is becoming increasingly popular and gaining greater international visibility.

4.9. Citation Counts of the Publications

When "Type of Analysis" is set to Citation, "Unit of Analysis" to Documents, and the "Minimum number of citations of a document" to one in VOSviewer, the visualization in Figure 9 is obtained. The size of the circles is determined by the number of citations. The top 15 most cited publications are presented in Table 2. A total of 132 publications have not yet been cited.

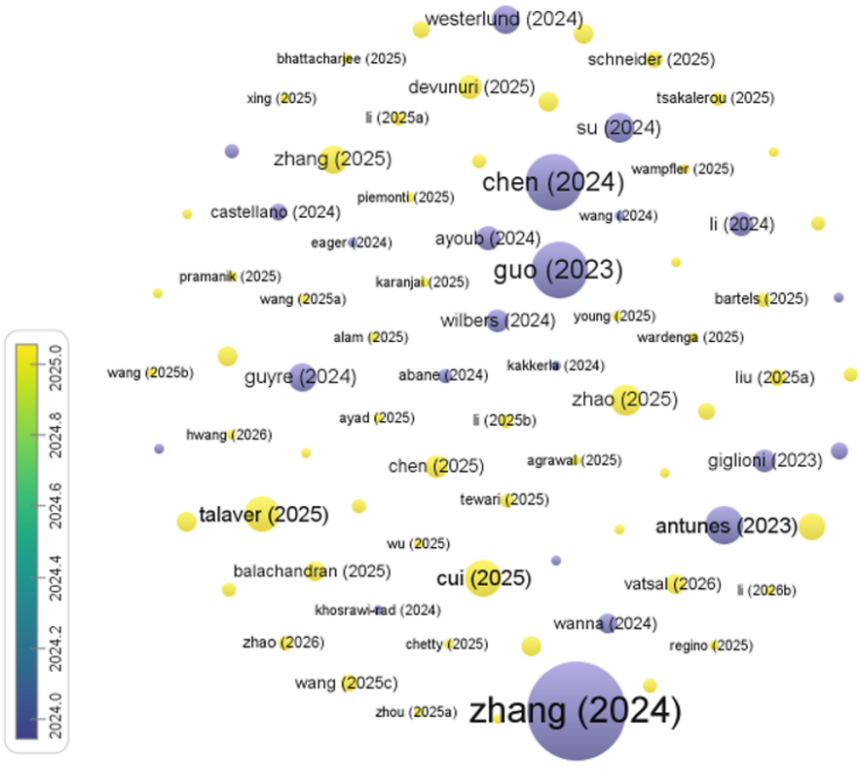


Figure 9. Citation counts of the publications

The citation distribution of studies published between 2023 and 2026 shows that, despite being a new field, it has rapidly gained visibility. Publications that received high citations in a short time have guided subsequent research through their methodological and conceptual contributions. The fact that studies published in 2025 and 2026 have not yet been cited can be considered normal for newly released works, reflecting that the field is still developing and its visibility process is ongoing. Therefore, monitoring which publications will stand out in the future is crucial for understanding research trends.

Table 2. The top 15 most cited publications

No.	Document	Citation Count
1	Zhang et al. (2024)	97
2	Chen et al. (2024)	32
3	Guo et al. (2023)	31
4	Antunes et al. (2023)	15
5	Cui et al. (2025)	14
6	Talaver and Vakaliuk (2024)	13
7	Zhao et al. (2025)	10
8	Su et al. (2024)	9
9	Zhang et al. (2025)	8
10	Guyre et al. (2024)	8
11	Westerlund and Shcherbakov (2024)	8
12	Du et al. (2025)	7
13	Devunuri and Lehe (2025)	6
14	Li et al. (2024)	6
15	Ayoub et al. (2024)	6

4.10. Sources That Have the Highest Number of Publications and Citations

In VOSviewer, when "Type of Analysis" is set to Citation, "Unit of Analysis" to Sources, "Counting method" to Full counting, "Minimum number of documents of a source" to one, and "Minimum number of citations of a source" to one, the visualization in Figure 10is obtained. The size of the circles is determined by the number of published documents. It is observed that the largest number of publications, nine in total, appeared in Ceur Workshop Proceedings, followed by five in

Communications in Computer and Information Sciences, three in Applied Sciences (Switzerland), and three in IEEE Access. It is observed that in the subsequent nine sources, each contains two publications.

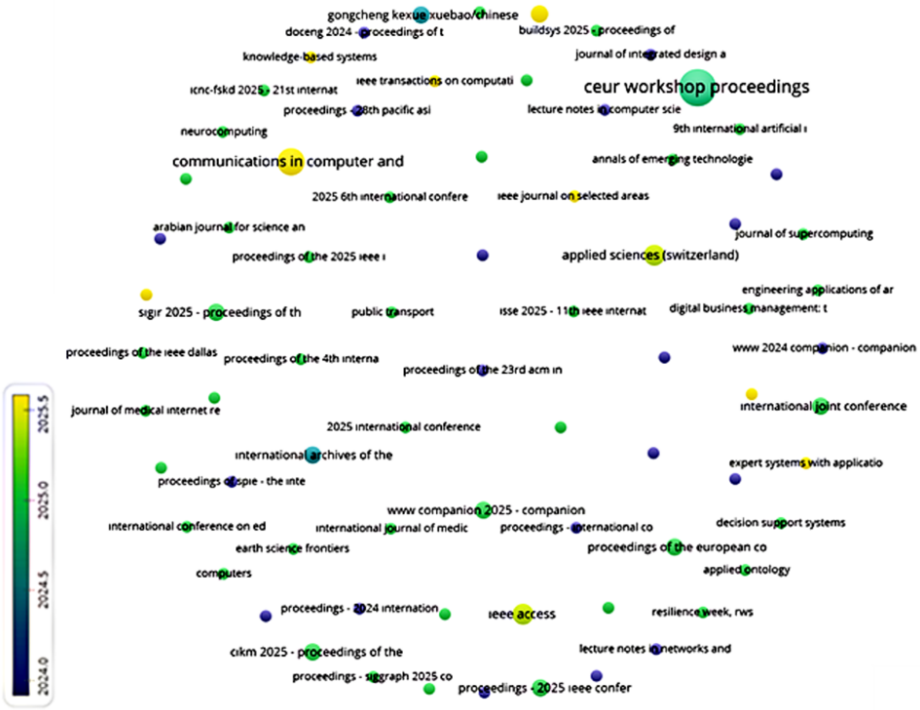


Figure 10. Journals with the highest number of publications

The top three sources with the highest citation counts are ranked as follows: Chemical Science with 97 citations, IEEE Robotics and Automation Letters with 32 citations, and Proceedings- 22nd IEEE International with 31 citations. The top 15 most cited sources, along with the number of published documents, are presented in Table 3.

Table 3. The top 15 most cited sources

No.	Source	Number of Documents	Citation Count
1	Chemical Science	1	97
2	IEEE Robotics and Automation Letters	1	32
3	Proceedings - 22nd IEEE International…	1	31
4	CEUR Workshop Proceedings	9	19
5	Proceedings of the 23rd ACM International…	1	15
6	SIGIR 2025 - Proceedings of the 48th International…	1	14
7	IEEE Transactions on Affective Computing	1	9

8	Proceedings - International Conference…	1	9
9	IEEE Access	3	8
10	Journal of Medical Internet Research	1	8
11	Lecture Notes in Networks and Systems	1	8
12	Proceedings of the 6th Conference on…	1	8
13	Neurocomputing	2	7
14	Gongcheng Kexue Xuebao / Chinese Journal…	2	6
15	Public Transport	1	6

When evaluated in terms of sources, it is observed that the studies are distributed across different publication platforms. This distribution suggests that the field has not yet consolidated around a few specific journals and that researchers from different disciplines are showing interest in the topic. On the other hand, the fact that the sources hosting the largest number of publications are not the same as those receiving the highest citations indicates that publication count alone is insufficient to explain scientific impact. In newly emerging research fields, conference papers play a crucial role as they enable the rapid dissemination of research findings. Conversely, the increasing publication of these studies in international peer-reviewed journals over time will contribute to the theoretical development of the field and enhance the academic visibility of prompt engineering literature from a KM perspective.

4.11. The Most Frequently Used Keywords

The co-occurrence analysis of author keywords examines the relationships between concepts used together in the same study and is widely employed as a bibliometric method to reveal the conceptual structure of a research field, its prominent themes, and the interconnections among these themes (Callon et al., 1983). Accordingly, a total of 697 author keywords obtained from 213 publications included in the analysis were subjected to structural examination using the VOSviewer software. In VOSviewer, "Type of Analysis" was set to Co-occurrence, "Unit of Analysis" to Author Keywords, and "Counting method" to Full counting. To reduce conceptual noise, eliminate marginal terms repeated only once or twice, and preserve current micro-trends in the field, after simulating different threshold values, "the minimum number of occurrences of a keyword" was set to three. The resulting data

visualization is presented in Figure 11. The distance between two concepts in the visualization approximately reflects their relative relatedness. In general, the closer two concepts are to each other, the stronger their relationship.

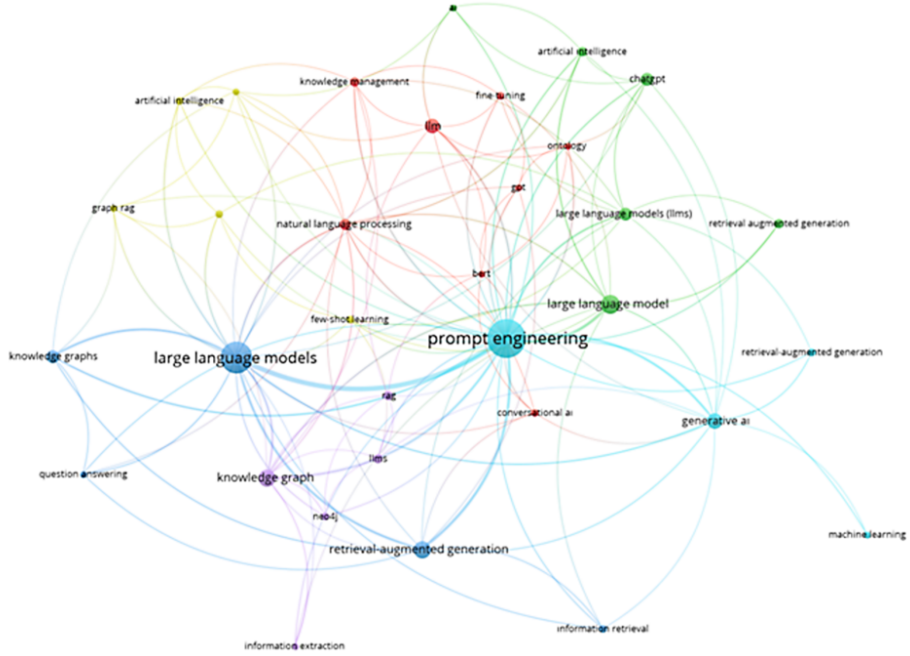


Figure 11. Most frequently used keywords

Among the 33 keywords that met the defined threshold, a total of 132 links and 306 total link strength were identified. The top 10 keywords ranked by occurrences, along with their Total Link Strength, are presented in Table 4.

Table 4. Occurrences and total link strength of keywords

No.	Keyword	Occurrences	Total Link Strength
1	Prompt engineering	92	146
2	Large language models	63	90
3	Large language model	23	33
4	Retrieval-augmented generation	18	36
5	Knowledge graph	18	30
6	Generative AI	13	27
7	LLM	11	14

8	Large language models (LLMs)	11	16
9	Knowledge graphs	10	22
10	ChatGPT	8	11

As a result of the clustering analysis, it has been observed that the literature is structured around six fundamental conceptual clusters that are interrelated yet differentiated in terms of their focal points. These clusters, which reflect the sub-disciplines and focal areas of the literature at the intersection of prompt engineering and KM, are summarized in Table 5 along with the themes they represent.

Table 5. Conceptual clusters formed within the keyword analysis

Cluster Number	Keywords	Represented Theme
Cluster 1	bert, conversational ai, fine-tuning, gpt, knowledge management, llm, natural language processing, ontology	Integration of KM and Language Model Architectures
Cluster 2	ai, artificial intelligence, chatgpt, large language model, large language models (llms), retrieval augmented generation	General AI Applications and Popular LLM Technologies
Cluster 3	information retrieval, knowledge graphs, large language models, question answering, retrieval-augmented generation	Information Retrieval and Intelligent Question-Answering Systems
Cluster 4	artificial intelligence, explainability, few-shot learning, graph rag, knowledge graph construction	Explainable AI and Graph-Based Knowledge Construction
Cluster 5	information extraction, knowledge graph, llms, Neo4j, rag	Information Extraction and Graph Database Architectures
Cluster 6	generative AI, machine learning, prompt engineering, retrieval-augmented generation (rag)	GenAI and Prompt Engineering Practices

When the constructed bibliometric network map is examined, it is observed that the two main focal points with the highest frequency are the concepts of LLMs and "prompt engineering". The central positioning of these two nodes indicates that a significant portion of the literature has been structured around this axis. However, when the clusters are analyzed, the repeated presence of "retrieval-augmented generation (RAG)" and

“knowledge graph” across multiple clusters reveals that these concepts function as bridges, supporting not only the technical infrastructure of the field but also its dimensions of accuracy and reliability. This situation, from another perspective, can be interpreted as a critical issue in KM related to prompt engineering, which involves preventing hallucinations and retrieving validated organizational knowledge. To briefly recall, RAG enables AI to access reliable external information, thereby reducing hallucinations, while the “knowledge graph” records information systematically like a ledger and verifies its accuracy. Therefore, other technical sub-concepts in the literature cluster around the central axis of LLMs and “prompt engineering”, while simultaneously shaping the field’s reliability and accuracy dimension through RAG and “knowledge graph”. Moreover, when Occurrences and Total Link Strength (intensity of relationships with other keywords) are examined together, it becomes evident that the keywords “prompt engineering”, LLMs, RAG, and “knowledge graph” not only appear frequently but also establish strong connections with other concepts, thereby shaping the structure of the field.

The analysis results demonstrate that the prompt engineering literature operates within a multi-layered structure, extending from information retrieval (information retrieval) to knowledge representation (ontology/knowledge graph), and from technical architectures (RAG, fine-tuning) to explainability (explainability). From the perspective of KM, it is evident that the literature is not confined to the question of "how to ask the model" but is directly integrated with the structuring of organizational knowledge (ontology, knowledge graph) and the reliable retrieval of this knowledge (RAG/graph RAG).

An examination of the keywords within the clusters reveals that synonymous expressions (LLM, LLMs, Large Language Model, etc.) appear across different clusters. The authors’ free choice of synonymous terms without employing a thesaurus indicates that the field is still in the process of achieving terminological maturity and that different research traditions are contributing their own linguistic patterns to the literature. Although it would have been possible to standardize the keywords prior

to analysis by consolidating variations such as "LLM, LLMs, Large Language Model, Large Language Models (LLMs)" under a single heading, this study deliberately refrained from such standardization. The primary reason for this choice was to make visible the terminological diversity in the literature and to highlight how different research traditions label the same concept. This methodological preference provides an analytical contribution by demonstrating that the field has not yet achieved full terminological standardization. Therefore, the dispersion of the same concept across clusters in different forms is considered a significant finding that reflects both the developmental trajectory of the field and its interdisciplinary diversity.

In brief, Cluster 1, representing the theme of Integration of KM and Language Model Architectures, examines how language models such as GPT and BERT are adapted and fine-tuned within KM processes alongside ontologies. The primary focus is the integration of AI text-processing architectures with organizational knowledge infrastructures. Cluster 2, representing the theme of General AI Applications and Popular LLM Technologies, encompasses widely used tools such as ChatGPT and LLMs. It reflects the broad-scale, application-oriented, and popular dimensions of AI usage in the literature. Cluster 3, representing the theme of Information Access and Intelligent Question-Answer Systems, includes information access mechanisms supported by infographics and retrieval-augmented generation (RAG). The goal is to access accurate information and develop automated question-answer systems. Cluster 4, representing the theme of Explainable AI and Graph-Based Knowledge Construction, focuses on explainability (XAI), few-shot learning, and graph-based RAG applications. Transparency in KM, justification of decisions, and modeling information through graph structures are emphasized. Cluster 5, representing the theme of Information Extraction and Graph Database Architectures, covers information extraction from raw text, graph database technologies such as Neo4j, and RAG implementations. The technical focus lies in processing, modeling, and securely storing data. Cluster 6, representing the theme of GenAI and Prompt Engineering Practices, encompasses generative AI processes, machine learning, and

prompt engineering applications. Its central focus is on the practical aspects of prompt design and the optimization of generative processes.

4.12. Thematic Areas That Stand Out in the Studies

A map based on text data was created in VOSviewer using article titles and abstracts, and it is presented in Figure 12. Binary counting was selected when configuring the analysis settings in VOSviewer. "The minimum number of occurrences of a term" was set to six. To reduce semantic noise in the dataset and ensure conceptual purity, different threshold values for the minimum number of occurrences were simulated, and efforts were made to determine the most appropriate value. The critical point here is to exclude noise-generating words while preserving those that are meaningful for the analysis. The relevance score, which determines how thematically distinctive the selected terms are, was set at the default value of 60%. In this configuration, 110 terms, 5 clusters, 3,261 links, and a total link strength of 7,110 were identified.

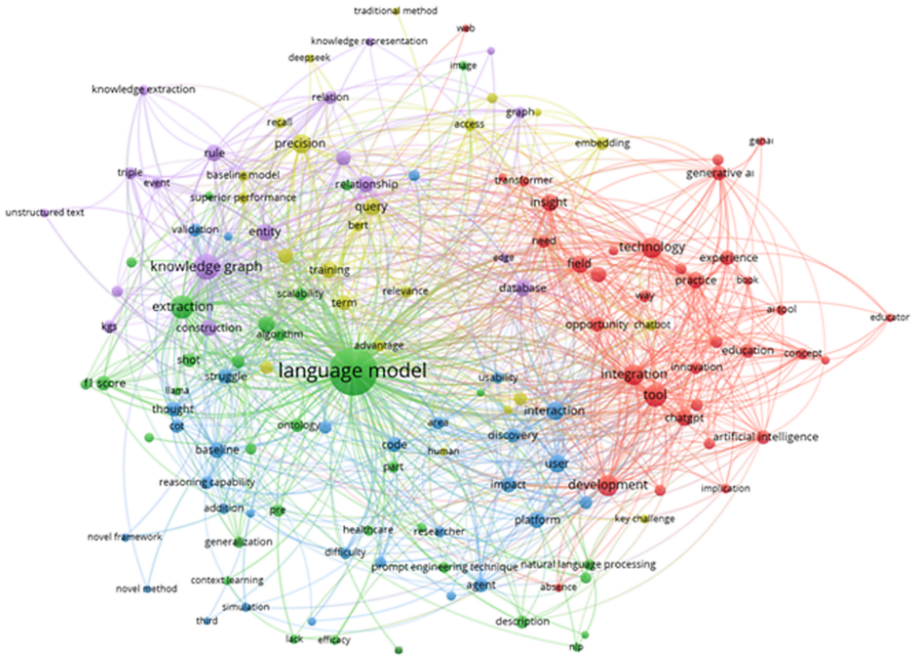


Figure 12. Heighted thematic areas

As a result of the co-occurrence analysis conducted with the VOSviewer text-mining tool, 110 terms in the prompt engineering literature from a KM perspective were grouped into five distinct clusters based on their mathematical density. The terms and themes contained in the resulting clusters are presented in Table 6.

Table 6. Themes that emerged within the scope of co-occurrence analysis

Cluster Number	Terms	Represented Theme
Cluster 1	alignment, baseline model, bert, complexity, construction, context learning, deepseek, domain knowledge, entity, experimental result, extraction, f1 score, generalization, hallucination, high quality, importance, kgs, knowledge distillation, knowledge extraction, knowledge graph, knowledge graph construction, knowledge representation, language model, llama, novel framework, ontology, part, pre, precision, query, recall, relation, robustness, rule, scalability, shot, shot learning, superior performance, term, training (43 terms)	Integration of Language Model Architecture with KM and Performance Reliability
Cluster 2	agent, ai tool, artificial intelligence, book, chatbot, chatgpt, creation, database, decision, development, education, educator, embedding, experience, factual accuracy, field, future research, gap, gemini, generative ai, healthcare, impact, industry, insight, integration, interaction, key challenge, knowledge management, natural language process, nlp, number, organization, platform, practice, prompt engineering tech, review, student, technology, tool, transparency, user, way (42 terms)	Socio-Technical Dimension and Organizational Adaptation
Cluster 3	addition, area, baseline, benchmark, chain, code, cot, difficulty, extensive experiment, http, novel, reasoning capability, researcher, significant improvement, struggle, thought, usability (17 terms)	Reasoning Capacity and Performance Testing
Cluster 4	graph, interpretability, lack, methodology, pipeline, relationship, structure (7 terms)	Graph Structures and Explainability
Cluster 5	Image (1 terms)	Visual Data and Visualization-Oriented Studies

The keyword clusters obtained through VOSviewer are considered as structures that reveal research focuses and thematic densities in the literature. In these clusters, concepts closely related to each other are

grouped together, showing which topics are addressed jointly, which areas exhibit concentration, and which research trends emerge. Thus, the keyword clusters reveal not only the frequency of terms but also their interrelations and shared themes. In this respect, interdisciplinary connections, methodological approaches, and application domains in the literature are mapped, offering researchers a holistic perspective. Consequently, the keyword clusters generated by VOSviewer function as an analytical framework for understanding the axes along which knowledge production in the examined field is concentrated and which themes dominate the literature.

In cluster analysis, the reason why some clusters contain a large number (e.g., 42-43) of words/concepts while others contain very few (or even only one) word/concepts is explained by the fact that the algorithm used by VOSviewer takes into account the density of connections between concepts, and particularly the "clustering resolution" parameter. Within this framework, concepts that establish strong connections are grouped into larger clusters, whereas those unable to form sufficient links are left independent or in smaller clusters (Sciaraffa et al., 2025). Below are comments regarding the themes represented in each cluster:

Cluster 1, representing the theme of the Integration of Language Model Architecture with KM and Performance Reliability, focuses on the development of LLMs (BERT, LLaMA, DeepSeek) and their integration into KM processes. Ontologies and knowledge graphs are employed for the representation of organizational knowledge, while terms such as precision, recall, and robustness highlight performance and reliability. Concepts such as hallucination and alignment indicate accuracy and quality issues in prompt engineering, whereas terms like context learning and shot learning pertain to enhancing the reasoning capacity of the model. Therefore, the cluster is structured around the axes of language model architecture, knowledge representation, and performance reliability.

Cluster 2, representing the theme of Socio-Technical Dimension and Organizational Adaptation, reflects the use of AI tools (ChatGPT,

GenAI, NLP) across diverse application domains (education, healthcare, industry, organizations) and their integration into KM processes. Terms such as knowledge management, integration, and database illustrate the adaptation of technologies to organizational knowledge infrastructures, while terms like factual accuracy, transparency, and impact emphasize reliability and ethical dimensions. Methodological expressions frequently appearing in abstracts, such as embedding, future research, and review, are considered reflections of the standard structural elements of academic summaries rather than indicators of thematic focus. Therefore, the cluster represents the socio-technical adaptation and organizational integration of AI and prompt engineering applications.

Cluster 3, representing the theme of Reasoning Capacity and Performance Testing, reflects research methods aimed at evaluating the reasoning ability and performance of LLMs. Terms such as benchmark and baseline reveal the comparative performance of models, while terms like extensive experiment and researcher indicate methodological expressions frequently appearing in abstracts. Terms such as Chain-of-Thought (CoT), reasoning capability, and thought emphasize the logical inference power and problem-solving capacity of the models. Terms like code, usability, and http highlight the technical implementation and practical dimension of these processes. Terms such as significant improvement, difficulty, and struggle reflect the challenges encountered and the progress achieved during the development of the models. Therefore, the cluster is structured around the axes of reasoning capacity, experimental validation, and performance testing.

Cluster 4, representing the theme of Graph Structures and Explainability, highlights the use of graph-based structures (graph, structure, relationship, pipeline) in the AI and prompt engineering literature, emphasizing the dimension of interpretability. Expressions such as methodology are considered to reflect the standard structural language of abstracts rather than the thematic orientation of the field. The term lack indicates limitations and areas requiring further development. Therefore, the cluster is structured around the axes of graph structures and

explainability, representing research trends focused on transparency and the recognition of limitations in the field.

Cluster 5, representing the theme of Visual Data and Visualization-Oriented Studies, is shaped around a single concept, "image". The use of visual data in the context of prompt engineering and KM, visualization techniques, and the integration of visual content constitute the core direction of this cluster. Its single-term composition indicates that this area represents a more marginal or independent research direction within the literature. Therefore, the cluster serves as a specific focal point highlighting the role of visual data in KM and AI applications.

5. Conclusion and Recommendations

In this study, conducted to reveal the current state of the prompt engineering literature from a KM perspective and to identify gaps and future research areas, data obtained from the Scopus database were subjected to bibliometric analysis. Findings related to the research questions defined in line with the study's purpose are summarized below.

The distribution by subject area reveals that, from a KM perspective, prompt engineering is strongly represented in technical disciplines, but there is a significant research gap in the context of KM and social sciences. This situation, as emphasized in the motivation of the study, indicates that research conducted from a KM perspective can provide original contributions to the literature.

The distribution of document types reveals that prompt engineering within the KM literature is still at an early stage and is predominantly shaped through conference papers. This finding indicates the need for more articles, reviews, and book studies in the future and highlights the necessity of strengthening the theoretical foundations of the concept within the KM context.

The distribution of languages demonstrates that prompt engineering in the KM literature progresses globally through English; however, research conducted in local languages is considered capable of providing original contributions to the field.

The distribution of source types indicates that, from a KM perspective, the prompt engineering literature is still predominantly shaped by conference proceedings; journal and book publications remain limited, yet such outputs are expected to increase over time, carrying the potential to strengthen the theoretical and methodological foundations of the field.

Findings on open access reveal that different access models are being utilized. Considering Turkey's national policy documents and the binding open access requirements in the European Union's Horizon 2020 and Horizon Europe programs, open access rates are expected to increase in the coming years.

The distribution across countries reveals that the literature has developed unevenly on a global scale. Countries such as China and the United States hold dominant positions in research production, while emerging academic ecosystems contribute only in a limited capacity. This situation points to both opportunities and areas of need for future research.

Although Turkey's contribution to prompt engineering from a KM perspective remains limited, national policies and growing academic interest suggest that this contribution will strengthen in the coming period. It is believed that Turkey's focus on research in this field will make a significant contribution to filling the gap in both national and international literature.

An examination of the distribution of publications over the years reveals that the field began with only a few pioneering studies in 2023, and there has been a remarkable increase in the number of publications over the years. This upward trend demonstrates that, from a KM perspective, the prompt engineering literature has rapidly attracted academic interest, become increasingly popular, and gained greater visibility.

An analysis of citation counts indicates that while some studies published between 2023 and 2026 quickly received high citations and shaped the field, others are considered to hold potential for impact in the future.

An examination of the sources from which the publications are made reveals that they are distributed across different platforms and are not yet concentrated around a few specific journals. The fact that the most published sources and the most cited sources are different indicates that publication count alone does not explain scientific impact. Although conference proceedings are important for rapid dissemination, future publications in international peer-reviewed journals will contribute to the theoretical development and visibility of the field.

The co-occurrence analysis shows that the most frequently used keywords are "large language models" and "prompt engineering", while other concepts cluster around these two centers to form six thematic groups. In particular, concepts such as LLMs and RAG emerge as critical nodes that connect different themes. The findings demonstrate that, from a KM perspective, the literature is multidimensional, terminologically diverse, and grounded in both practice and theory. These findings indicate that the prompt engineering literature is becoming an increasingly strategic research area in KM and will be further enriched through interdisciplinary interactions in the coming period.

The co-word and bibliometric network analysis conducted on the titles and abstracts of the studies reveals that five main thematic areas stand out in the examined literature. However, when the literature is considered as a whole, it is observed that the "prompt engineering from a KM perspective" body of work concentrates on two main axes: on one side, the technical/algorithmic infrastructure that transforms organizational data into knowledge graphs and ontologies; and on the other, the managerial/applied dimension that enables the adaptation of these technologies to organizational platforms, education, and professional practices. The other smaller clusters function as intermediary domains supporting these two main axes; reasoning capacity, explainability, and visual data-driven studies act as bridges between the technical and applied dimensions, thereby reinforcing interdisciplinary coherence.

When keyword-based clustering is evaluated together with clustering derived from word repetitions in titles and abstracts, it is observed that thematic concentrations in the literature display both similarities and differences. Keyword analysis primarily reflects the conceptual focuses used by researchers in classifying their articles, whereas abstract-based analysis reveals the content orientations and contextual relationships of the studies. Both analyses highlight language model architecture, knowledge management, and the socio-technical dimensions of AI applications; however, abstracts additionally emphasize more content-oriented themes such as reasoning capacity, explainability, and the use of visual data. This indicates that keywords point to general trends and popular concepts in the literature, while abstracts reflect the deeper content and methodological diversity of the research. Therefore, when both approaches are considered together, the conceptual framework and content richness of the field become visible in a holistic manner.

The findings of this study indicate that the prompt engineering literature, from a KM perspective, is still in a developmental stage. Future research should primarily focus on increasing methodological diversity and integrating approaches from different disciplines. Empirical studies that examine the role of prompt engineering in decision support systems, digital transformation strategies, KM processes, and tacit-explicit knowledge conversion processes will help fill existing gaps in the field. Moreover, the impact of cultural differences on KM processes, AI literacy, and ethical dimensions (such as data privacy, hallucination risks, and transparency) need to be addressed more comprehensively. In the context of organizational KM, applied research evaluating prompt libraries, training programs, and organizational adaptation processes (experiences in integrating AI and prompt engineering into KM infrastructure) will provide valuable contributions both academically and practically.

In the context of this study, no publications were found in the Scopus database when searching with the keywords "knowledge management", "prompt engineering" and "bibliometric". This finding highlights a significant gap in the literature and underscores the originality of the present research. Accordingly, the study can be considered one of

the first bibliometric contributions that explores the intersection between KM and prompt engineering, offering a unique perspective and paving the way for future investigations in this emerging field.

This study has certain limitations and assumptions. First, the analysis is based solely on the Scopus database, excluding publications from other databases. The study covers data up to June 29, 2026, and subsequent developments are not reflected. It is assumed that the data and filtering system provided by Scopus functioned correctly and that the analyses conducted with VOSviewer software were error-free. Additionally, it is assumed that the keywords used fully represent the literature. The study relies only on abstracts and bibliographic data, without full-text analysis; this may limit contextual diversity in thematic interpretations. Since terms may carry different meanings depending on context across articles, thematic interpretations are based only on shared patterns within clusters and may not capture the full contextual diversity of the literature. AI-based tools such as Copilot and Gemini were utilized in the thematic analysis. Thematic inferences are constrained by the algorithmic limitations and recommendation capacities of these tools. In conclusion, the findings are limited to the framework provided by the chosen database, software, and methods.

Declarations

Ethics Committee Approval: This study does not fall within the scope of research requiring ethics committee approval, such as those involving the collection of data from participants through surveys, interviews, focus groups, observations, experiments, or other qualitative and quantitative approaches; the experimental or scientific use of humans or animals (including materials/data); clinical studies conducted on humans; studies conducted on animals; or retrospective studies subject to personal data protection legislation. Therefore, ethics committee approval was not deemed necessary.

Use of Artificial Intelligence: In this chapter, AI tools such as Copilot and Gemini were utilized during the thematic analysis (TA) process—as explained in the chapter—and occasionally for language refinement. The author retains full responsibility for the content of the chapter.

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