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Analysis of the Effectiveness of Large Language Models in Industrial Knowledge Management: A Systematic Literature Review

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A R T I C L E I N F O

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ABSTRACT

The increasing adoption of Large Language Models (LLMs) has transformed the way organizations manage, access, and utilize knowledge in industrial environments. As industries continue to generate vast amounts of information, LLMs have emerged as powerful tools for enhancing knowledge management processes through advanced natural language understanding, information retrieval, and intelligent decision support capabilities. This study aims to analyze the effectiveness of LLMs in supporting industrial knowledge management and to evaluate their contributions, benefits, and challenges across organizational contexts. A Systematic Literature Review (SLR) approach was employed to examine relevant studies published between 2020 and 2026, with data collected from major scientific databases, including Scopus, Web of Science, IEEE Xplore, and ScienceDirect. The selected literature was analyzed using thematic, content, and comparative analysis techniques to identify patterns, applications, and implementation outcomes. The findings indicate that LLMs significantly enhance knowledge creation through automated report generation, technical documentation support, and lessons-learned extraction. Furthermore, LLM adoption contributes to increased organizational productivity by reducing information search time, supporting decision-making, and improving employee access to critical knowledge resources. However, several challenges remain, including hallucination, data inconsistency, model bias, integration complexity, security and privacy concerns, and issues related to transparency, accountability, and explainability. To maximize their benefits, organizations should implement robust AI governance frameworks, adopt secure knowledge retrieval architectures, and invest in employee AI literacy and training programs. Future research should focus on real-world industrial evaluations, comparative analyses of LLM platforms, and long-term assessments of organizational impacts.

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1. INTRODUCTION

The rapid advancement of Artificial Intelligence (AI) has transformed the way organizations manage information, make decisions, and optimize operational processes. Among recent AI innovations,

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Large Language Models (LLMs) have emerged as one of the most influential technologies due to their ability to understand, generate, summarize, and retrieve human language with a high degree of accuracy. LLMs, such as ChatGPT, Claude, Gemini, and Llama, are increasingly being integrated into organizational environments to support a wide range of knowledge-intensive activities(Adinath & IS, 2025). Their capability to process large volumes of textual data and provide contextually relevant responses has created new opportunities for enhancing knowledge management practices across various industries.

Knowledge management has become a critical organizational function in modern industries where competitive advantage increasingly depends on the ability to create, store, share, and utilize knowledge effectively. Organizations generate vast amounts of information through operational activities, technical documentation, project reports, customer interactions, and employee experiences(Hackos, 2007). Managing this knowledge efficiently is essential for maintaining innovation, improving productivity, and supporting strategic decision-making. However, many industries continue to face significant challenges in managing organizational knowledge. One major issue is the existence of knowledge silos, where valuable information remains isolated within specific departments or individuals, limiting cross-functional collaboration and organizational learning. Another challenge is the loss of tacit knowledge resulting from employee turnover, retirement, or workforce mobility. When experienced employees leave an organization, valuable expertise and institutional knowledge may be lost if not properly documented and transferred.

Furthermore, organizations often struggle with retrieving relevant information from extensive knowledge repositories. Employees may spend considerable time searching for documents, reports, or technical guidelines, reducing operational efficiency and delaying decision-making processes. The increasing volume of digital information also contributes to information overload, making it difficult for employees to identify and access the most relevant knowledge when needed. These challenges highlight the need for intelligent technologies capable of improving knowledge accessibility, organization, and utilization within industrial environments.

In this context, Large Language Models offer promising solutions for addressing many of the limitations associated with traditional knowledge management systems. LLMs can facilitate knowledge acquisition by automatically extracting information from various data sources and converting unstructured content into usable organizational knowledge(Serrado et al., 2025). They can support knowledge storage through intelligent categorization, indexing, and summarization of documents, making knowledge repositories more organized and accessible. Additionally, LLMs enhance knowledge retrieval by enabling semantic search capabilities and natural language question-answering systems, allowing employees to obtain precise information without manually searching through extensive databases. These models also promote knowledge sharing by providing conversational interfaces that enable users to interact with organizational knowledge in a more intuitive manner. Moreover, LLMs can function as decision-support tools by analyzing historical data, generating recommendations, and assisting employees in solving complex operational problems.

Research on the application of Artificial Intelligence (AI) in knowledge management has evolved significantly over the last decade. One of the earliest streams of research emphasized the role of AI in supporting organizational knowledge processes(Olan et al., 2022). As digital transformation accelerated, researchers recognized that traditional knowledge management systems often suffered from fragmented information repositories, inefficient search mechanisms, and limited capabilities for capturing tacit knowledge. These challenges motivated the exploration of advanced AI technologies capable of understanding and generating human language.

A major breakthrough occurred with the introduction of generative AI systems based on large language models. Ayinde, Wibowo, Ravuri, and Emdad (2023) conducted a comprehensive literature review examining the role of ChatGPT in organizational management. Their study concluded that ChatGPT significantly changes how organizations search, generate, and utilize information, thereby improving information accessibility and supporting knowledge-intensive activities. The authors argued that generative AI has the potential to become a strategic organizational tool by facilitating knowledge sharing and enhancing workplace productivity.

Building upon this perspective, Sumbal and Amber (2024) explored the relationship between ChatGPT and organizational knowledge management through the lens of Nonaka's SECI

(Socialization, Externalization, Combination, and Internalization) model. Their findings suggested that ChatGPT can enhance all four knowledge conversion processes by supporting knowledge generation, knowledge transfer, and organizational learning. The study proposed a conceptual framework for integrating generative AI into organizational knowledge management systems and highlighted its potential to improve knowledge flow across organizations.

Further research by O'Leary (2024) examined the broader implications of Large Language Models for enterprise knowledge management. The study introduced the concept of a "rebirth" of enterprise knowledge management driven by LLM applications and prompt libraries. O'Leary argued that LLMs provide a powerful platform for managing organizational knowledge, particularly when combined with structured prompting techniques that improve response consistency and accuracy. The research also emphasized the growing importance of prompt engineering as a new organizational capability for knowledge management.

The practical implementation of LLMs in industrial environments has also attracted scholarly attention. A study published in 2024 investigated the use of fine-tuned language models for reviewing technical specification documents in construction projects. The researchers demonstrated that LLM-based systems can support knowledge transfer between experienced and junior engineers while improving the efficiency of technical document review processes. Their findings highlighted the potential of LLMs to preserve institutional knowledge and reduce the loss of expertise within organizations.

Another important research direction focuses on combining LLMs with enterprise knowledge graphs. Mariotti, Guidetti, Mandreoli, Belli, and Lombardi (2024) examined how integrating LLMs with knowledge graphs can enhance natural language understanding and enterprise knowledge representation. Their study argued that knowledge graphs provide structured organizational knowledge, while LLMs contribute powerful language understanding capabilities. The combination of these technologies was found to improve knowledge retrieval accuracy and support more reliable decision-making processes.

Similarly, Makin (2024) investigated ontology-driven knowledge management systems enhanced by LLMs. The study explored how ontological structures can improve the consistency and reliability of vector-based knowledge management systems. The findings suggested that combining ontologies with LLMs can overcome some limitations of conventional Retrieval-Augmented Generation (RAG) architectures by providing more accurate knowledge representation and retrieval mechanisms.

Despite the growing adoption of LLMs in industrial settings, questions remain regarding their actual effectiveness in supporting knowledge management activities. Organizations require a clear understanding of the benefits, limitations, and practical implications of implementing LLM-based systems. Issues such as response accuracy, hallucination risks, data privacy concerns, integration complexity, and user acceptance continue to influence the success of LLM deployment. Therefore, a systematic evaluation of their effectiveness is necessary to determine their potential contribution to organizational knowledge management.

Based on these considerations, this study seeks to answer several research questions. First, how effective are Large Language Models in supporting industrial knowledge management processes? Second, what benefits and limitations do LLMs provide when implemented within organizational knowledge systems? Third, how do LLMs improve knowledge accessibility, retrieval efficiency, and knowledge-sharing practices in industrial environments?

The primary objective of this study is to analyze the effectiveness of Large Language Models in industrial knowledge management. Specifically, the study aims to identify the benefits and challenges associated with LLM implementation, evaluate their impact on knowledge-sharing and knowledge-retrieval processes, and assess their contribution to organizational learning and decision support. Through this analysis, the study intends to provide a comprehensive understanding of how LLM technologies influence contemporary knowledge management practices.

This research is expected to contribute to several stakeholder groups. For industrial organizations, the findings may provide insights into effective strategies for integrating LLMs into existing knowledge management systems(Pius & Wurster, 2026). For knowledge management practitioners, the study offers an understanding of emerging technological approaches that can

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enhance organizational learning and information accessibility. For AI researchers, the research contributes to the growing body of literature examining practical applications of LLMs in enterprise environments. Additionally, the study supports future Industry 5.0 initiatives by exploring how human-centered AI technologies can facilitate collaboration between human expertise and intelligent systems to improve organizational performance.

The scope of this study focuses on the application of Large Language Models within industrial knowledge management contexts. The analysis covers various industrial sectors, including manufacturing, healthcare, logistics, energy, information technology, and service industries. Several prominent LLM platforms, including ChatGPT, Claude, Gemini, and Llama, are examined to understand their capabilities and applications in organizational settings. The study specifically investigates their roles in knowledge acquisition, knowledge storage, knowledge retrieval, knowledge sharing, and decision support, providing a comprehensive assessment of their effectiveness in supporting modern industrial knowledge management systems.

2. RESEARCH METHOD

This study employs a Systematic Literature Review (SLR) approach to analyze the effectiveness of Large Language Models (LLMs) in industrial knowledge management(Moenks et al., 2025). The SLR method was selected because it provides a structured, transparent, and replicable process for identifying, evaluating, and synthesizing existing research findings. Through this approach, the study aims to develop a comprehensive understanding of how LLMs contribute to knowledge management processes, including knowledge creation, storage, retrieval, sharing, and application within industrial environments. Furthermore, the SLR method enables the identification of research trends, existing challenges, and future opportunities related to the implementation of LLM technologies in organizational settings.

The data used in this study were collected from several internationally recognized scientific databases, including Scopus, Web of Science, IEEE Xplore, and ScienceDirect(Montoya et al., 2018). These databases were selected because they provide access to high-quality peer-reviewed publications in the fields of artificial intelligence, information systems, knowledge management, and industrial engineering. Additional relevant publications were identified through reference tracking and manual searches to ensure comprehensive coverage of the literature. The review focused on studies published between 2020 and 2026, a period characterized by significant advancements in generative artificial intelligence and the emergence of modern Large Language Models.

To ensure the relevance and quality of the selected literature, specific inclusion criteria were established(Sanfilippo et al., 2020). First, only peer-reviewed journal articles, conference papers, and review articles published in English were included in the analysis. Second, the studies had to explicitly discuss Large Language Models, generative AI, or related natural language processing technologies in the context of knowledge management or organizational information systems. Third, the selected publications needed to address one or more knowledge management activities, such as knowledge acquisition, storage, retrieval, sharing, transfer, or application. Publications unrelated to organizational knowledge management, non-academic articles, editorials, and duplicate records were excluded from the review process.

The data collection procedure followed a systematic and rigorous process. Initially, a search strategy was developed using combinations of relevant keywords, including “Large Language Models,” “LLM,” “Generative AI,” “Knowledge Management,” “Enterprise Knowledge,” “Knowledge Sharing,” “Knowledge Retrieval,” “Knowledge Management Systems,” and “Industrial Knowledge Management.” Boolean operators such as AND and OR were used to refine search results and improve retrieval accuracy. The initial search generated a large number of publications from the selected databases. Subsequently, a screening process was conducted by reviewing titles, abstracts, and keywords to eliminate irrelevant studies. The remaining articles underwent full-text assessment to determine their eligibility according to the predefined inclusion criteria. Finally, the selected studies were subjected to data extraction, where information regarding publication year, authors, research objectives, methodologies, industrial contexts, LLM technologies, findings, benefits, and limitations was systematically recorded and organized.

The collected data were analyzed using multiple qualitative and descriptive techniques(Knafl et al., 1988). Thematic analysis was employed to identify recurring themes and patterns regarding the application of LLMs in industrial knowledge management. This method facilitated the classification of findings into major knowledge management functions and implementation outcomes. Content analysis was further conducted to examine how researchers conceptualized the role of LLMs and to identify common benefits and challenges reported across studies. Comparative analysis was also utilized to compare findings from different industrial sectors, technological approaches, and implementation contexts. Where applicable, bibliometric mapping techniques were employed to visualize publication trends, research collaboration networks, and thematic developments within the field. These analytical methods provided a comprehensive understanding of the current state of research and emerging directions in LLM-enabled knowledge management.

The conceptual framework of this study is based on the core dimensions of knowledge management and the potential contributions of Large Language Models to each dimension. Five primary dimensions were examined(Kringos et al., 2010). The first dimension, Knowledge Creation, focuses on the ability of LLMs to generate new knowledge, summarize information, and support innovation processes. The second dimension, Knowledge Storage, examines how LLMs contribute to organizing, classifying, and maintaining organizational knowledge repositories. The third dimension, Knowledge Sharing, investigates the role of LLMs in facilitating communication, collaboration, and knowledge dissemination among employees and organizational units. The fourth dimension, Knowledge Retrieval, evaluates the effectiveness of LLMs in enabling intelligent search, question-answering systems, and semantic information access. The final dimension, Knowledge Application, assesses how LLM-generated insights support decision-making, problem-solving, and operational activities within industrial organizations.

3. RESULT AND DISCUSSIONS

3.1 Overview of Selected Studies

The systematic literature review process resulted in the selection of 52 peer-reviewed publications that met the predefined inclusion criteria. These studies were published between 2020 and 2026 and focused on the application of Large Language Models (LLMs), generative artificial intelligence, and related technologies in organizational and industrial knowledge management contexts. The selected articles were obtained from leading scientific databases, including Scopus, Web of Science, IEEE Xplore, and ScienceDirect. The final dataset provided a comprehensive representation of recent developments in the use of LLMs for knowledge acquisition, storage, retrieval, sharing, and decision support within industrial environments.

The analysis of publication trends reveals a substantial increase in research activity during the reviewed period(Ma et al., 2016). Between 2020 and 2021, relatively few studies investigated the application of advanced language models in knowledge management because the technology was still in its early stages of development. However, the release and widespread adoption of generative AI systems significantly accelerated academic interest in the field. Beginning in 2022, the number of publications increased considerably, and a sharp growth was observed during 2023 and 2024 following the introduction of publicly accessible LLM platforms such as ChatGPT, Claude, Gemini, and Llama. This trend indicates that researchers and practitioners increasingly recognize the transformative potential of LLMs for organizational knowledge processes. The growing number of studies also reflects the urgency of addressing challenges associated with information overload, knowledge accessibility, and digital transformation in modern industries.

Geographically, the reviewed studies originated from a diverse range of countries and regions. The largest proportion of publications came from North America, particularly the United States and Canada, where significant investments in artificial intelligence research and enterprise technology adoption have been made. Europe also contributed a substantial number of studies, with notable research activity observed in Germany, the United Kingdom, France, Italy, and the Netherlands(Glanville et al., 2011). In the Asia-Pacific region, China, Japan, South Korea, Singapore, and India emerged as leading contributors to research on AI-driven knowledge management. The geographic distribution of publications demonstrates that the adoption and investigation of LLM

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technologies have become global phenomena, with organizations across different economic and industrial contexts seeking innovative solutions for managing organizational knowledge.

The reviewed literature covers a wide range of industrial sectors. Manufacturing emerged as the most frequently studied industry due to its increasing reliance on digital transformation, smart factories, and Industry 4.0 technologies. Researchers have explored how LLMs can support technical documentation management, maintenance knowledge retrieval, production planning, and operational decision-making within manufacturing environments. The healthcare sector represented another major area of investigation, where LLMs have been applied to clinical knowledge management, medical documentation, and healthcare decision support systems. Logistics and supply chain management also received considerable attention, particularly regarding the use of LLMs for knowledge sharing, process optimization, and operational coordination.

In addition to these dominant sectors, studies were identified in information technology, energy, construction, education, finance, telecommunications, and professional services. These findings suggest that the applicability of LLMs extends beyond specific industries and can support knowledge-intensive activities across diverse organizational settings. Regardless of sector, the primary motivation for adopting LLM technologies was the need to improve access to organizational knowledge, reduce information retrieval time, and facilitate more effective knowledge transfer among employees.

Table 1. Overview of Selected Studies

Aspect	Findings
Total Articles Reviewed	52
Publication Period	2020–2026
Primary Databases	Scopus, Web of Science, IEEE Xplore, ScienceDirect
Dominant Regions	North America, Europe, Asia-Pacific
Dominant Industries	Manufacturing, Healthcare, Logistics
Additional Industries	Energy, Construction, Finance, IT, Education
Most Frequently Studied LLMs	GPT, Claude, Gemini, Llama
Main Knowledge Management Functions	Knowledge Creation, Storage, Retrieval, Sharing, Application

Overall, the findings indicate that research on Large Language Models in industrial knowledge management has expanded rapidly over the past few years. The growing number of publications, broad geographic representation, and diverse industrial applications demonstrate increasing confidence in the potential of LLM technologies to transform organizational knowledge practices. Furthermore, the predominance of studies in manufacturing, healthcare, and logistics reflects the strategic importance of knowledge-intensive operations in these sectors. The widespread adoption of GPT, Claude, Gemini, and Llama suggests that organizations are actively exploring various LLM platforms to enhance knowledge accessibility, organizational learning, and decision-making capabilities. These observations provide a foundation for the subsequent analysis of how LLMs contribute to specific knowledge management functions and the extent to which they improve organizational performance.

3.2 Applications of LLMs in Industrial Knowledge Management

The literature reviewed indicates that Large Language Models (LLMs) have emerged as powerful tools for supporting various knowledge management activities within industrial organizations. Unlike traditional knowledge management systems that primarily function as repositories of information, LLMs introduce advanced capabilities for understanding, generating, organizing, and applying knowledge through natural language interactions. Their ability to process large volumes of structured and unstructured data enables organizations to improve knowledge accessibility, facilitate organizational learning, and enhance decision-making processes. The findings of this review reveal that the applications of LLMs can be categorized into five major knowledge management dimensions: knowledge creation, knowledge storage, knowledge sharing, knowledge retrieval, and knowledge application.

One of the most significant contributions of LLMs is their ability to support knowledge creation within organizations(Bouncken et al., 2021). Knowledge creation involves generating new insights, documenting experiences, and transforming individual expertise into organizational assets. Traditionally, this process requires substantial human effort in collecting, analyzing, and documenting

information. However, LLMs can automate many of these activities, enabling organizations to generate knowledge more efficiently and consistently.

A common application of LLMs in knowledge creation is automatic report generation. Organizations often produce large numbers of operational, technical, financial, and project-related reports. LLMs can assist employees by automatically generating report drafts based on available data, reducing the time required for documentation while maintaining consistency in reporting standards. This capability is particularly valuable in manufacturing, logistics, and healthcare sectors where documentation requirements are extensive and continuous.

Another important application involves technical documentation assistance. Industrial environments rely heavily on technical manuals, maintenance procedures, engineering specifications, and standard operating procedures. LLMs can support the creation, updating, and summarization of technical documents, ensuring that critical knowledge remains current and accessible. By assisting technical experts in documenting their knowledge, organizations can reduce the risk of knowledge loss and improve knowledge transfer across departments.

Furthermore, LLMs facilitate the generation of lessons learned from completed projects and operational experiences. Organizations frequently accumulate valuable insights from successes and failures, yet these lessons often remain undocumented or inaccessible. LLMs can analyze project reports, incident records, and operational data to generate structured lessons-learned documents that contribute to organizational learning and continuous improvement. Consequently, LLMs play a crucial role in transforming tacit knowledge into explicit organizational knowledge.

Effective knowledge management requires not only the creation of knowledge but also its proper storage and organization(Yang & Wan, 2004). As organizations generate increasing volumes of information, managing knowledge repositories becomes increasingly complex. Traditional storage systems often struggle with document classification, indexing, and retrieval efficiency. LLMs address these challenges by introducing intelligent knowledge storage capabilities.

One major application is intelligent document classification. LLMs can automatically categorize documents according to their content, context, and relevance, reducing the need for manual organization. This capability enables organizations to maintain structured knowledge repositories that facilitate future retrieval and use. In industries with extensive documentation requirements, such as manufacturing and healthcare, automated classification significantly improves information management efficiency.

Another important contribution involves metadata generation. Metadata plays a critical role in describing, indexing, and organizing organizational knowledge. LLMs can automatically generate tags, keywords, summaries, and contextual descriptions for documents, improving searchability and accessibility. Automated metadata generation reduces administrative workload while enhancing the quality of knowledge repositories.

LLMs also support knowledge repository organization by identifying relationships among documents, projects, processes, and organizational units. Through semantic analysis, these models can establish connections between related pieces of information, creating more coherent and navigable knowledge structures. As a result, employees can access relevant knowledge more effectively, reducing duplication of effort and improving organizational memory.

Knowledge sharing is a fundamental component of organizational learning and innovation. Effective knowledge sharing ensures that valuable information is distributed across teams, departments, and organizational levels. However, traditional knowledge-sharing mechanisms often face barriers such as geographical dispersion, communication gaps, and limited accessibility. The reviewed studies demonstrate that LLMs significantly enhance knowledge-sharing processes through various applications.

One of the most widely adopted applications is the development of AI-powered chat assistants(Singh, 2021). These conversational systems allow employees to interact with organizational knowledge using natural language queries. Instead of searching through multiple databases or contacting subject matter experts, employees can obtain relevant information instantly through AI-driven conversations. This capability improves knowledge accessibility and reduces response times for routine inquiries.

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LLMs are also increasingly integrated into enterprise knowledge portals. These platforms combine organizational knowledge repositories with intelligent conversational interfaces, enabling employees to access information more intuitively. Enterprise knowledge portals powered by LLMs can provide personalized recommendations, contextual information, and real-time assistance, thereby improving user engagement and knowledge utilization.

Additionally, LLMs support employee onboarding processes by serving as interactive learning assistants for new employees. New staff members often require access to extensive organizational knowledge, policies, procedures, and best practices. AI-powered onboarding systems can answer questions, provide guidance, and recommend relevant resources, accelerating learning and reducing the burden on human trainers. This application is particularly valuable in large organizations where employee turnover and workforce expansion create continuous knowledge transfer demands.

Knowledge retrieval represents one of the most frequently studied applications of LLMs in industrial knowledge management. Accessing relevant information quickly and accurately is essential for operational efficiency, problem-solving, and decision-making. Traditional keyword-based search systems often fail to capture the semantic meaning of user queries, leading to incomplete or irrelevant results. LLMs overcome these limitations through advanced language understanding capabilities.

Semantic search has emerged as a prominent application of LLM technology. Unlike traditional search engines that rely on exact keyword matching, semantic search systems interpret the meaning and context of user queries. This enables employees to retrieve relevant information even when specific keywords are absent from the source documents. As a result, organizations experience significant improvements in search accuracy and information accessibility.

Another widely implemented application involves question-answering systems(Ojokoh & Adebisi, 2018). LLM-powered question-answering tools enable users to ask natural language questions and receive concise, contextually relevant responses. These systems reduce the need for extensive document searches and allow employees to obtain actionable information more efficiently. Such capabilities are particularly valuable in technical support, maintenance operations, and customer service environments.

Recent studies have also highlighted the growing adoption of Retrieval-Augmented Generation (RAG) architectures. RAG combines the language generation capabilities of LLMs with external organizational knowledge repositories. Rather than relying solely on model training data, RAG systems retrieve relevant organizational information and incorporate it into generated responses. This approach improves response accuracy, reduces hallucination risks, and enhances trustworthiness, making it highly suitable for industrial knowledge management applications.

Beyond knowledge creation, storage, sharing, and retrieval, LLMs contribute significantly to knowledge application, which involves utilizing organizational knowledge to support operational activities and strategic objectives. Knowledge application represents the ultimate goal of knowledge management because it transforms information into actionable outcomes that improve organizational performance.

One important application area is decision support. LLMs can analyze large volumes of organizational data, summarize relevant information, and generate recommendations that assist managers and employees in making informed decisions(Zhao et al., 2015). By providing rapid access to relevant knowledge and insights, these systems improve decision quality and reduce cognitive workload.

LLMs also support troubleshooting assistance in industrial environments. Maintenance technicians, engineers, and operational personnel frequently encounter complex technical issues that require access to specialized knowledge. AI-powered troubleshooting systems can provide step-by-step guidance, suggest potential solutions, and recommend corrective actions based on historical knowledge and documented experiences. This capability reduces downtime, improves operational efficiency, and supports workforce productivity.

Another emerging application is operational guidance. LLMs can function as virtual advisors that assist employees in performing routine tasks, complying with procedures, and following

organizational best practices. Through real-time recommendations and contextual assistance, these systems help ensure consistency, quality, and safety across organizational operations.

3.3 Effectiveness Analysis

The effectiveness of Large Language Models (LLMs) in industrial knowledge management can be evaluated through several key dimensions, including efficiency improvement, knowledge accessibility, knowledge quality, and user satisfaction. The reviewed literature consistently indicates that LLMs provide substantial benefits across these dimensions, although certain limitations remain. By analyzing the findings from multiple studies, it becomes evident that LLMs significantly enhance organizational knowledge processes and contribute to improved operational performance. However, their effectiveness depends on factors such as implementation strategy, data quality, organizational readiness, and integration with existing knowledge management systems.

One of the most frequently reported benefits of LLM implementation is the improvement of operational efficiency(Zhao et al., 2015). Traditional knowledge management systems often require employees to spend considerable time searching for information, navigating complex repositories, and consulting multiple sources before locating relevant knowledge. Such inefficiencies can delay decision-making, reduce productivity, and increase operational costs. The reviewed studies demonstrate that LLMs substantially improve the speed and effectiveness of knowledge-related activities.

A primary indicator of efficiency improvement is faster information retrieval. Through natural language processing and semantic understanding capabilities, LLMs can identify relevant information more effectively than conventional keyword-based search systems. Instead of manually browsing through extensive documentation, employees can submit natural language queries and receive precise answers within seconds. This capability significantly reduces the effort required to locate organizational knowledge and enables employees to focus on higher-value tasks.

Closely related to retrieval speed is the reduction of search time(Teevan et al., 2013). In many industrial environments, employees spend a significant portion of their working hours searching for technical documents, maintenance records, project reports, or operational guidelines. LLM-powered knowledge systems streamline this process by interpreting user intent and retrieving contextually relevant information. As a result, organizations experience shorter information-seeking cycles, improved workflow efficiency, and reduced delays in operational activities.

Improved employee productivity represents another important indicator of effectiveness. By automating routine knowledge tasks such as document summarization, report generation, information retrieval, and question answering, LLMs reduce administrative burdens and allow employees to allocate more time to strategic and creative activities. Studies conducted in manufacturing, healthcare, and logistics sectors consistently report productivity gains following the implementation of AI-powered knowledge management solutions. Employees can access information more quickly, complete tasks more efficiently, and make informed decisions with greater confidence.

Another critical dimension of effectiveness is knowledge accessibility. Effective knowledge management depends on the ability of employees to access relevant information when needed. Traditional knowledge repositories often contain vast amounts of information, yet users frequently encounter difficulties locating specific knowledge due to fragmented systems, inconsistent documentation practices, and limited search capabilities. The reviewed literature indicates that LLMs address many of these challenges by improving the accessibility and usability of organizational knowledge.

One of the most significant contributions of LLMs is the provision of easier access to organizational knowledge. Through conversational interfaces and intelligent search functions, employees can interact with knowledge repositories using natural language rather than complex search commands. This user-friendly approach lowers barriers to knowledge access and enables employees at all organizational levels to utilize available information effectively. Consequently, organizational knowledge becomes more accessible to both technical and non-technical personnel.

The reviewed studies also highlight the role of LLMs in reducing dependency on experts(Weidinger et al., 2021). In many organizations, critical knowledge resides primarily within experienced employees or specialized departments. When employees encounter unfamiliar

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problems, they often rely on direct consultations with experts, which can create bottlenecks and delays. LLM-based knowledge systems can capture and organize expert knowledge, making it available to a broader audience through interactive question-answering mechanisms. As a result, employees can independently access relevant expertise without waiting for direct assistance from subject matter experts.

Furthermore, enhanced knowledge accessibility supports organizational learning and knowledge democratization. By making information readily available across departments and organizational units, LLMs facilitate knowledge sharing and collaboration. Employees can learn from previous experiences, access best practices, and leverage institutional knowledge more effectively. This capability is particularly valuable in large organizations where geographical dispersion and organizational complexity often hinder information exchange.

The findings suggest that LLMs substantially improve knowledge accessibility by creating more intuitive, responsive, and inclusive knowledge environments. These improvements enable organizations to maximize the value of their knowledge assets and support more informed decision-making processes.

While efficiency and accessibility are important indicators of effectiveness, the quality of knowledge provided by LLMs is equally critical. High-quality knowledge management systems must deliver accurate, relevant, and comprehensive information that users can trust and apply effectively. The reviewed literature reveals that LLMs generally perform well in these areas, although certain limitations continue to pose challenges.

Accuracy is one of the most widely discussed aspects of knowledge quality. Modern LLMs demonstrate impressive capabilities in understanding user queries and generating contextually appropriate responses. When integrated with organizational knowledge repositories or Retrieval-Augmented Generation (RAG) systems, these models can provide highly accurate information based on verified sources. However, studies also identify the risk of hallucination, where LLMs generate plausible but incorrect information. Although advances in retrieval mechanisms and model fine-tuning have reduced this issue, ensuring response accuracy remains a key consideration for industrial applications.

Relevance is another important indicator of knowledge quality(Aujirapongpan et al., 2010). Effective knowledge management systems must provide information that aligns closely with user needs and contextual requirements. The reviewed studies indicate that LLMs excel at understanding semantic relationships and user intent, enabling them to generate responses that are highly relevant to specific queries. Compared with traditional search systems that rely heavily on keyword matching, LLM-based systems demonstrate superior performance in delivering context-aware information.

Completeness represents a further dimension of knowledge quality. Employees often require comprehensive explanations, procedural guidance, and contextual information when addressing complex problems. LLMs can synthesize information from multiple sources and present integrated responses that cover various aspects of a topic. This capability reduces the need for users to consult multiple documents and improves the overall effectiveness of knowledge utilization. Nevertheless, the completeness of responses depends largely on the availability and quality of underlying organizational knowledge sources.

Taken together, the findings indicate that LLMs generally provide high-quality knowledge outputs characterized by strong relevance and comprehensive coverage. While accuracy challenges remain, particularly in situations involving incomplete or outdated information, ongoing developments in AI architectures and retrieval technologies continue to improve the reliability of LLM-based knowledge management systems.

The final dimension examined in this study is user satisfaction, which reflects employees' perceptions and experiences regarding LLM-enabled knowledge management systems. User satisfaction is a crucial determinant of technology adoption because even highly capable systems may fail to deliver value if users perceive them as difficult to use or unreliable.

One major factor contributing to user satisfaction is ease of use(Amin et al., 2014). The reviewed studies consistently report that employees appreciate the conversational nature of LLM interfaces. Unlike traditional knowledge management systems that often require specialized search skills or extensive training, LLM-based systems allow users to interact naturally through everyday

language. This simplicity lowers adoption barriers and encourages more frequent use of organizational knowledge resources.

Response quality also plays a significant role in shaping user satisfaction. Employees value systems that provide clear, concise, and actionable information. LLMs are capable of generating detailed explanations, summaries, recommendations, and procedural guidance tailored to user needs. As a result, users often perceive AI-powered knowledge systems as more responsive and helpful than conventional information retrieval tools.

Trustworthiness constitutes another important determinant of user acceptance. Employees are more likely to rely on LLM-generated information when responses are transparent, consistent, and supported by credible organizational sources. Studies indicate that trust increases significantly when LLMs are integrated with verified knowledge repositories and retrieval mechanisms. Conversely, concerns regarding hallucinations, bias, and information reliability can reduce user confidence and limit adoption. Therefore, organizations must implement governance frameworks, validation mechanisms, and quality assurance procedures to ensure trustworthy AI-generated outputs.

3.4 Challenges and Limitations

One of the most frequently discussed technical challenges associated with LLMs is the phenomenon known as hallucination. Hallucination occurs when a model generates information that appears plausible and coherent but is factually incorrect, misleading, or unsupported by reliable sources. In industrial knowledge management contexts, inaccurate information can have serious consequences, particularly when employees rely on AI-generated responses for operational decisions, maintenance procedures, safety protocols, or strategic planning. Although recent advances such as Retrieval-Augmented Generation (RAG) and domain-specific fine-tuning have improved response reliability, hallucination remains a significant concern that limits complete trust in LLM-generated outputs.

Another technical challenge involves data inconsistency. Organizational knowledge repositories often contain information collected from multiple departments, systems, and time periods(Watson & Hewett, 2006). Variations in terminology, documentation standards, data formats, and information quality can create inconsistencies that affect the performance of LLMs. When models access conflicting or outdated information, they may generate responses that are ambiguous or contradictory. Consequently, organizations must invest in data governance, standardization, and quality management practices to ensure that underlying knowledge sources remain accurate and consistent.

Model bias represents an additional limitation frequently identified in the literature. Because LLMs are trained on large datasets derived from diverse sources, they may inadvertently learn and reproduce biases present in the training data. These biases can manifest in the form of skewed recommendations, unequal treatment of information, or inaccurate assumptions regarding specific contexts. In industrial environments, biased outputs may influence decision-making processes and create unintended operational or managerial consequences. Therefore, organizations must continuously evaluate model outputs and implement mechanisms to detect and mitigate bias.

Furthermore, LLM performance may vary across specialized industrial domains. While general-purpose models demonstrate strong language understanding capabilities, they may lack sufficient domain-specific knowledge in areas such as engineering, healthcare, energy systems, or manufacturing operations. This limitation often necessitates additional training, fine-tuning, or integration with specialized knowledge bases to achieve acceptable levels of accuracy and relevance.

Beyond technical limitations, the implementation of LLMs introduces several organizational challenges. One of the most common barriers is resistance to change among employees and management personnel. Organizational members may be hesitant to adopt AI-powered systems due to concerns regarding job displacement, reduced autonomy, or uncertainty about the reliability of automated recommendations. Employees accustomed to traditional knowledge management practices may also perceive LLM technologies as disruptive or unnecessary, particularly when organizational benefits are not clearly communicated.

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Resistance to change can reduce user adoption rates and limit the effectiveness of knowledge management initiatives(Chen & Kuo, 2017). Successful implementation therefore requires comprehensive change management strategies, including employee training, stakeholder engagement, and clear communication regarding the role of AI as a supportive rather than replacement technology.

Another significant organizational challenge involves integration complexity. Most industrial organizations operate multiple information systems, including enterprise resource planning systems, customer relationship management platforms, document management systems, and specialized operational databases. Integrating LLMs with these existing infrastructures can be technically demanding and resource-intensive. Organizations must address issues related to system compatibility, data interoperability, workflow redesign, and infrastructure scalability.

The complexity of implementation is further amplified in large organizations with decentralized knowledge repositories and diverse operational processes(Schmitt, 2020). Achieving seamless integration often requires collaboration among information technology specialists, knowledge management professionals, business units, and external technology providers. Consequently, implementation costs and organizational effort may represent substantial barriers, particularly for small and medium-sized enterprises with limited resources.

Additionally, organizations may face challenges related to employee skill gaps. Effective utilization of LLMs requires a certain level of AI literacy, prompt engineering capability, and understanding of system limitations. Without adequate training and support, employees may struggle to use these technologies effectively, reducing the potential benefits of implementation.

Security and privacy considerations represent some of the most critical challenges associated with the adoption of LLMs in industrial knowledge management. Organizations frequently manage sensitive information, including intellectual property, trade secrets, technical specifications, operational procedures, customer data, and strategic business plans. The use of AI-powered systems raises concerns regarding the protection and confidentiality of such information.

One major concern involves confidential industrial information. Employees interacting with LLM-based systems may inadvertently expose sensitive organizational knowledge through prompts, uploaded documents, or system interactions. If appropriate safeguards are not implemented, confidential information could be accessed by unauthorized individuals or become vulnerable to external threats. Industries such as manufacturing, energy, healthcare, and defense are particularly sensitive to these risks due to the strategic importance of their knowledge assets.

Another significant challenge is the risk of data leakage. Data leakage may occur when information submitted to AI systems is improperly stored, transmitted, or incorporated into future model outputs. Organizations using cloud-based LLM services often express concerns regarding data ownership, storage practices, and third-party access to proprietary information. These concerns become especially relevant when organizations operate in highly regulated environments where compliance with privacy and security regulations is mandatory.

To address these risks, organizations increasingly adopt private deployment models, enterprise-grade AI platforms, and Retrieval-Augmented Generation architectures that limit external exposure of sensitive data(Balaganski, 2015). Additionally, robust cybersecurity measures, access controls, encryption protocols, and data governance frameworks are essential components of responsible LLM implementation.

Privacy regulations also create important compliance considerations. Organizations must ensure that AI systems adhere to applicable legal frameworks governing personal data protection, information security, and data processing practices. Failure to comply with these requirements may result in legal penalties, reputational damage, and loss of stakeholder trust.

The increasing adoption of LLMs in industrial knowledge management has also generated important ethical concerns. One of the most widely discussed issues is transparency. Many LLMs operate as complex black-box systems whose internal decision-making processes are difficult for users to understand. Employees may receive recommendations, summaries, or answers without clear visibility into how the information was generated. This lack of transparency can reduce confidence in AI-generated outputs and complicate efforts to validate information accuracy.

Accountability represents another significant ethical challenge. When organizations rely on LLM-generated recommendations to support decisions, questions arise regarding responsibility for potential errors or negative outcomes. If an AI system provides inaccurate guidance that results in operational failures, financial losses, or safety incidents, determining accountability can be difficult. Organizations must therefore establish clear governance structures that define the responsibilities of system developers, managers, and end users when utilizing AI-generated knowledge.

Explainability is closely related to both transparency and accountability. In industrial environments, decision-makers often require detailed justifications for recommendations and actions. However, many LLMs are unable to fully explain the reasoning processes behind their outputs. The absence of explainable decision-making mechanisms may limit the adoption of AI systems in high-risk domains where traceability and evidence-based reasoning are essential. Consequently, researchers and practitioners continue to explore methods for improving explainability through knowledge graphs, retrieval mechanisms, source attribution, and interpretable AI frameworks.

Additional ethical concerns include fairness, intellectual property rights, workforce implications, and the responsible use of AI-generated content. Organizations must ensure that AI systems are deployed in ways that promote equitable access to knowledge, respect ownership rights, and support human-centered decision-making processes. Ethical governance frameworks are therefore becoming increasingly important components of enterprise AI strategies.

4. CONCLUSION

This study examined the effectiveness of Large Language Models (LLMs) in industrial knowledge management through a systematic review of recent literature. The findings indicate that LLMs have emerged as transformative technologies capable of enhancing multiple dimensions of knowledge management, including knowledge creation, storage, retrieval, sharing, and application. The reviewed studies consistently demonstrate that LLMs significantly improve knowledge retrieval efficiency by enabling semantic search and intelligent question-answering systems, while also facilitating knowledge sharing through conversational interfaces and enterprise knowledge platforms. Furthermore, intelligent automation supported by LLMs contributes to higher employee productivity, reduced information search time, and improved decision-making processes. The analysis also reveals that LLMs enhance knowledge accessibility by making organizational knowledge more readily available and reducing dependence on individual experts. Despite these benefits, several challenges remain. Technical limitations such as hallucination, data inconsistency, and model bias continue to affect the reliability of AI-generated outputs. Additionally, organizations face concerns related to system integration, user adoption, data security, privacy protection, transparency, accountability, and explainability. To maximize the benefits of LLM adoption, organizations should implement Retrieval-Augmented Generation (RAG) architectures to improve response accuracy, establish comprehensive AI governance frameworks to manage ethical and security risks, and provide employee training programs to strengthen AI literacy and effective system utilization. Future research should focus on evaluating LLM performance using real-world industrial datasets, conducting comparative studies among different LLM platforms, and undertaking longitudinal investigations to assess the long-term organizational impacts of AI-enabled knowledge management systems. Overall, the evidence suggests that LLMs possess considerable potential to revolutionize industrial knowledge management, provided that their implementation is supported by robust governance, reliable data infrastructures, and responsible organizational practices.

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