Knowledge Management Systems: A Review of Artificial Intelligence Integration and Technologies

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Abstract. Knowledge Management Systems (KMS) have become so imperative in organizations today because they are efficient in knowledge capture, storage, and dissemination. This paper reviews different types and technologies of KMS, placing special emphasis on AI-based systems, such as Knowledge-Based Expert Systems (KEBS), Neural Networks (NN), and Case-Based Reasoning (CBR). This work will also discuss, to an extent, KMS adopted by governmental organizations, process-oriented KMS, and contingency KMS by describing the benefits and challenges that come with each. Further, this paper will increase the possibilities of knowledge representation and knowledge retrieval by discussing Knowledge Graph Technology. In addition, it discusses issues that arise during implementation; issues such as poor quality data and how to balance human expertise with AI-driven automation. Thereafter, it will shed some light on future trends and recommendations about how to have optimal adoption of KMS in different types of industries.

Keywords: Knowledge Management Systems · tacit knowledge · knowledge-based expert systems · Neural Networks · Case-based reasoning systems · Knowledge-based Information System

1 Introduction

In the contemporary digital economy, knowledge has become one of the most valuable assets for organizations [1]. Effective knowledge management enhances decision-making and operational efficiency and also fosters innovation and sustains competitive advantage [2]. To this end, Knowledge Management Systems (KMS) have emerged as structured technological solutions that support the collection, organization, dissemination, and utilization of both explicit and tacit knowledge.

Recent advancements in Artificial Intelligence (AI) have significantly transformed the landscape of KMS by enabling systems to learn from data, adapt to changing environments, and emulate human reasoning [3–13]. The integration of AI into KMS enhances

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their intelligence and responsiveness, especially in domains requiring dynamic decision support and knowledge-based automation.

Recent literature includes several studies that review or analyze the design and implementation of Knowledge Management Systems, focusing on their organizational impact and enabling technologies. For instance, in [14], the authors examined critical success factors in KMS adoption, emphasizing the moderating role of organizational culture, while in [15], the authors explored governmental KMS utilization across various countries. In [16], the authors provided a technical overview of AI-supported mechanisms in KMS, such as expert systems and neural networks, whereas in [17], the authors proposed a practical KMS design tailored for IT consulting companies, highlighting architectural considerations and system components. However, these works either center on isolated technologies or context-specific implementations [21]. A comprehensive and comparative review that integrates AI-driven approaches—such as KEBS, Neural Networks, and Case-Based Reasoning—within a broader framework that includes both enterprise and governmental KMS applications remains underdeveloped. This paper aims to address that gap by synthesizing the technical and operational dimensions of AI-enhanced KMS across sectors.

In view of the above, this paper provides a structured review of AI-integrated KMS, with a focus on three major AI approaches: Knowledge-Based Expert Systems (KEBS), Neural Networks (NN), and Case-Based Reasoning (CBR). These technologies are examined in terms of their functionalities, advantages, and challenges within organizational and governmental contexts. The review also explores the role of Knowledge Graph Technology in improving knowledge representation and retrieval, and discusses additional categories such as process-based and contingency-based KMS. Moreover, the paper highlights practical implementations of KMS in public sector environments and evaluates the key obstacles to successful deployment, including data quality, system integration, and the need to balance AI automation with human judgment. The paper concludes with a discussion on future research directions and the importance of ethical and human-centric design in the evolution of intelligent knowledge systems.

2 Knowledge Management Systems

A Knowledge Management System, or KMS, is a framework that enables organizations to capture, organize, and share their knowledge assets effectively. By centralizing information and fostering collaboration, KMS allows employees to access relevant data quickly, which enhances decision-making and supports innovation. These systems are particularly critical in a knowledge economy where the ability to harness the skills and knowledge of the workforce is key to gaining and sustaining competitive advantage.

KMS is a knowledge management tool for the different operational areas and units (businesses, IT, Government). More than an instrument for the organization of explicit knowledge, such as documented procedures and reports, it prioritizes tacit knowledge stemming from the experience and creativity of the employees. The latter type of knowledge is responsible for innovation and the achievement of strategic goals and is hence hard to map and replicate. KMS enables the transformation of tacit insights into strategic actionables by filling the gap between individual expertise and organizational goals with the integration of advanced technologies.

KMS consists of five components that work together for supporting the effective acquisition, organization, and dissemination of knowledge [14]. These key components are:

- **Strategy**: It defines the purpose, direction, and expected outcomes of KMS, ensuring that knowledge contribute to competitive advantage and innovation.
- **People**: It refers to the individuals and teams who create, share, and apply knowledge.
- **Process**: It includes the workflows, procedures, and routines that show how knowledge is captured, stored, retrieved, and used.
- **Technology**: It refers to the digital infrastructure, such as databases, networks, and AI tools, that enables the access, analysis, and sharing of knowledge.
- **Culture**: It represents the values, norms, and behaviors that influence how knowledge is perceived and handled.

Figure 1 illustrates the KMS components.

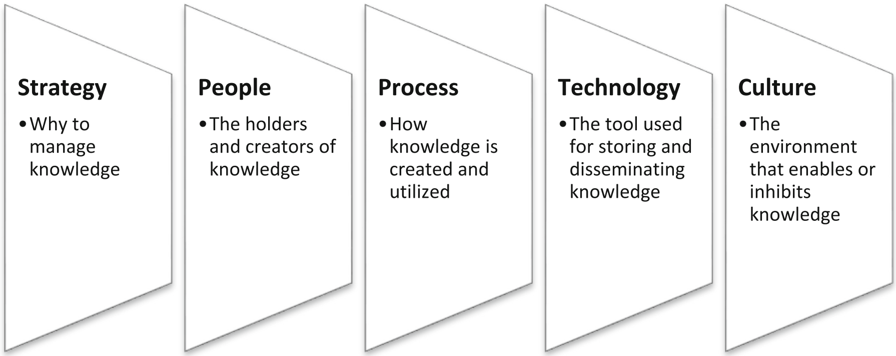

Fig. 1. KMS Components.

3 Different Technologies of KMS

In the course of our research, we conducted a rather widespread review of the recent literature on Knowledge Management Systems (KMS), identifying a diverse range of types and technologies, each with distinct advantages and limitations. These systems leverage various methodologies, including artificial intelligence techniques, to facilitate knowledge acquisition, storage, and dissemination. Understanding the strengths and challenges of each KMS is crucial for selecting the most suitable approach based on organizational needs and contexts.

The following table provides a detailed overview of the identified KMS types, highlighting their core characteristics, potential applications, and limitations. Additionally, the table references the specific scholarly articles from which these insights were drawn, offering a comprehensive perspective on the current state of KMS research (Table 1).

Table 1. Technologies/Types of KMS

Technologies/Types of KMS	Paper
Knowledge-based expert systems (KEBS)	[16]
Neural Networks (NN)	[16]
Case-based reasoning systems (CBR)	[16]
Knowledge-based Information System	[15]
Decision Support System (DSS)	[15]
Knowledge Framework	[15]
Lesson Learned System (LLS)	[15]
process-based knowledge management systems (PKS)	[19]
KMS of Contingency	[18]
Knowledge Graph	[20]

3.1 Implementing AI into KMS

Artificial Intelligence (AI) systems thus deal with knowledge management by aiding knowledge value chain models and enabling efficient knowledge system classification. With the acquisition and processing of data, AI technologies turn into integral parts of intelligent organizations and drive knowledge generation, acquisition, and management. AI develops from intelligent simulation and learning to provide significant enhancements in enterprise knowledge creation, organization, and application processes. This integration shows that there is a crucial requirement for interactions between management and technology on smooth lines for effective implementation. Out of the different AI-based approaches in knowledge management systems, the three major functional categories are neural networks, case-based reasoning systems, and knowledge-based expert systems [16].

3.1.1 Knowledge-Based Expert Systems (KEBS)

Knowledge-Based Expert Systems (KEBS) are rule-driven systems that simulate expert reasoning by applying structured logic to a predefined knowledge base. These systems are particularly effective in domains where problems are well-defined and expert rules can be explicitly encoded, such as in diagnostic support or regulatory compliance environments.

The strengths of KEBS include their high interpretability, consistency in decision logic, and ease of updating based on expert input. For example, in healthcare settings, KEBS have been used to replicate clinical decision-making processes, enabling non-specialists to access expert-level advice [16].

However, KEBS face limitations when dealing with ambiguous, incomplete, or constantly evolving knowledge. Their effectiveness is largely dependent on the completeness and accuracy of the rule base, which requires continuous human oversight and domain-specific updates [16].

Compared to more flexible AI methods such as Neural Networks (NN), KEBS offer greater transparency but lower adaptability. They are best suited for domains where decisions must be explainable and rules remain relatively stable over time.

Figure 2 presents the architecture of a knowledge-based expert system that incorporates rule-based logic and factual experience to support intelligent reasoning and decision-making [16]. The input data of the system include user queries or contextual information relevant to the problem domain. These inputs are processed by the inference engine, which is responsible for applying logical rules to factual knowledge. As such, it utilizes the rule base that contains structured, expert-defined rules that provide a framework for decision logic, and the fact base that stores empirical data and situational facts. The inference engine also interacts with two key modules: a. the knowledge acquisition module that continuously updates the system's rule and fact base with new knowledge acquired from human experts or external sources, and b. the explanation module that provides users with justifications for the system's conclusions. The output data of the system include recommendations, decisions, or diagnostics, delivered through a user interface, which acts as a communication bridge between the system and the end user.

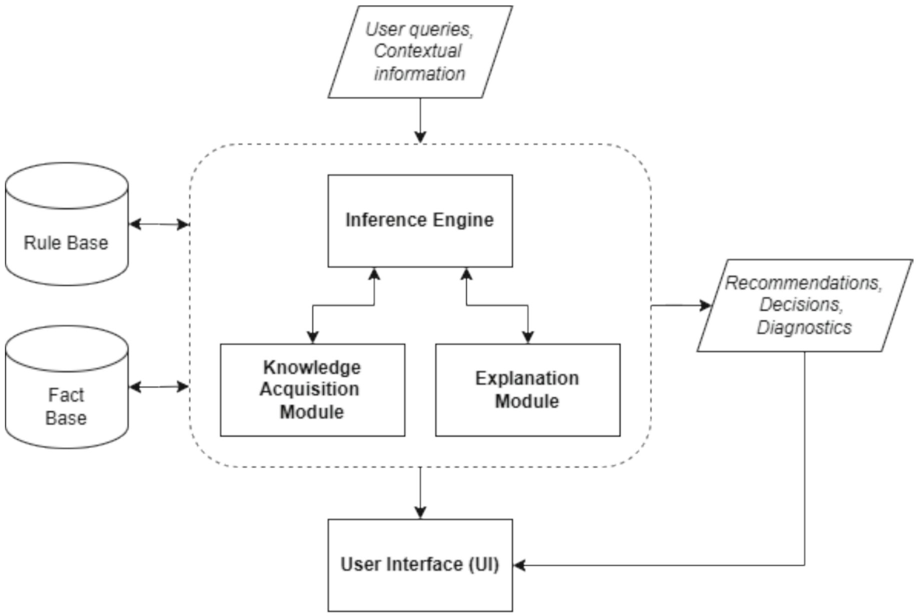

Fig. 2. Knowledge-based Expert System.

3.1.2 Neural Networks (NN)

Neural Networks (NN) are AI models inspired by the structure and functioning of the human brain. They consist of layers of interconnected nodes ("neurons") that process input data and learn patterns through weighted connections. Neural networks are especially powerful in analyzing large volumes of unstructured data, making them ideal for tasks such as image recognition, predictive analytics, and natural language processing.

One of the main advantages of NNs is their capacity to learn autonomously from data and generalize across diverse problem domains. Unlike rule-based systems, they do not require explicit programming for every possible scenario. Their ability to iteratively improve performance through training cycles allows for high accuracy in pattern recognition and classification tasks [16].

Despite their strengths, NNs are often criticized for their lack of transparency. Their internal decision-making process can be opaque—a characteristic often referred to as the "black box" problem. Furthermore, neural networks require substantial computational power and large, well-annotated datasets to achieve optimal performance, which may limit their applicability in resource-constrained environments.

In comparison to KEBS, neural networks offer greater flexibility and adaptability, but at the expense of explainability. They are also less intuitive than CBR systems, which use past human-like cases to solve new problems. In knowledge management contexts, NNs are most useful in automating classification, trend detection, and decision support under uncertainty [16].

Figure 3 illustrates the structure of a neural network system. It consists of three main layers: the input layer, hidden layer, and output layer. The input layer receives multiple types of information, which are then processed through interconnected neural nodes in the hidden layer. In this hidden layer, algorithms are applied to extract patterns and perform computations based on weighted connections. Finally, the output layer generates a final decision, representing the recommendation or prediction produced by the model.

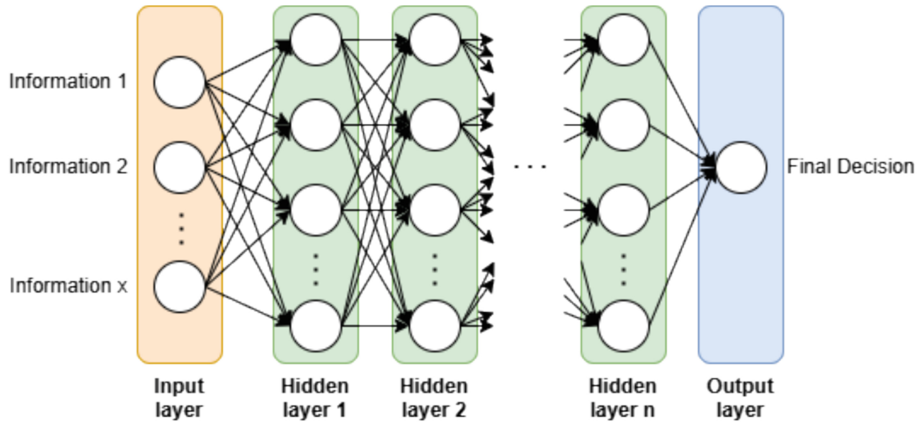

Fig. 3. Neural Network System.

3.1.3 Case-Based Reasoning Systems (CBR)

Case-Based Reasoning (CBR) systems are a class of AI methods that solve new problems by reusing solutions from previously encountered, similar cases. This approach mimics human reasoning, where decisions are often guided by analogies to past experiences rather than abstract rules.

CBR systems excel in domains where problems are complex, varied, and not easily reducible to fixed rules. Their main strength lies in their ability to adapt old solutions to new situations, making them ideal for applications such as customer support, legal case analysis, and software fault diagnosis. These systems can evolve over time, expanding their case base and improving their effectiveness with continued use [16].

However, CBR systems depend heavily on the quality and organization of their case repositories. Poorly indexed or outdated case libraries can lead to irrelevant or inaccurate recommendations. Additionally, adaptation mechanisms must be carefully designed to ensure that past solutions remain valid in new contexts.

Compared to KEBS, which rely on predefined rules, CBR systems offer more flexible, experiential reasoning. They are also more transparent than Neural Networks, as their problem-solving process involves retrieving and modifying specific, human-interpretable cases. This makes CBR a valuable component of KMS in environments where nuanced judgment and contextual knowledge are required [16].

Figure 4 shows the workflow of a CBR system [16]. The process begins with a new problem as input in the system. The Case Retrieval module utilizes the Case Base in order to retrieve prior problem-solution pairs that match with the input case. If a suitable match is found, the system directly retrieves the corresponding solution. If no exact match is identified, the system proceeds to a modification process where existing solutions are adapted to better fit the current problem. This case refinement updates the Case Base properly, enriching the knowledge pool for future use.

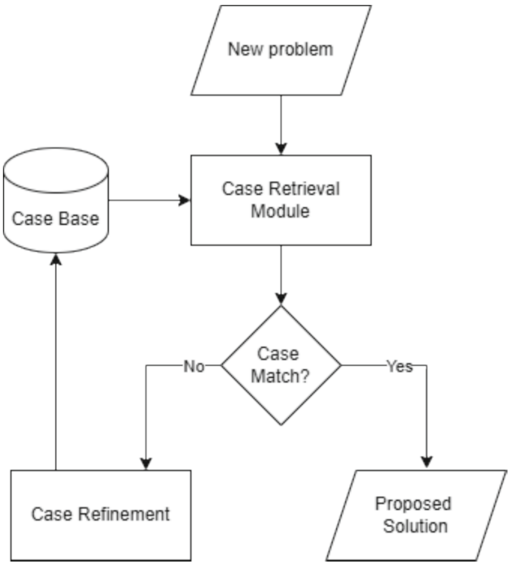

Fig. 4. Case-based reasoning system.

3.2 KMS Utilized by Government Use

KMS is becoming essential for governments to support their operations and improve their services to the general public. Enabling the government to solve the most complicated issues by organizing, sharing, and applying, and at the same time reach better decisions faster. The following section therefore portrays some KMS implementation cases that apply to different countries through description while laying much attention on their most relevant characteristics [15].

The following table summarizes the major types of knowledge management systems adopted by various governments across the world, their purpose, their features, and examples (Table 2).

Table 2. Types of KMS Utilized by Government

Type of KMS	Description	Key Feature
Knowledge-based Information System	Knowledge serves as the primary information source in managerial systems	Most used KMS
Decision Support System (DSS)	Offers Support by offering choices for policy or decision-making	Uses heuristic approach
Knowledge Semantic System	Literal system of interpreting information and supports the entire KM lifecycle	Automatically extract features from both structured and unstructured text
Knowledge Framework	A Framework for business operations and decision-making that helps plethora sectors to succeed	Adaptable framework that provides the guidelines or methods that government agencies must follow
Lesson Learned System (LLS)	Documents lessons from past experiences for future reference	Converts successful and failed experiences into actionable knowledge

3.3 Process-Based Knowledge Management Systems PKS

Process-based knowledge management systems are one type of knowledge management system that aims to integrate knowledge management practice into business processes, especially for KIP, which is deeply involved with highly complex tasks. These systems address two core meta-requirements: appropriate knowledge management support and integration into business processes. With the fulfillment of these requirements, the PKMS will enable organizations to align knowledge flows with operational demands and strategic goals [19].

3.4 Knowledge Management System of Contingency

In tricky and ever-changing settings, like supply chains, handling crises needs quick and smart choices. Systems that manage knowledge (KMS) made for emergencies are key to tackling these issues. These systems tap into databases that record past problems suggested fixes, and useful tips helping companies deal with disruptions effectively [18].

A good example is the Decision Making Model for Emergency Management of Supply Chain. This model brings together know-how from all parts of a company to guide crisis solving. It follows a clear plan starting with gathering and looking at data on the ground then moving up to big-picture choices and tweaks in the supply chain. By joining forces this way, companies get tougher, shift gears fast when things change, and lessen how much crises mess up their work [18].

3.5 Knowledge Graph in KMS

Knowledge graphs are technologies that apply computational methods to the structured representation and interlinking of knowledge in order to make complex information easier to search, retrieve, and understand. The key characteristics of this technology include data interlinking through semantic relationships, the use of NLP mechanisms, and automated structuring of knowledge [16, 22].

One such promising application of Knowledge Graphs in KMS will help to solve data falsification, information fragmentation, and inability to correlate heterogeneous data. While enabling the integration with techniques like NLP, Computer Vision, Automatic Construction, Human-Computer Interaction, Knowledge Graph Technology surely is going to further increase the precision and transparency of Enterprise Knowledge Management [20].

4 Discussion

Knowledge Management Systems address important organizational problems related to the analysis of problems, decision-making, and processing of data [17]. What has had a great impact on knowledge-related processes within the integration of KMS is the inclusion of AI technologies such as KEBS, NN, and CBR; it modernizes workflows, enhances decision-making capabilities, and tailors those to the needs of an organization. KEBS allows for expert-level reasoning; NN improves the prediction with incomplete data; and CBR accelerates problem-solving by drawing on past experiences [16]. All these developments together make KMS more responsive and adaptive to the complex organizational demands.

However, embedding AI into KMS is not without its challenges. A big one is dependence on extensive and well-structured databases, as these will directly impact the quality of the outputs from the system. The creation of such databases is marked by both complexity and high resource demands [17]. What is more, even highly comprehensive datasets are subdued by the fundamentally unpredictable nature of markets, which undermines the accuracy of extrapolations created by artificial intelligence and, therefore, their applicability in strategic decision-making processes. Another critical challenge is the excessive focus on the technical aspects that ultimately leads to a downgrading of human-centric knowledge management aspects like discernment, intuition, and ethical reasoning. These human-centric elements become key enablers for artificial intelligence to take up complex decision-making tasks and to fully realize its capabilities in broader contexts [16].

An integrated approach is, therefore, the way to tackle these challenges. A combination of the latest advancement in technology with knowledge of the human dimension of knowledge management guarantees a holistic solution. Organizations have to balance the benefits of AI automation and the irreplaceable value derived from human expertise in their ranks [20].

In government settings, KMS have been found to be effective in areas like policy formulation, crisis management, and service delivery. DSS and KBIS allow the sharing of knowledge in the public administration while Process-Based KMS and Contingency KMS offer systematic approaches to managing knowledge in dynamic business environments [18]. However, challenges still abound, especially the high costs of creating databases and complexity in integration of systems. Furthermore, Knowledge Graph Technology enables structuring knowledge in a more meaningful way and making it retrievable, albeit at the expense of massive computational resources and special expertise [20].

Looking ahead, further development of Knowledge Graph Technology and human-computer collaboration will probably further enhance KMS capacities. The knowledge graphs are thus capable of structuring knowledge in a far more retrievable and meaningful way than has been able to be instantiated up to now, albeit by availing substantial computational resources and specialized expertise. Organizations should view technology as augmenting human intellect, not a replacement. Subsequent studies are set out to explore ethical, social, and organizational consequences related to the deployment of AI-driven KMS for developing increasingly adaptive and sustainable frameworks [20].

Recent research has also expanded the understanding of KMS by exploring context-aware and domain-specific implementations. For instance, in [23], the authors demonstrate how Self-Organizing Maps can be effectively leveraged for cultural content delivery, enabling intelligent clustering and personalization in knowledge dissemination. In organizational settings, in [24], the authors examine the impact of knowledge management systems on customer perspectives, showing how AI-enhanced KMS contribute to satisfaction and loyalty by aligning knowledge flows with customer expectations. Additionally, the KRIOTA framework proposed by [25] highlights the potential of dynamic task assignment and reference information management in hybrid edge-cloud environments, especially in mission-critical operations such as robot-assisted decision support. These contributions reinforce the evolving versatility and domain adaptability of KMS, while also indicating future directions in edge computing and user-centered knowledge personalization.

5 Conclusion

A Knowledge Management System serves as an effective medium for facilitating the sharing and dissemination of knowledge within an organization. When consistently utilized to document the daily activities of employees, it can foster a culture of continuous learning and knowledge exchange. Moreover, a knowledge management system can be employed as a tool for capturing valuable insights and ideas, enabling the development of innovative product concepts and driving organizational growth.

Many contemporary knowledge management systems already incorporate artificial intelligence techniques to enhance their capabilities. These systems leverage AI technologies to automate knowledge acquisition, extraction, and dissemination processes, thereby improving decision-making and problem-solving efficiency. Given the rapid and ongoing advancements in artificial intelligence, the future evolution of knowledge management systems is expected to be increasingly shaped by AI-driven features, such as natural language processing, machine learning, and predictive analytics.

Therefore, it is imperative to explore effective strategies for integrating artificial intelligence functionalities within knowledge management systems to maximize their potential. This includes investigating how AI can enhance knowledge discovery, personalization, and adaptive learning, ultimately transforming knowledge management practices in the digital age.

Knowledge Management Systems are important in organizations for better utilization of their knowledge and to gain efficiency in operations. AI-based KMS, like KEBS, NN, and CBR, have completely changed the face of industry by automation of knowledge processes and making better decisions. Applications in government and enterprise prove the versatility and impact of KMS in various fields. Challenges to overcome for successful implementation include data quality, integration issues, and striking a balance between AI-driven automation and human expertise.

The future in KMS development goes on evolving at each step of development in the field of AI and Knowledge Graph Technology and is also in Human-Computer Collaboration. Organizations shall use a strategic approach while adopting the KMS so that the complementary human intelligence gets utilized. In the future also, research on ethical and organizational issues related to AI in knowledge management will logically lead to more robust and adaptive solutions.

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