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A Framework for Building Cognitive Knowledge Management Systems

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ABSTRACT

Knowledge Management Systems (KMSs) are a critical component of economic development and growth. The accumulation and effective utilization of knowledge capabilities allow firms to create value and improve competitiveness. However, recent technological advances in KMSs have outpaced research in this area, which continues to be siloed and characterized by a lack of cohesive frameworks and a limited focus on cognitive learning. This paper provides a conceptual framework for the development of cognitive KMSs. The proposed framework comprises of strategy, people, processes, learning, and technology that are designed to improve knowledge management and organizational memory.

Keywords: knowledge management systems, organizational knowledge schemes, big data management, cognitive systems, network structure

INTRODUCTION

Knowledge Management Systems (KMSs) are technologies that facilitate the generation and sharing of knowledge to serve the needs of organizations in diverse sectors (Lee & Chen, 2012). KMSs have been the focus of attention in data management for over two decades, with research estimating that half of US companies had worked on KMS capabilities at the beginning of the 21st century (Bonner, 2000). However, there has been a growing emphasis on the insufficiency of mere technical solutions, and thus, attempts have been made to incorporate human and social aspects to complement KMSs (Garavelli et al., 2004; Rubenstein-Montano et al., 2001). The lack of standardization, the diversity of business environments, and the growing complexity of digital environments have created a disjointed KMS landscape, where not all KMSs and related strategies are created equally. For example, Rubenstein-Montano and colleagues performed a systematic evaluation of existing KMS frameworks and found that KMSs lack cohesiveness and have a limited emphasis on learning, which is a critical component of KMS (Rubenstein-Montano et al., 2001).

Cognitive knowledge management systems (CKMSs) represent the next step in the natural evolution of KMSs. A key enabler of CKMSs is the ability to form memory and develop intelligence, which are two crucial attributes of cognition in both animal brains as well as in Artificial Intelligence (AI; Matzel & Kolata, 2010). In this paper, we present an overview of knowledge management systems (KMSs) and propose a framework for AI-enabled CKMSs.

Figure 1 shows the three main phases in the evolution of KMSs. In the first phase, KMSs were largely geared toward passive data collection repositories or warehouses. The goal was to capture and query raw data for basic reporting, codification, and classification purposes, without the application of advanced data analytics methods. As a result, these systems were designed primarily for relatively short, predictable-update transactions, and point-in-time historical data (Bontempo & Zagelow, 1998). The second phase of KMSs was characterized by transforming common data into meaningful information that could be used to make informed decisions. This phase included the application of Business Intelligence (BI) tools and data analytics layers to provide descriptive and predictive analytical knowledge. BI systems, which are commonly integrated within most enterprise resource planning (ERP) solutions, combine operational data with analytical insights to present complex and competitive information to stakeholders (Negash, 2004). Finally, the third and current phase emphasizes intelligent learning to improve and adapt KMSs over time with enhanced predictive analytical capabilities. From Figure 1, we can see that AI has been gradually introduced in KMS development, beginning with BI tools and moving on to AI-enabled KMSs for intelligent learning.

Figure 1 also shows the mapping between these phases and the knowledge hierarchies that were outlined in (Steyn, 2004), as well as sample KMS types that conform to these phases and hierarchies. These knowledge hierarchies proceed in the following manner: data, information, knowledge, and cognition. As shown, CKMSs fall within the third and current phase of KMS evolution and possess cognitive abilities powered by AI algorithms to generate contextual insights.

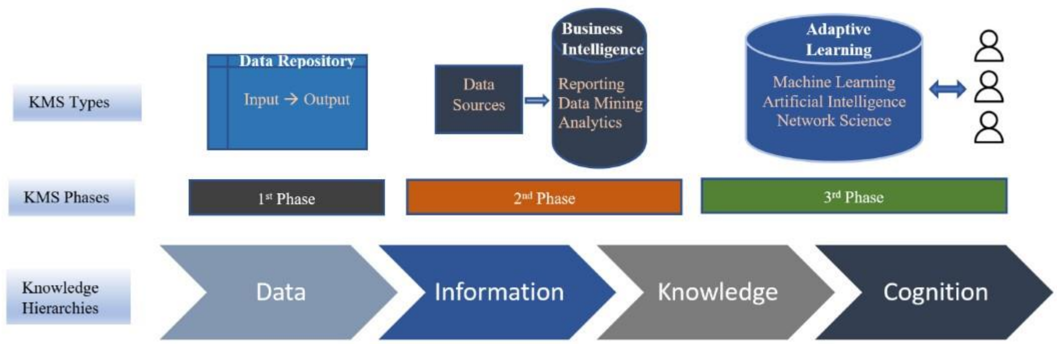

Figure 1: Phases of KMS evolution

The contributions of our paper are as follows. First, we propose a conceptual framework for CKMSs, which we define as deep-learning solution informed by strategy, people, processes, and technology, and learning ability. Such a framework, which is based on AI, incorporates knowledge, learning, memory, and intelligence to improve knowledge management through adaptive mechanisms. While Machine Learning (ML), which is a subset of AI designed to enable machines to learn from data with limited guidance, has been deployed in deep-learning, it is data-driven and lacks the full awareness of its environment to optimize knowledge management (Gacanin, 2019). Our proposed framework incorporates multidimensional components as an integral part of decision systems, providing the infrastructure and processes that enable organizations to develop deep-learning computational models composed of multiple organizational processing layers (LeCun et al., 2015), through the consideration of strategic, social, and technological aspects. Further, unlike limited data-driven implementations, the feedback mechanism outlined in the framework allows for the ability to make real-time and continuous adjustments to CKMS deep-learning architectures to calibrate solutions and mitigate risks such as AI hallucinations.

Second, we provide a CKMS structure that examines a CKMS through the lens of network constructs (nodes, edges, and layers) to describe the associative relationships between the CKMSs compositional elements. The rest of this paper is organized as follows. In the next section, we provide a literature review to identify prior research in this area. Next, we outline a framework for CKMSs that elaborates on the individual constructs making up a CKMS, followed by a discussion on the

CKMS structure and individual components. Finally, the paper discusses limitations and challenges of CKMSs and concludes with topics for future research.

LITERATURE REVIEW

According to a recent finding, more than 90% of the data that exists in the world has been created in the last two years alone (Petrov, 2021). The transformation from data to knowledge remains a wiry challenge, especially in the face of stupendous growth in the amount of data generated. As knowledge is generated and shared, it has the potential to enhance a firm's value by enhancing its ability to respond to uncertain and turbulent environments (Choi et al., 2008). While information refers to organized data that comprise raw facts, knowledge is a deeper state which entails the interpretation of useful information for decision making and can be optimized through the utilization of KMSs (Birzniece, 2011).

Prior scholars have outlined the important role that KMSs play in facilitating knowledge management activities by removing boundaries to communication and knowledge flows to support organizational knowledge-based view (Santoro et al., 2018). In addition, empirical evidence showed that many organizations recognize the ability of traditional KMSs to solve complex problems and encourage employees to improve creativity levels and performance (Jallow et al., 2020; Del Giudice & Della Peruta, 2016; Santoro et al., 2018). However, despite their wide-spread use, traditional KMSs implementations and tools lacked a focus on learning and were comprised of general technical solutions, rather than systems specific to knowledge management activities (Edwards et al., 2005; Garavelli et al., 2004).

On the other hand, the recent developments in the AI field have introduced opportunities for industries to improve knowledge management capabilities through applications such as chatbots that are based on natural language processing (NLP) technologies (Huang & Chueh, 2021). While several definitions exist in prior literature, AI is understood as the capability of machines to perform tasks that would normally require human intelligence, through the creation of formal models and simulation of behaviors (Jallow et al., 2020; Furmankiewicz et al., 2014). Prior research has highlighted the role of AI developments in optimizing traditional KMSs, for example, work in Al-Sharaf et al. (2022) developed a theoretical model based on the expectation confirmation model combined with knowledge management factors to better understand the use of AI-based chatbots in education. Further, research in Jallow et al. (2020) suggested that AI can play a critical role in improving knowledge management capabilities within the construction industry and emphasized the research gaps in the combined fields of AI and KMSs.

However, it is important to note that despite the promising results of CKMSs in improving organizational abilities to capture and process knowledge for timely decision making, there are potential risks that need to be considered. Birzniece (2011) discussed risks and challenges of combining intelligence-capabilities with KMSs (i.e., CKMSs), including difficulties in updating the knowledge base from experiences generated by AI technologies, the development of tools capable of capturing tacit knowledge, and the objective assessment of the degree in which AI is embedded in KMSs. Further, AI hallucinations and biases presents challenges for the development and implementation of CKMSs. Hallucination can be described as the false, unverifiable, and conflicting information provided by AI-based technologies (Salvagno et al., 2023), which would make it difficult to rely on CMKSs to execute tasks and facilitate knowledge management.

The objective of this research is to build on existing literature and bridge the gap stemming from the lack of studies on the evolution of KMSs and the integration of related intelligence capabilities to streamline knowledge management (Jallow et al., 2020). In addition, this study provides a background of the main phases in the evolution of KMSs and discusses potential risks and challenges. Further, given that technology-centric CKMS implementations often fail to consider multidimensional aspects such as organizational collaboration, (Mirzaee & Ghaffari, 2018; Jallow et al., 2020), the proposed framework encompasses a holistic approach of strategy, people, learning, and processes and technology for CKMS solutions. The proposed CKMS framework is discussed in the following section.

A FRAMEWORK FOR CKMS

CKMSs form an integral part of decision systems, providing the infrastructure and processes that enable organizations to collect, analyze, and consume knowledge in a timely manner, while providing a feedback mechanism for continuous improvement. In this section, we elaborate on each of the four foundational constructs of CKMS – the role of network effects, organizational knowledge schemes, big data management, and cognitive abilities. These constructs are adaptively refined using feedback loops. Each of these foundational constructs, combined with feedback mechanisms, draw upon salient features of AI applications. Figure 2 shows the interplay of the constructs of our CKMS framework. Each of these four foundational constructs correspond to strategy, people, process and technology, and learning. Below, we describe each of these four foundational constructs.

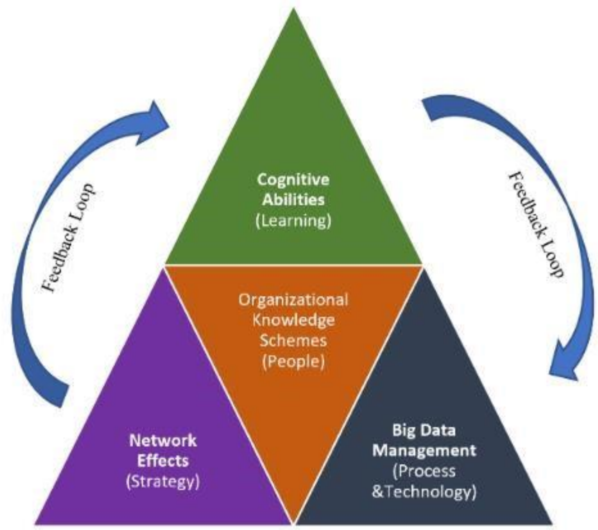

Figure 2: Proposed CKMS framework

Network Effects

The network effect phenomenon denotes the opportunities that are available due to embeddedness within network structures (Uzzi, 1996). Within organizations, network effects take root when KMSs components and social networks engage with each other (internal networks), and in business activities with other stakeholders such as customers and suppliers (external networks). CKMSs can effectively leverage the characteristics of network structure to provide organizations with valuable insights, while simultaneously enabling the flow of information and resources to maximize knowledge-based actions (Lin et al., 2009). Further, network effects can be used to describe the value of a product or a service that arises from the availability of interconnected links within networks (Hendler & Golbeck, 2008). Firms, like other stakeholders participating in multi-sided economic exchanges, develop social and economic networks that are embedded through a web of interactive participants which can enhance the value of offerings. Therefore, due to the interconnected and embedded nature of such networks, organizations can capture value from the wealth of data points that can be translated into meaningful knowledge to enhance decision-making and improve competitiveness.

The network characteristics proposed in Lin et al. (2009) are extended to this research to propose that networks with centrality and structural hole positions characteristics enable organizations to build robust and embedded knowledge management repositories. Network effects centrality is related to the extent that a firm can occupy a central position in relation to its external interconnected links, which allow for the ability to access information that can be captured and exploited through a CKMS. Structural hole positions characteristic on the other hand, emphasizes the dynamic aspects of strategic control that can be gained from the brokerage positions within networks, related to the timing and access of such information, representing the firms' ability to monitor and manipulate the flow of information to its benefit. The extent that these two characteristics (centrality and structural hole positions) are present within networks is an indication of the level of strength that differentiate them from other ones that lack such a structure.

To demonstrate the strategic component of network effects and related attributes of network centrality and structural hole positions, Google Maps is used as an example. Google Maps has a large network of participants and relies on users' driving patterns and location to determine traffic conditions and optimize route mapping. The greater the number of users, the better Google Maps artificial intelligence (AI) can accurately "learn" and update the mapping information. Furthermore, Google Maps' broker position, which connects customers and suppliers, allows it to capture behavioral patterns to customize advertisement campaigns and improve revenue from third-party members which are connected to this network. The application's centrality, and structural hole position, allows it to capture important data points from network members and use it to increase revenue and improve its product offerings.

Organizational Knowledge Schemes (OKSs)

Organizational knowledge schemes (OKS) represent the core of KMSs by utilizing knowledgeas-a-resource for decision-making. Thus, put simply, KMSs represent organizational memory.

Here, we adopt Tulving's distinction of semantic and episodic memory to describe the granularity of information available in CKMSs (Tulving, 1972). While semantic memory relates to the essence of the process or a relationship, episodic memory relates to individual details and fine-grained information related to a process or relationship (Greenberg & Verfaellie, 2010). Therefore, OKSs offer an AI-enabled mechanism to represent semantic memory by storing and processing the information in an organization's KMSs. CKMSs can also enable episodic memory, where elaborate analytics can provide fine-grained information about information flow in KMSs.

Systems that do not foster knowledge-sharing find it difficult to effectively translate and consolidate data points into a CKMS; they may fail to translate the collective internal knowledge into meaningful insights, and thus suffer from "lapses" or "flaws" in organizational memory. This is especially true in our interconnected environments that are constantly changing, and systems must be able to efficiently harness the power of knowledge sharing and to outperform the competition (Lemon & Sahota, 2004; Nag & Gioia, 2012). Therefore, OKS can be optimized through stakeholders, such as employees, who play a critical role in organizational memory within a CKMS context. Organizations can achieve a high-level of knowledge sharing schemes by setting the tone through procedures, leading by example at the executive level, providing training, and by rewarding behaviors that promote collaboration.

Big Data Management

The continuous innovation and increasing popularity of interconnected devices have introduced unprecedented amounts of data that need to be properly sourced, secured, and delivered to optimize value creation (Bhadani & Jothimani, 2016). The big data discipline has emerged a response to address these data storage and access challenges. Big data management is a combination of technology, processes, and strategies that enable organizations to absorb large amounts of data for predictive and descriptive analytics (De Mauro et al., 2016). While research has extensively discussed the benefits of big data management, the specific attributes of big data that contribute to building robust CKMSs are less known. However, the scope of big data also offers a varying amount of risk in decision-making. Without proper risk mitigation controls in place, big data may provide a false sense of value during decision-making (Dubey et al., 2019). In addition, efficient access to data is critical for reducing operational costs associated with big data management and streamlining data delivery.

Cognitive Abilities

The cognitive aspect of CKMSs utilizes intelligent information practices using advanced technologies and incorporates feedback mechanisms to improve the KMS's overall capabilities in near real time. While traditional KMSs have played an important role in creating new innovative services, they do not systematically collect and synthesize information to provide users with insights extracted from deep learning abilities (Rubenstein-Montano et al., 2001; Li et al., 2019; Sun et al., 2019). On the other hand, CKMSs can identify gaps in the information and related attributes and offers AI-enabled mechanisms to address such limitations, by actively gathering and persistently preserving large amounts of user and network observations.

CKMS STRUCTURE

Simon's ant famously refers to the problem of understanding data in context (Simon, 1968). Watching an ant move across the beach and documenting its wavy path might prompt one into thinking that the ant is following a pre-determined complex route, only to realize that the beach's obstacle-filled terrain was the real precursor to the ant's trajectory of motion. In this section, we propose a framework for a CKMSs, which avoids the pitfalls of a Simon's ant-like KMS that follows all the rules of a repository in terms of structure but reveals little to no information about the context of information flow. CKMSs provides the context – the information about the jagged terrain – in mapping the relationship between various OKS schemes and KMS components.

CKMSs have two main components: nodes and layers (see Figure 3). The nodes represent infrastructure and processes to capture, store, and process information. Edges represent the relationships between nodes, where the information is transferred between nodes. The transfer of information is facilitated by mechanisms for multi-sided information exchanges. CKMSs are characterized by associative relationships between the following compositional elements.

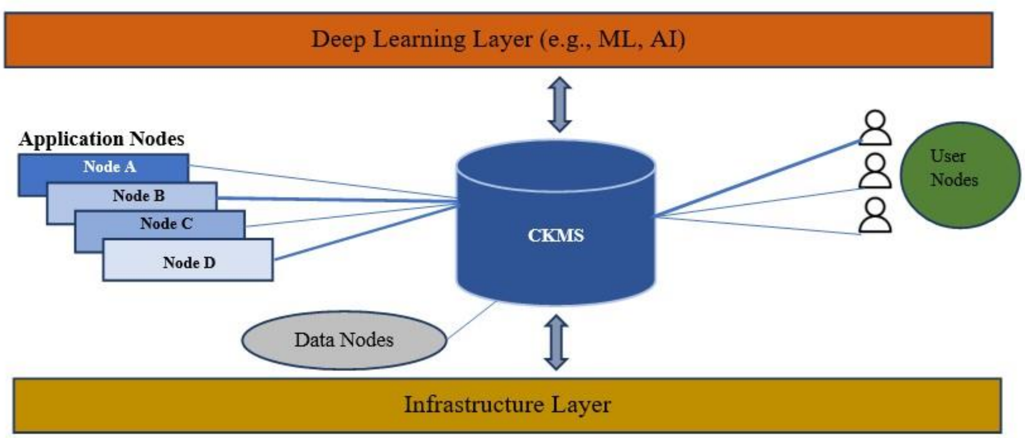

Figure 3: Interaction between CKMS nodes and layers

Nodes

The various types of nodes in a CKMS, as shown in Figure 3, are as follows. Application nodes provide services to ensure that effective communication between users occurs through application programs in a network. Data nodes contain functionality for the identification, sensing, and communication of data. Finally, user nodes process information about user activities and profiles that are synthesized with the other nodes for cognitive analysis of the CKMS.

Layers

CKMSs comprise of two layers: the deep learning layer and the infrastructure layer. The deep learning layer is typically used to extract target attributes and discover the surrounding environment (Li et al., 2019). The deep-learning layer represents intelligence-mimicking technologies under the AI umbrella comprised of artificial neural networks that utilize multiple layers in the network (LeCun et al., 2015). It includes the cognitive software application within the context of CKMSs, that can be optimized to produce deep learning, based on the fusion of information collected from the various nodes. On the other hand, the infrastructure layer consists of basic building blocks that support applications and end-users, such as servers, networks, and telecommunication. The infrastructure layer provides the backbone for the implementation and usage of CMKSs and includes the physical elements to extract, store, process, and relay information.

While a typical organization has hundreds of processes and infrastructural components, a CKMS network can reveal information about the most important and influential nodes using various centrality indices. A CKMS can map links between individual elements of a system and offers mechanisms to cognitively analyze these links in the context of network structure. Further, there are certain processes in an organization are indelibly linked to prescribed relationships, such as the registrar's office at an institution of higher education is associated with student grades, enrollment statistics, and graduation records among others. When a particular process (represented as a node) is invoked, it "activates" the relationships (edges) associated with it that connect the process to other processes (see Figure 3). Repeated activations of a relationship contribute to the formation of a memory in the organizational knowledge scheme (OKS).

DISCUSSIONS AND LIMITATIONS OF CKMS

In this paper, we have developed a CKMS framework that leverages network effects, big data management and organizational knowledge to cognitively learn and create organizational memory, which can be continuously fine-tuned for system enhancement. However, CKMSs can be impeded by the challenges that confront the spectrum of AI applications. These challenges are related to the fundamental distinction between data and information, and how context can make a world of difference for different kinds of information derived from the same dataset. Below, we highlight some of these challenges confronting CKMSs.

Algorithmic Biases

The algorithms that underlie AI/ML capabilities have been shown to harbor and exacerbate biases, often with drastic outcomes. These outcomes have implications for a range of social situations. CKMSs are poised to inherit the shortcomings of biased algorithms, and risk building defective KMSs that are detrimental to the goals of enhancing business processes, achieving marketplace competitiveness, and efficiency of business operations.

Network Structure

While network structure can reveal valuable information, including latent variables of significance, it is important to avoid the pitfall of Simon's ant in relying too much on network structure and downplaying the accompanying context. CKMS frameworks already have a challenging mandate – that of combing through complex datasets and network structures to derive simplified, meaningful insights.
While network structures can offer invaluable perspectives about points of interest, it is important to also consider the points of non-interest. While the nodes with high centrality values are significant, their relationships with other seemingly non-significant variables must be considered in a holistic manner (Dablander & Hinne, 2019).

Organizational Knowledge

Since a CKMS acts as a curator of organizational knowledge, it would be in the best interests of interoperability to have a set of basic guidelines for organizations for the design and development of CKMSs. These guidelines would serve as a starting point for best practices, similar to the NIST guidelines for cybersecurity and the AAAI guidelines for responsible use of AI. Such guidelines would help to determine the appropriate level of granularity of information required for various applications and would spur new lines of research in the development of cognitive repositories, while paving the path for the next phase of KMS evolution.

Ethics, Security, and Privacy

Since CKMSs are built on the foundation of big data management and cognitive capabilities (whose algorithmic biases were discussed above), it is imperative to develop comprehensive frameworks to incorporate ethical aspects of data collection and use. Frameworks such as the OECD guidelines, and the EU GDPR offer guidance in how to approach the complex tradeoffs of privacy, usability, security, and functionality.

CONCLUSION

Knowledge management systems form an integral part of decision systems, providing the infrastructure and processes that enable organizations to extract insights from data. In this paper, we have proposed a novel framework for cognitive knowledge management systems that integrates strategy, people, learning, process, and technology. cognitive knowledge management systems, thus, function like repositories for inferring the context and content of information flow. They also provide several avenues for future research. Validation of these cognitive systems within an organizational context can yield tremendous insights regarding the challenges and opportunities offered by cognitive knowledge management systems.

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