Applying Knowledge Management to Support Artificial Intelligence Chatbot Applications

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Abstract: As the diversity and complexity of Artificial Intelligence (AI) systems increase, there is a growing need for advanced knowledge representation methods to enhance decision-making capabilities. Existing research indicates a gap between AI and Knowledge Management (KM), emphasizing the necessity of coordinating learning and knowledge creation processes between humans and machines. Despite the widespread use of generative AI, as seen through the growing popularity of conversational AI tools like chatbots powered by Large Language Models in recent years, the absence of a theoretical framework for effectively managing the knowledge they generate could mean missing out on significant opportunities. This work seeks to bridge this gap between KM and IA through an integrated framework that aims to apply KM to support IA chatbot applications, adapted from the Internet of Everything Integrated Knowledge Management Model (IoE IKM Model). The IoE IKM Model's original goal is to support knowledge creation in IoE applications, but here, we show how it can be adapted to bring KM to the context of AI. We accomplish this by explaining the development process of the IoE IKM Model, identifying shared aspects between IoE and AI general applications, and adapting necessary elements to establish our integrated KM framework tailored for supporting AI chatbot applications. The resulting framework is then discussed, and examples of how it can be applied to enhance human interaction with a chatbot, namely Open AI's ChatGPT. Research has been conducted to demonstrate the advantages of applying AI in KM. However, we aim to take a different approach by showing how KM can contribute to AI applications. We expect this work to be helpful for those whose professional activities may involve the usage of AI systems by providing them with the necessary tools to manage the knowledge generated by these same AI systems and by offering a Knowledge Manager's perspective on how to boost human-machine interaction.

Keywords: Artificial Intelligence, Knowledge Management, Internet of Everything, Chatbots, ChatGPT

1. Introduction

Artificial Intelligence (AI) has become an important and vast field with fast-growing usage recently (Liu *et al.*, 2018). Its applications range from natural language processing to predictive analytics, image recognition, etc. Nonetheless, as AI systems become more diverse and complex, they continuously require more sophisticated knowledge representation and management methods to support their decision-making competencies. The more AI studies and technology expand, the more it interacts with humans (Real de Oliveira and Rodrigues, 2021), thus increasing the need to coordinate human and AI systems' learning and knowledge-creation processes.

Research on Knowledge Management (KM) has focused on understanding the complex relationships between data, information, and knowledge creation, how they are impacted and benefited by the sources of data and information, and the contexts in which they are analyzed and shared (Philip, 2018). Research in the AI and KM fields of studies suggests a gap between those two, which needs to be filled so studies can continue (Jallow, Renukappa and Suresh, 2020). This work proposes an integrated framework to apply KM to support chatbot applications, adapted from the Internet of Everything Integrated Knowledge Management Model (IoE IKM Model) (Costa and Souza, 2022).

The original purpose of the IoE IKM Model was to assist in knowledge creation within the context of IoE applications (Costa and Souza, 2022). However, in this case, we will demonstrate how the model can be adjusted to incorporate KM (Knowledge Management) in the context of AI (Artificial Intelligence). We will achieve this by elucidating the development process of the IoE IKM Model, highlighting the commonalities between IoE and general AI applications, and customizing the necessary elements to create our integrated KM framework, specifically designed to support AI chatbot applications.

2. Methodology

Design Science Research (DSR) is a research paradigm that employs the principles of Design Science to create artifacts, i.e., objects intentionally created by humans to solve practical problems. Within the domain of information systems design, the Soft Design Science Research (SDSR) methodology serves as an approach for artifact development. It encompasses the formulation of hypotheses, the construction of artifacts through experimentation, and the evaluation of results within a continuous iterative loop that iterates between the development of artifacts and the evaluation of these artifacts until their usefulness and validity are achieved and verified (Baskerville, Pries-Heje and Venable, 2009).

However, developing a new artifact from scratch is only sometimes necessary. Dresch (2021) suggests that, first, searching for an existing artifact that solves the overall problem is necessary. In this work, the practical problem could be summarized as follows: the lack of a framework that assists in managing the knowledge generated by artificial intelligence applications. Suppose an existing artifact has characteristics that identify it as a potential solution. In that case, this artifact should be addressed to ensure that the research is well-developed and will offer a relevant contribution to a specific class of problems (Dresch, Lacerda and Antunes Júnior, 2021).

Initially, we conducted a brief literature review on possible interactions between KM and AI. The practical problem to be solved was the potential need for a framework guiding the application of KM to AI applications. The research question was, "What are the possible theoretical models that integrate KM with AI applications?" This step is necessary to raise awareness of the problem. We were presented with some key concepts summarized in Section 3. The research returned an ideal ready-made artifact: the IoE IKM Model could solve our stated practical problem. Thus, Section 4 is dedicated to showing how the model can be effectively applied to solving the knowledge management problem of AI applications.

3. Key Concepts

Before introducing the framework that will ground this work, we shall discuss the nature of knowledge and its classification. Knowledge is divided into five categories: Explicitness, Structure, Trust, Outcome, and Act. For this work, only Explicitness will be addressed. The Explicitness category has three subcategories: Tacit, Explicit, and Implicit (Ein-Dor, 2008).

Tacit knowledge in AI refers to individuals' expertise, intuition, and skills in AI development and application. It is often difficult to express. It includes insights gained through experience, an understanding of complex patterns, and the ability to make intuitive decisions based on expertise. This tacit knowledge plays a crucial role in designing AI models, selecting appropriate algorithms, and making informed decisions during the AI development (Ein-Dor, 2008).

Explicit knowledge in AI refers to the knowledge that can be articulated, codified, and shared formally and systematically. It includes documented information, algorithms, models, datasets, and best practices that others can easily communicate and understand. It is typically stored in knowledge repositories, documentation, and technical specifications. It can be easily accessed, shared, and transferred between individuals and AI systems (Ein-Dor, 2008).

Implicit knowledge in AI refers to the knowledge embedded within the AI system or the data it processes. It is not explicitly expressed or documented but is derived from the patterns, correlations, and relationships discovered through AI algorithms and machine learning techniques. It is often hidden within large volumes of data and can be extracted through data analysis, pattern recognition, and machine learning models. It may involve insights and information that are not readily apparent or explicitly stated (Ein-Dor, 2008).

Next, we present the two main KM models that influenced the development of the IoE IKM Model: the SECI model (Nonaka and Toyama, 2003) and the SERI cycle (Kim, 2019). Their significance in KM studies cannot be overstated, as they, along with the Hierarchical Model for Knowledge Management proposed by Prat (2006), form the foundation of much of the KM methodology.

The knowledge-creation model expresses the SECI process (Nonaka and Konno, 1998), consisting of four knowledge conversion processes: Socialization, Externalization, Combination, and Internalization (Nonaka and Toyama, 2003). Socialization involves creating opportunities for individuals to interact, collaborate, and engage in face-to-face or direct communication; Externalization involves articulating and expressing tacit knowledge in a form that can be captured and shared with others; Combination involves collecting, organizing, and synthesizing explicit knowledge from various sources to create new insights, perspectives, and ideas, and Internalization involves the absorption, assimilation, and internal adoption of explicit knowledge by individuals.

According to Kim (2019), the SERI cycle defines the evolution of products and services as a spiral trajectory encompassing four evolution quadrants: Servitization, Establishment, Reinforcement, and Infrastructure:

- *Servitization* represents the initial phase of the product or service evolution. In this stage, the focus is on shifting from a product-centric approach to a service-oriented approach. Companies have started to offer value-added services alongside their core products. For example, a manufacturing company may begin offering maintenance, repair, and training services related to their products.
- *Establishment* is characterized by the growth and consolidation of the service offerings. At this stage, companies refine their service capabilities and develop expertise in delivering the added services. They establish processes, frameworks, and service standards to deliver consistent, high-quality service. This quadrant is about solidifying the foundation of the service-oriented business model.
- *Reinforcement* is when the focus shifts towards strengthening the integration between the product and service components. The goal is to create a seamless and mutually beneficial relationship between the product and the associated services. This quadrant may involve enhancing product features to support better service delivery or adapting services to take full advantage of the product's capabilities. The reinforcement quadrant aims to maximize the synergy between products and services.
- *Infrastructure* represents the final stage of the SERI cycle. In this stage, companies develop the necessary infrastructure and systems to support the delivery of integrated products and services at scale. Infrastructure also includes implementing advanced technologies, establishing robust service management frameworks, and creating efficient service delivery and customer support processes. The infrastructure quadrant ensures the long-term sustainability and scalability of the integrated product-service system.

Finally, the Hierarchical Model for Knowledge Management proposed by Prat (2006) provides an effective conceptual representation of knowledge management from a strategic point of view and proved to be adequate for distinguishing knowledge management processes between strategic processes and operational processes, making it possible to abstract the concepts of value and trust (more strategic point of view regarding knowledge identification and evaluation), from the way knowledge is managed, shared and stored. The evaluation process guides the evaluation of knowledge, knowledge systems, and projects.

4. The IoE IKM Model

Gao et al. (2017) reviewed the definitions of KM. They concluded that despite the vast amount of definitions and descriptions of KM, the essence of KM is to support learning efficacy and integrate different information resources to improve competitiveness advantages. This work suggests using an integrated KM model to support the effective governance of AI applications and help managing the knowledge generated by them. The Internet of Everything Integrated Knowledge Management Model (IoE IKM Model) proposed by Costa and Souza (2022) will be adapted to harness the insights gained from intelligence sources in AI applications, considering AI enablers and observation capabilities, supporting governance and knowledge creation in the AI ecosystem.

The IoE IKM Model was developed by integrating service science and knowledge management research. It leverages awareness of intelligence sources in IoE applications, considering IoE enablers, observation capabilities, supporting e-governance, and knowledge creation (Costa and Souza, 2022). The model integrates the knowledge creation model (SECI process) and service evolution cycles to support the design of intelligent services centered around creating knowledge and value in the IoE context (Costa and Souza, 2022). Figure 1 shows a visua representation of the IoE IKM Model.

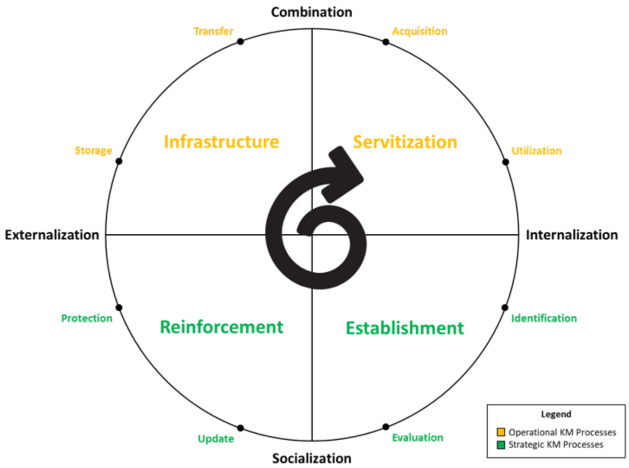

Figure 1: The IoE IKM Model, adapted from Costa and Souza (2022).

The purpose of the IoE IKM Model is to provide a specific knowledge management model that supports knowledge creation in IoE applications (Costa and Souza, 2022). As the model aims to facilitate KM by designing and implementing strategies that consider collaboration between machines, people, and processes, it appeared as a good choice for solving the practical problem stated before.

To adapt the work to AI applications, the focus should be on integrating AI algorithms into the existing knowledge-based strategy for machine-to-machine, human-to-human, and machine-to-human interactions in IoE applications. This integration would enhance the intelligent services provided by the applications by leveraging AI capabilities to process and analyze data more efficiently. Table 1 below shows the adaptations necessary in the defined contextual recommended activities that guide the application of the IoE IKM Model in order to create our AI-adapted IM Model.

Table 1: AI-adapted IKM Model. Adapted from Costa and Souza (2022).

AI-adapted IKM Model			
Service Design	**Knowledge Management Strategy**		
Service Cycle Process	**Knowledge Conversion Process**	**Knowledge Management Process**	**Contextual recommended activities**
Servitization	Combination and Internalization	Acquisition	Analyze data generated by various sources and devices, analyze generated social data to achieve collective intelligence, maintain context-awareness of social relationships from users and devices, maintain context-awareness of infrastructure capabilities as well as information semantic perspective, and support contexts for different individuals to internalize tacit knowledge using the explicit knowledge communicated through the AI applications.
		Utilization	Offer personalized services and customized content according to the user's social context, use of artificial social agents to generate and manage actionable social knowledge within the application environment, allow devices in the execution of automatic tasks without the involvement of the humans, support collaboration and cooperation between AI applications, maintain context-awareness and record the resulting interactions between humans and machines and learn by doing, and interact with analytical software to gain experience.
Establishment	Internalization and Socialization	Identification	Support intelligence orchestration in interactions between humans and machines, understand the AI contexts and customize services and applications accordingly, and foster human-to-machine interactions in a shared time and different places.

AI-adapted IKM Model			
Service Design	**Knowledge Management Strategy**		
Service Cycle Process	**Knowledge Conversion Process**	**Knowledge Management Process**	**Contextual recommended activities**
		Evaluation	Maximize the system knowledge about the social dimension of the users, maximize context-awareness of knowledge in AI applications, computational capability perspective as well as information semantic reasoning perspective, and evaluate knowledge sources, knowledge systems, and KM strategy for service evolution.
Reinforcement	Socialization and Externalization	Update	Develop machines' thinking abilities side-by-side with their social integration abilities, maintain tight coupling of AI techniques merged with the humans' and machines' social context, and cultivate a serendipitous environment through the collaboration of users of AI applications.
		Protection	Evaluate the trust level of AI-generated content, implement a social privacy preserving scheme to support trust, protect the social properties of users as sensitive information to support the customization of offered services, and provide a knowledge protection strategy on behalf of critical knowledge identified for AI applications.
Infrastructure	Externalization and Combination	Storage	Support data management activities at every application, involving pre-processing and filtering tasks, such as data aggregation and data compression, support data acquisition for future training of AI models and AI-generated content.
		Transfer	Use social networks to solve AI-related issues, support service recommendation system to leverage the social relationships between AI applications users, support a socially connected community of users, integrate communication and processing technologies near end-user devices, improve AI application performance and foster information exchange between users, and provide state-of-the-art technologies, software, databases, and repositories.

5. Evaluation

Many AI systems could have been used in this evaluation. A quick Internet search could find examples like BARD, Copilot, SciSummary, AI Lawyer, Dall-E, Midjourney, and Stable Diffusion, to name a few. For now, and for convenience, we will focus on the Large Language Models chatbot applications, which have Open AI's ChatGPT as the most popular. One of the various generative AI, i.e., AI capable of generating new content, such as text, images, or music, based on patterns learned from large datasets, the GPT-3.5 (Generative Pre-trained Transformer 3.5), a transformer-based language model capable of generating coherent and context-relevant texts. GPT-3.5 is trained using a large amount of textual data for translation, text summarization, and dialog generation, among other applications. ChatGPT is a specific implementation of the GPT-3.5 model focused on conversation. It can answer questions, provide information, assist with problem-solving, and engage in natural language dialogues.

The emergence of ChatGPT signifies the advancement of technologies facilitating processing, inference, and dissemination in the realm of information and knowledge. In the field of KM, which encompasses continuous processes such as acquisition, audit, organization, dissemination, value creation, and application of knowledge to achieve business goals, intelligent processing and communication technologies are particularly crucial (Hassanzadeh, 2022). Using these technologies will make access to specific knowledge faster and tailored to individual needs, solving problems related to content, language, and search skills. Dynamic and intelligent systems improve knowledge applicability, bridging the knowledge gap and promoting acquisition. Auditing and replacing outdated information enhances knowledge application (Hassanzadeh, 2022). ChatGPT presents an innovative opportunity for designers to acquire knowledge by providing a comprehensive and integrated platform for knowledge retrieval. Within this centralized system, designers can access a wide range of knowledge, including common sense, domain-specific, engineering, and technical knowledge (Hu *et al.*, 2023).

Integrating AI and KM can potentially boost innovations in diverse sectors such as wireless networks, education, healthcare, businesses, and organizations. Research indicates that AI has already made significant advancements in enhancing the quality and effectiveness of KM. It has proven beneficial in various areas, including knowledge acquisition, problem-solving strategies, knowledgeable tutoring, optimal solution systems, organization, and modeling (Taherdoost and Madanchian, 2023).

Thera are yet many more examples of contributions that ChatGPT in particular can make to the field of KM. Jarrari et al. (2023) highlight potential AI application in different KM processes such as sifting through organizational data and discovering relationships in knowledge creation processes, harvesting, classifying, organizing, storing, and retrieving explicit knowledge in knowledge storing and retrieving, and promoting equitable access to knowledge without fear of reprisal or social cost in knowledge application. Other authors state that organizations ma adopt ChatGPT to store, transform, and distribute organizational data (Korzynski *et al.*, 2023). However, we aim to take a different approach by showing how KM can contribute to AI applications.

The effectiveness of KM is increasing and fostering connections between knowledge and business tasks within organizations. AI agents assist in creating comprehensive conceptual networks, improving the understanding and utilization of organizational knowledge. We asked ChatGPT about how it could be used together with KM. More particularly, we started from the hipotetical existence of an implemented KM system that could benefit from ChatGPT. The question posed was "Imagine I already have a well-established Knowledge Management System (KMS) in my organization. Instead of using ChatGPT to improve it, I want to use it to enhance my interactions with ChatGPT. What would you suggest?" The suggestions given by ChatGPT and their relationship with our proposed AI-adapted IKM Model are shown in Table 2.

Table 2: How KM can benefit ChatGPT?

How KM can benefit ChatGPT?		
Suggestion	**Description**	**Relation with AI-adapted IKM Model**
Integration of ChatGPT with KMS	Integrate ChatGPT directly with your KMS so that it can access relevant information and provide more accurate and up-to-date responses based on the stored data.	Acquisition, Utilization and Identification processes.
Use of Plugins or APIs	If your KMS offers plugins or APIs, explore ways to connect ChatGPT to these resources so it can fetch real-time information and provide contextualized responses.	Transfer process.
Training ChatGPT with Data from the KMS	Feed ChatGPT with data from your KMS during training so that it can learn to interpret and respond to queries more accurately and relevantly.	Update and Storage processes.
Feedback and Continuous Learning	Use interactions with ChatGPT as an opportunity to provide feedback on the quality of responses compared to your KMS. This will help improve the model over time.	Utilization, Identification, Update and Storage processes.
Personalization of Responses	Configure ChatGPT to personalize responses based on specific information from your KMS, such as policies, procedures, or relevant documents.	Utilization, Identification, Update and Storage processes.
Monitoring and Performance Analysis	Track and analyze interactions with ChatGPT to identify areas for improvement and opportunities to optimize the KMS.	Update, Evaluation and Protection processes.
Integration with Workflows	Integrate ChatGPT with existing workflows in your KMS to automate tasks and improve operational efficiency.	Transfer process.

6. Discussion

As can be seen in Table 2, chatbot applications can benefit directly from specific KM processes taking place. The research showed relationships between contextual activities recommended by our AI-adapted IKM Model and the suggestions given by ChatGPT itself. The first one is that knowledge acquisition can enhance integration between chatbots and a KMS, fostering human-to-machine interactions and helping Interternalization processes. If there are well-structured knowledge transfer processes, integrating a KMS using plugins and APIs to search for contextualized responses is possible. Knowledge transfer practices can also guarantee a good integration with existing workflows in a KMS to automate tasks. Knowledge storage processes can have multiple uses: stored knowledge can be used to train chatbots to give better answers and provide personalized responses. Knowledge storage itself can help make new knowledge generated by AI enduring. Knowledge evaluation and knowledge update processes have the potential to make the performance of AI systems even better. Even though the application of AI seems to be all beneficial, there are still some ethical discussions regarding the use of AI solutions.

Responsible AI entails the ability of AI to provide ethical and legally compliant guidance from a human-centric perspective. The research and development of natural language models significantly emphasize their reliability (Jang *et al.*, 2021). This reliability directly impacts the accuracy of the generated content, which in turn influences the acceptance and effectiveness of the AI. However, the presence of false and outdated information that carries inherent biases can lead to incorrect output, ultimately undermining the reliability of the AI system and eroding user trust.

Also, promoting transparency in AI is a crucial aspect of responsible development. As AI technology advances, the community has a growing consensus to prioritize transparency in decision-making systems. Transparency enables users to understand the underlying basis and sources of their responses, allowing them to verify the accuracy of the provided information (Felzmann *et al.*, 2020).

To address the lack of empirical evidence, we suggest that future research include an empirical study to validate and refine our AI-adapted IKM Model. This empirical study could involve implementing our model in various organizations, ranging from small businesses to large enterprises, ensuring broad applicability. Over six to twelve months, data could be collected on performance metrics such as response time, accuracy of responses, user satisfaction, and the efficiency of knowledge transfer and storage processes. Additionally, user feedback could be gathered through surveys and interviews to gain insights into the human-centric perspective on AI and KM integration.

Detailed case studies of these implementations could be documented, highlighting specific challenges, solutions, and the overall impact on organizational knowledge management and AI performance. These case studies would provide rich qualitative data and practical insights. Ethical considerations would be a key focus, assessing transparency, reliability, user trust in AI systems, data usage, and privacy.

Based on the empirical data, the effectiveness of our model could be evaluated, and areas for improvement could be identified, refining the model to enhance its practical applicability and address any shortcomings. This comprehensive empirical study would provide robust evidence supporting our theoretical framework and demonstrate its real-world effectiveness, contributing significantly to the broader field of knowledge management and artificial intelligence integration.

7. Conclusion

Artificial Intelligence (AI) has grown significantly in recent years. However, there is a gap between this rapid growth and our ability to harness the full potential of knowledge generated by AI-based systems. The field of Knowledge Management (KM) can not only benefit from the application of AI but also provide the theoretical framework and best practices necessary to bridge the existing gap between the two areas. Thus, if correctly applied, KM processes can also enhance AI-based systems and applications.

This work has contributed to the effort to strengthen the relationship between AI and KM by suggesting the adaptation of a KM model initially developed for Internet of Everything applications. This model can be easily adapted for AI application KM, with the necessary adaptations presented and discussed. An evaluation of how appropriate this adaptation was has also been made, specifically for chatbots.

The objective was to pinpoint an effective framework that could seamlessly integrate KM principles into AI applications. Amidst the vast literature, the focus was on finding a holistic framework that clearly merges KM with AI. This endeavor was motivated by the need for a structured method that ensures the efficient use of knowledge assets in AI systems, thereby enhancing their functionality. The aim was to fill the existing knowledge gaps and offer organizations a definitive, actionable guide for incorporating KM in their AI initiatives, effectively enhancing AI's capabilities through the strategic management of knowledge.

When it comes to AI applications such as chatbots based on Large Language Models like ChatGPT, we evaluated the suitability of our adapted KM model for AI by asking ChatGPT itself what possible contributions knowledge management—or an already implemented knowledge management system—could bring to the use of applications like ChatGPT. We concluded that each suggestion would be related to a KM process in the model and to the contextual recommended activities freely adapted from the original IoE IKM model.

The evaluation of the model was limited and represents only a suggestion for the application of our AI-adapted IKM Model. Further testing must be done for the model to prove helpful in incorporating KM practices into the development of AI applications. It would be interesting for the KM field to obtain evidence that the application of KM techniques does indeed bring tangible and measurable benefits in terms of AI system performance. Confirmation of this point could renew interest in the area of KM applied to knowledge generated by AI. Another possible future work would be the development of strategies to externalize the implicit knowledge in algorithms and already trained systems.

In conclusion, integrating knowledge management processes with artificial intelligence applications, particularly chatbots, presents significant potential for enhancing technological and organizational efficiencies. Our AI-adapted IKM Model's theoretical framework offers a structured approach for this integration, detailing the benefits of knowledge acquisition, transfer, storage, and evaluation in AI contexts. Although our study primarily focuses on theoretical insights, future empirical research could provide concrete validation of these concepts. By implementing our model in diverse organizational settings and collecting performance data, we could offer robust evidence of its practical applicability and effectiveness. This empirical work would substantiate our theoretical claims and contribute to refining the model, ensuring it addresses real-world challenges and optimizes AI functionalities. Ultimately, this dual theory and empirical validation approach would provide a comprehensive understanding of the relationship between knowledge management and artificial intelligence, paving the way for more efficient, transparent, and user-centric AI systems.

We expect this work to be helpful for those whose professional activities may involve the usage of AI systems by providing them with the necessary tools to manage the knowledge generated by these same AI systems and by offering a Knowledge Manager's perspective on how to boost human-machine interaction.

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