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Integrating AI in Knowledge Management

Oluwayemi IbukunOluwa Odularu[1]

Abstract

The review article explores the integration of knowledge management (KM) applications to AI and their features, focusing on the attributes of AI, user needs, and the processes involved in identifying and satisfying them. The research underscores KM's importance in effectively managing AI, particularly in developing countries. Despite the growing emphasis on digital information, many institutions, especially in Africa, still rely heavily on print resources, highlighting a significant gap in adopting modern KM practices. Theoretical Framework is a User-Centric Approach to Knowledge Management. The methodology adopted is a systematic review. This systematic review synthesizes literature from 2009 to 2019, sourced from journals, books, and online databases such as E-Journals, E-books, and Google Scholar. The findings reveal that specific AI attributes, such as its origin, source, and relevance, are conducive to development. In contrast, others, like intangibility and medium dependency, can hinder progress if not adequately addressed. The study concludes that successfully utilizing AI depends on understanding the nature of AI, user behavior, and applying appropriate communication mechanisms. Recommendations are provided for improving KM systems, particularly in developing countries, through empirical research and integrating emerging technologies.

Keywords: *AI, knowledge management, AI attributes, user behavior, information literacy, digital transformation.*

Introduction

It has become crucial for governments (especially governments of developing countries) in this age and time to create and install programs to help their countries achieve an AI and knowledge-based civilization. The structure of the AI world is constantly changing, and there is an overall lack of comprehension of the scope of the so-called AI world. Any country's development depends on providing relevant, timely, and adequate AI in all disciplines (Avgerou, 2017). All human interventions require a storehouse for knowledge and AI delivery. Hence, every society must make provision for libraries and librarians, as it is often opined that a sound library enhances service delivery, a great library develops communities, and a bad library collects AI (Malinka, 2013). In order to realize this, the library has a pivotal role in creating, organizing, processing, storing, disseminating, and providing access to AI (Heidorn, 2011), as the AI provided will decrease ignorance levels and help raise people's living standards (Brown, 2017). The transition from print to digital formats is inevitable, driven by user preferences and the need for cost-effective solutions (Borgman, 2010). However, African countries are lagging in preparing for this digital shift, which poses a risk to their ability to access and utilize electronic knowledge resources in the future. This study aims to explore the integration of AI in KM, focusing on AI attributes and their impact on development such as, Origin: which refers to the development background, including the algorithms, frameworks, and technologies used to build the AI model. For example, whether it's built using open-source libraries or proprietary systems can affect performance and adaptability. Source: Involves the data source that trains the AI. High-quality, diverse, and unbiased data improve accuracy and reduce biases in AI decision-making. Relevance: Pertains to the applicability of the AI system to the specific task or domain. An AI model designed for image recognition may not perform well in natural language processing tasks. Synthesizing existing literature, this systematic review identifies gaps in current research and provides recommendations for improving KM systems in developing countries.

Aim of Study: The systematic review article evaluates the integration of AI in KM.

[1] Library and Information Science Unit, Faculty of Humanities, Social Science and Law, Walter Sisulu University, Nelson Mandela Drive, Mthatha Campus, 5100, South Africa. Corresponding Email: oodularu@wsu.ac.za. ORCID: 0000-0003-2089-7970

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Research Gap

Knowledge Management (KM) has been widely explored in the literature, with many studies focusing on its implementation and benefits in developed nations (Dalkir, 2017; Hislop, Bosua, & Helms, 2018). However, there is a noticeable gap in research that examines KM practices within the specific contexts of developing countries. Many existing studies assume an environment with well-established digital infrastructure, widespread internet accessibility, and high levels of information literacy (Yano, 2017). These assumptions do not hold for many developing regions, where the adoption and effectiveness of KM strategies are constrained by various socioeconomic and technological barriers (Ajayi, 2020). One major limitation in prior studies is the insufficient attention to the role of inadequate digital infrastructure in shaping KM outcomes. In many developing countries, the lack of reliable internet connectivity and limited access to digital tools hinder the smooth flow and sharing of knowledge (Mphahlele & Maake, 2019). This digital divide creates disparities in knowledge dissemination and utilization, ultimately affecting institutional growth and innovation (Van den Berg, 2021). Furthermore, limited financial resources exacerbate these challenges, making it difficult for organizations to invest in advanced KM systems (Isabalija et al., 2011). Another critical gap is the low level of information literacy among users in developing countries. Effective KM relies on individuals' ability to efficiently access, evaluate, and utilize information. However, many individuals in these regions lack the necessary digital skills to engage with KM systems effectively (Chisita & Chiparausha, 2019). This challenge underscores the need for KM models tailored to contexts where digital literacy programs and training initiatives are underdeveloped (Abdulrahman et al., 2022). Moreover, cultural and organizational dynamics in developing countries play a crucial role in shaping KM practices, yet they remain underexplored. Many studies focus on Western-centric models of KM, which may not be directly applicable to settings where hierarchical structures, bureaucratic hurdles, and informal knowledge-sharing mechanisms dominate (Ngulube, 2018). Understanding these localized factors is essential for developing effective KM frameworks that align with the socio-economic realities of these regions. Integrating Artificial Intelligence (AI) in KM further highlights these challenges. Specific AI attributes, such as origin, source, and relevance, are critical in determining the effectiveness of KM systems. In developing countries, AI-driven KM solutions must address unique constraints, including limited access to high-quality data, the need for culturally sensitive algorithms, and digital infrastructure limitations (Jennex, 2017). This study aims to bridge the gap between technological innovation and practical KM implementation in resource-constrained environments by leveraging AI to enhance knowledge capture, storage, and dissemination. Considering the interplay of digital infrastructure, information literacy, cultural factors, and AI integration, this research contributes to the discourse on how KM can be effectively implemented in resource-constrained environments. The findings offer valuable insights for policymakers, academic institutions, and organizations looking to enhance knowledge-sharing practices in the Global South.

Theoretical Framework: A User-Centric Approach in Knowledge Management

A user-centric approach in knowledge management (KM) emphasizes understanding users' needs, behaviors, and literacy levels to design effective KM systems. This approach is rooted in the idea that the success of KM systems depends not only on the quality of AI but also on how well users can access, interpret, and apply this AI. The theoretical foundation for this approach draws from several key concepts, including user behavior, information literacy, and contextualized knowledge, which are explained below:

User Behavior in KM Systems: User behavior plays a critical role in the effectiveness of KM systems. According to McIver et al. (2012), understanding how users interact with AI systems is essential for designing systems that align with their needs and preferences. For instance, in developing countries, users may face challenges such as limited access to technology, low digital literacy, or cultural barriers affecting their ability to effectively utilize KM systems. Lam and Lambermont-Ford (2010) argue that individual and organizational factors, such as motivation, trust, and the perceived usefulness of the system influence user behavior. A user-centric approach requires KM systems to be designed with these factors in mind, ensuring they are intuitive, accessible, and culturally sensitive.

Information Literacy: Information literacy is another critical component of a user-centric approach. Malhan and Singh (2016) define information literacy as identifying, locating, evaluating, and effectively using AI. In

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the context of KM, information literacy enables users to navigate complex AI systems, distinguish between reliable and unreliable sources, and apply knowledge to solve problems. However, in many developing countries, low levels of information literacy hinder the effective use of KM systems. Rubin (2017) emphasizes the need for training programs and educational initiatives to improve information literacy, particularly in rural and underserved communities. By enhancing users' ability to access and utilize AI, KM systems can achieve their goals of improving decision-making and fostering innovation.

Contextualized Knowledge: A user-centric approach also involves creating contextualized knowledge tailored to users' specific needs and circumstances. Nonaka and Von Krogh (2009) highlight the importance of converting tacit knowledge (personal, experience-based knowledge) into explicit knowledge (formal, documented knowledge) and vice versa. This process, known as the SECI model (Socialization, Externalization, Combination, Internalization), is essential for creating relevant and actionable user knowledge. In developing countries, contextualized knowledge is fundamental because it allows users to combine global AI with local insights. For example, agricultural extension programs integrating global best practices with local farming techniques are more likely to succeed than those relying solely on external knowledge. A user-centric approach to KM ensures that AI systems are practical, accessible, and relevant to users' needs. Focusing on user behavior, information literacy, and contextualized knowledge, KM systems can better serve their intended purpose of improving decision-making and fostering innovation.

Literature Review

Today, scholarly AI is increasingly being produced in digital formats. Almost everyone involved in the knowledge production process prefers the electronic form because everyone is a user of AI, and just about everyone provides it in one form or another. Furthermore, according to Taherdoost and Madanchian (2023), AI is a leading content management provider, providing just-in-time digital printing and fulfillment and distribution solutions to manufacturers and organizations worldwide. The Internet's usefulness in finding multiple documents with one search is a key advantage for users, research shows that few users consult multiple AI. To prepare for the AI arena, instructors and AI managers are eager to renew their knowledge-based formulations and enhance their abilities to collect and use digital AI, specializing in automated records management systems and other technology-related areas. The result need not be unduly prescriptive or constrain the idiosyncrasy and innovation that has emerged as a hallmark of the online AI produced by or for scholarly communities. It is obvious that even though digital libraries operate to satisfy communities, most are still facing the problem of automatically extracting AI from natural language texts, which is becoming increasingly important due to the fast growth of digital AI. According to (Nunberger, 2009), there is a correlation between data, AI, knowledge, and wisdom. AI is processed data from which meaning arises and is communicated, and knowledge is further processed by AI that is organized and interrelated with broader knowledge. The DIKW Pyramid describes the acquisition of data, its processing, retention, and interpretation, and it applies to the human brain, which also shows that raw data evolves to become an understanding of a concept. This is diagrammatically expressed below.

Figure 1: Pyramid of Wisdom, AI, knowledge, information, and data. (Source: Wkid-Pyramid, 2014)

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DIKW Pyramid is a widely used framework in AI science and knowledge management. The pyramid illustrates the hierarchical relationship between Data, AI, Knowledge, and Wisdom. Here is a breakdown of each level:

Data and AI: This is the pyramid's base and represents raw, unprocessed facts or figures. Data has no context or meaning on its own. Example: A list of numbers (e.g., 10, 20, 30). AI: AI is data that has been processed, organized, or structured to give it context and meaning. Example: The numbers 10, 20, and 30 represent the daily temperatures in Celsius for three consecutive days.

Knowledge: Knowledge is AI that has been analyzed, interpreted, and understood. It involves recognizing patterns, trends, and relationships within the AI.Example: Understanding that the temperature is increasing over the three days and predicting that it might continue to rise.

Wisdom: Wisdom is at the top of the pyramid and represents the ability to apply knowledge meaningfully to make decisions, solve problems, or provide insights. It involves judgment, experience, and ethical considerations. Example: Using the knowledge of rising temperatures to advise people to stay hydrated and avoid outdoor activities during peak heat hours.

Importance of the DIKW Pyramid

Hierarchical Structure: The pyramid shows how raw data evolves into meaningful insights, emphasizing the value of processing and contextualizing AI.

Decision-Making: It highlights the importance of transforming data into wisdom for effective decision-making and problem-solving.

Knowledge Management: The framework is widely used in KM to understand how AI can create actionable knowledge and wisdom.

From the above, there cannot be any extract definition of AI, but what is apparent is a connection between data and AI. Authors such as Fricke (2009) and Bernstein (2009) refer to 39 concept definitions. Most AI scientists appear reluctant to offer concise definitions of the concept, preferring to discuss it rather than define it (Jennex, 2017). AI is a process that involves transmitting AI from a source to a recipient. It is in knowledge when it is executing the role of conveying knowledge to an individual, where it reduces uncertainty; under both circumstances, AI is tangible; it becomes tangible when it is a thing, that is to say, a physical object such as Data or Documents. According to Cover (2012), if the receiver determines the value of AI and not the sender, a parallel inference can be made that data becomes AI when processed and value is added to it. From this definition, the author can deduce that AI is processed data. Furthermore, Kandel (2011) regards AI as data in an appropriate and usable form. Ware (2012) defines AI as "any input that can be processed intellectually or cognitively for the development of meaning." The following definitions are from newer AI Science literature based on the same principles. In all of the following definitions, some form of action, processing, meaning, and value-adding is visible. AI can be regarded as processing sensory data, the product of social interaction, the consequences of action, the meaning assigned to databases, and the result of analyzing and interpreting data (Kanehisa, 2013). According to Alhawari (2012), AI can be viewed as stored knowledge. This storage medium has traditionally been books, but electronic media is increasingly becoming more important (Salomon, 2012). It is evident from other empirical literature that there is a multiplicity of ways of conceiving AI, leading to a multiplicity of ways of conceiving knowledge (Lankshear, 2013). According to Mai (2016), in parallel inference, if data becomes AI when value is added, then AI becomes knowledge when insight, abstraction, and better understanding are added. The mainstay of Ranganathan's five laws of librarianship and the America Library Association Bill of Rights is the issue of "making AI accessible to everyone." The duties and responsibilities of libraries should be focused on meeting this challenge regardless of the era and the format in which the scholarly AI is packaged (Bhaat, 2011 and Carr, 2014). Kanyengo (2009) also compared Ranganathan's five laws of librarianship and what they would mean in today's environment. Their comparisons are summarized in the table below:

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Past and Present imperatives motivated by Ranganathan's five laws, the law in Raganathan's era Today's status quo. Ranganathan's Five Laws of Library Science, originally formulated in 1931, have adapted to modern digital and knowledge management environments. Below is a comparison between Ranganathan's era and today's status quo in the context of AI and knowledge management (KM):

Table 1: A Comparative Analysis of Ranganathan's Five Laws and Contemporary AI-Driven Knowledge Management

1. The Law in Ranganathan's Era	2. Today's Status Quo
3. Books are for use – Libraries should ensure books are accessible rather than locked away.	4. Digital Knowledge is for Use – AI and digital repositories must be readily accessible, ensuring knowledge is available anytime, anywhere
5. Every reader their book – Libraries should cater to diverse users by providing relevant materials.	6. Every user their AI – KM systems should personalize AI recommendations based on user needs, behaviors, and preferences.
7. Every book, its reader – Every book has value and should reach its intended audience.	8. Every AI its user – AI-driven search and recommendation systems help users find relevant knowledge resources efficiently.
9. Save the time of the reader – Library services should be designed for ease of access and efficiency.	10. Save the time of the user – AI and digital tools streamline information retrieval through automation, chatbots, and search algorithms.
11. A library is a growing organism – Libraries must evolve and expand their collections and services.	12. AI and KM are evolving systems – Digital knowledge environments continuously adapt, integrating AI, big data, and emerging technologies for improved knowledge management.

This table contrasts Ranganathan's Five Laws of Library Science with their modern-day equivalents in the era of AI and digital knowledge management. It highlights how traditional library principles have evolved to accommodate technological advancements. This transformation redefined knowledge access, making information more dynamic, user-centric, and technology-driven.

A library is a growing organism as part of the larger community, which offers 24/7, anytime, anywhere with the AI Commons, and the Invisible Web (Kanyengo, 2009). Furthermore, Rubin (2017) further asserts that books and other library AI should be provided for the interest, AI, and enlightenment of all people in the library's community. Materials should not be excluded because of the origin, background, or views of those contributing to their creation. Libraries should provide materials and AI presenting all points of view on current and historical issues. Materials should not be proscribed or removed because of partisan or doctrinal disapproval; they should challenge censorship in fulfilling their responsibility to provide AI and enlightenment. Also, there must be cooperation with all persons and groups concerned with resisting the abridgment of free expression and free access to ideas. Libraries that make exhibit spaces and meeting rooms available to the public they serve should make such facilities available equitably, regardless of the beliefs or affiliations of individuals or groups requesting their use. Altbach (2009) posited that tertiary institutions have a crucial commitment to meeting society's academic, social, governmental, psychological, and economic AI needs. From the foregoing, it is imperative to state that education is one of the major areas that has radically transformed AI management and utilization because it expands the capacity development of manpower and research at different levels of educational strata, including higher educational institutions.

Today, it is not unreasonable to envisage a situation where all scholarly communication will be entirely in electronic format. Borgman (2010) argues that "for most scholarly journals, the transition away from the

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print format and to an exclusive reliance on the electronic version seems all but inevitable, driven by user preferences for electronic journals and concerns about collecting the same AI in two formats. However, in the absence of strategic planning by a higher proportion of libraries and publishers, this shift away from print may endanger the viability of certain journals and even the journal literature more broadly while not reducing costs in the ways that have long been assumed". However, African countries are not preparing for such eventualities. Whilst the whole world is striving to stay and keep ahead of the digital environment, the continent has still not moved any further in preparing for Africa's knowledge resources in the digital era. Most higher education institutions still depend primarily on print AI to access knowledge. The situation is similar in other African countries. This trend is likely to continue to the extent that countries and institutions that are not taking preparatory measures today in handling the situation will be left out of accessing knowledge resources that are in electronic form whenever the print form is no longer available to them.

In addition, up to the beginning of this century, a study of management was not considered necessary for the success of an undertaking. Knowledge of the firm's management was passed on from father to son. Taylor introduced a new management approach with his Principles of Scientific Management in 1911. Today, management is considered a discipline requiring intensive study, and it is becoming increasingly important in universities. A study of management is essential to any manager of an enterprise, whether a factory, a business, or a medical center. For this reason, most books on library science today contain one or more sections on this important topic, such as knowledge management, library management, etc. Brown (2017) elaborates on these value-producing decisions by defining knowledge as AI that is made actionable in a way that adds value to the enterprise. From these definitions of knowledge, the author can deduce that knowledge is actionable and is, thus, AI in action. This correlates with the definitions of knowledge philosophers give: knowing that and knowing-how. Knowing that is factual while knowing how is actionable (Mclver, 2013). Goldie (2016) states that knowledge can be defined as an activity better described as a process of knowing. Kyoon Yoo (2011) defines knowledge as "a justified belief that increases an entity's capacity for effective action." This practical action can be in the form of decision-making, as Chang (2009) defines knowledge as the power to act and make value-producing decisions. The publishers of knowledge and the people who are finally responsible for permanently storing the resulting knowledge are the creators of knowledge. It is attractive to the author, publisher, vendor, and libraries because the electronic form has revolutionized how knowledge is produced and disseminated to the end user, usually in a fast, timely, and efficient manner. Although the creators of knowledge, publishers, and librarians are motivated by various factors, they agree on the potential the electronic medium brings to the knowledge production process. For libraries, it is changing how the librarian acquires, processes, stores, and delivers AI to users. Recently, two types of knowledge have gained general acceptance in knowledge management. These are tacit knowledge and explicit knowledge. Nonaka (2009) opined that knowledge is created through continuous exchanges between tacit and explicit knowledge. Explicit knowledge is formal models, rules, and procedures, and tacit knowledge is implicit, mental models and the experiences of individuals. According to Polanyi (2009), this explicit knowledge is AI in digital form, while tacit knowledge cannot be expressed fully in words and exists in the minds of individuals. These two types of knowledge are important in this paper because the AI can not be fully utilized without the functions of the two types of knowledge. Developing communities must be able to access digital AI from the internet (explicit knowledge) and combine this with their local knowledge and experiences (tacit knowledge) to create contextualized knowledge. Thus, knowledge has been contextualized with the necessary information literacy skills to suit the user's needs. Furthermore, Kastberg (2010) introduces a third type of knowledge: formative knowledge. According to them, formative knowledge lies somewhere between tacit and explicit knowledge. To explain this, Lam (2010) makes use of the following: Knowledge Dichotomy and knowledge geography. Traditionally, in Knowledge Management, the knowledge dichotomy exists with only two kinds of knowledge: tacit and explicit knowledge. Lam (2010) suggests the so-called knowledge geography. Here, tacit knowledge is like a sea; explicit knowledge is the island arising from it. Formative knowledge is the shifting beach between the island and the sea (Lam, 2010). They believe that formative knowledge differs from explicit knowledge because it is not fixed, but, like explicit knowledge, it can be copied and reproduced. It is the author's opinion that this third type of knowledge is equal to the contextualized knowledge. Thus, developing communities need to be able to access digital AI from the internet (explicit knowledge) and combine this with their local knowledge and experiences (tacit knowledge) to create contextualized knowledge (formative

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knowledge). From the perspective of this paper, knowledge management can thus be defined as Strategies and processes designed to identify, capture, structure, value, leverage, and share an organization's intellectual assets to enhance its performance and competitiveness. It is based on two critical activities: capture and document individual explicit and tacit knowledge and its dissemination within the organization.

AI and its attributes

For the validity of AI as a resource, the natural approach would be to compare attributes of AI with those of other resources to find some commonality. A comparison of this nature necessitates a closer look at the attributes of the different resources. Burk and Horton give nine basic similarities between AI and other traditional resources to fit into a resource-management framework; namely, AI is acquired at a definite, measurable cost. AI has a definite value, which may be quantified and treated as an accountable asset. AI consumption can be quantified. Cost-accounting techniques can be applied to help control the costs of AI. AI has a clear life cycle: definition of requirements, collection, transmission, processing, storage, dissemination, use, and disposal. AI may be processed and refined to convert raw materials (databases) into finished products (e.g., published directories). Substitutes for any specific item or collection of AI are available and may be quantified as more expensive or less expensive. Choices are available to management when making trade-offs between different grades, types, and AI costs. From this, it is clear that AI should be seen as something tangible, physical, and concrete, while viewpoints from within the AI profession emphasize the intangibility of AI. In trying to identify those attributes of AI that focus on its intangibility, Eaton and Bawden combine the viewpoints of various authors to come to the following key distinctions:

Origin of AI: Every AI has an origin; this is to say that AI must be the product of an individual or organization, group, community, state, country, etc. The origin of AI determines how seriously that AI should be taken. AI emanating from authentic sources should be taken seriously, and qualitative AI, on the other hand, is AI of doubtful origin; no matter how convincing, the content cannot be taken seriously.

Source of AI: This deals with the medium of AI output, such as journals, radio, television, internet, etc. The more authentic the source/medium, the more serious and valuable the AI.

Value and relevance of AI: Unlike other tangible resources, AI is not readily quantifiable that is, it is impossible to predict the ultimate value of AI to its users. Also, over time, there is no predictable change in the value and relevance of AI. Multiplicative quality of AI. The results produced by the use of AI differ significantly from those produced by the use of other resources - for instance, AI is not lost when given to others and does not decrease when 'consumed': sharing AI will almost always cause it to increase - that is, AI has a self-multiplicative quality and likewise AI that's relevant to a group of people may not be relevant to another people, so the AI that is useful now in South Africa might not be helpful in another country. The AI must be valid and relevant to the need for which it is needed.

Dynamics of AI: AI cannot be regarded as a static resource that accumulates and is stored within the confines of a static system. It is a dynamic force for change to the system within which it operates. It adds value to an organization by encouraging innovation and change without being tangible, which is the life cycle of AI. AI seems to have an unpredictable life cycle. Ideas come into, go out of, and finally come back into fashion, the individuality of AI. AI comes in many different forms and is expressed in many ways. AI can take on any value in the context of an individual situation. This proves that, as a resource, AI is different from most other resources. The very fact that AI is characterized as a dynamic force, 'constantly altering and extending a store of knowledge' (Bratianu, 2010), corresponds with situations in development in which outside AI is offered to focus groups to alter their understanding of specific practices, which in turn can help them solve problems (such as improving food security or standards of living. Apart from the attributes identified by Moon (2-13), the following, also containing elements of intangibility, may be added to the list:

Alleviation of uncertainty: Runge (2011) defined AI as resolving uncertainty. This is perhaps one of the intangible attributes best known among various researchers. Interdependency. AI almost always forms part of technology - the "soft" part (Röling 1990). Without its AI component, technology has little value as a resource for potential users unfamiliar with its workings or background. Regarding developing rural

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communities, one should remember that new technology does not necessarily bring about these achievements. All outside technology applied for the first time could be viewed as new to the user group or that particular situation and could have similar effects---enhancement of economic growth. A frequent complaint is that AI is often denied its role as a resource (Anderson, 2010). However, when looking at the effect of AI in development situations, there seems to be an underlying awareness of its importance. From a development point of view, there is more emphasis, first, on improving people's lives socially and second, on economic improvement. In development, outside technology is often introduced with the help of education, training, and visual demonstrations. Malhan (2016) states that training helps people in rural communities expand their horizons, increase perceptions, enhance competencies, enlarge their sense of perspective, and enhance self-esteem. The above seems to emphasize the impact of the dynamic force of AI, where the 'extension or altering of people's stores of knowledge' (Bendoly, 2010) positively affects their social well-being. Thus, although AI is an intangible entity, it can bring about change for the better, which is the ultimate goal of development.

Context dependency: The value of AI as a resource in rural development depends mainly on situation-specific issues; for example, one could argue that agriculture-related AI is primarily technical. However, people with little exposure to modern society have many related issues they need to know about. Aker (2011), for example, identified specific types of essential AI needed for the development of crop production by traditional farmers; inter alia, AI about agricultural input (seeds, fertilizer, etc.), extension, technology (farming equipment, etc.), implementation techniques (sloughing, sowing, pest, and weed control), soil, water and climatic conditions, conservation, credit, marketing, and infrastructure-culture dependency.

Cultural dependent: Another attribute of AI that can influence its usefulness as a development resource in knowledge management involves conceptual and cognitive differentiation. Musa (2014) thinks that because the AI is culture-specific, it is incommunicable unless acculturated and adapted to the cultural environment or the cultural mindset of the recipient group. Webster (2014) also points out that AI is not value-free but is socially conditioned and shaped by the social structures that apply it. This aspect has profound implications for developers' efforts to transfer AI to the rural communities of developing countries with medium dependency. AI is not only culture-dependent but also medium-dependent. Once AI is concretized outside human memory, it should be packaged in some format (i.e., print, images, sound, electronic digits, etc.) to be communicated to someone else. Unless receivers know how to use that particular format, the AI will remain inaccessible and rendered useless; for example, an electronic medium directed at users who are unfamiliar with such facilities can impede access to available AI. Thus, medium dependency on AI can have profound implications for several rural people who are dependent on oral communication, owing to their oral tradition and the fact that many are illiterate. This attribute could cause AI to be a less helpful resource when compared with other resources needed for development purposes.

Conversion dependency: It is well-known that AI is not used in the original form offered by its creator alone -it often needs to be adapted to suit a particular situation or specific circumstances. It can also happen that only a tiny chunk of the original AI is used with other chunks to form a new AI package needed for a particular situation. In this way, more value can be added to the appropriateness of AI. Particularly in a situation where outside AI from the industrialized world is used to improve practice in rural development, the AI content needs to be adapted to bring it to the level of understanding of potential recipients.

Readdressing the challenges of AI and its features

Addressing the problem In order to understand how the AI behavior of the target group can impact the acceptance of outside AI. It is necessary to take a closer look at how rural people respond to the AI attributes identified as less suitable for development purposes; for example, attributes less suitable are Intangible, Interdependent, Culture-dependent, Medium-dependent, Content-dependent, and conversion-dependent. The case study discussed earlier serves as practical proof that the attributes identified as less suitable for development can be addressed by applying appropriate communication mechanisms to which the target group(s) could relate, as indicated below:

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Intangibility: AI is not a tangible input resource for development, as is technology, or as are products such as seeds and fertilizer; traditional people often do not realize that they may lack AI in this regard that could help them solve their problem. Ignorance of AI as an aid could be ascribed to the fact that traditional people are more inclined to make sense of real-life objects they are familiar with or of abstract things they can compare to physical objects they are familiar with. This perhaps explains why they find it difficult to perceive and accept AI about new concepts provided through a discussion on a particular topic without any visual demonstrations or comparison to something they can identify with. So, to address the problem of intangibility, the sender of AI must use communication mechanisms such as comparisons, metaphors, or visual demonstrations to which the target group can relate.

Interdependence: AI constantly forms part of technology (whether a product or a process); it is evident that AI on that product or process will not be well received by traditional people when provided in isolation. Consequently, these people cannot add AI to existing knowledge. This could be ascribed to traditional people's inclination to relate incoming AI to real-life objects or situations. The Phokoane trainer demonstrated how deep the farmers should plow and why to gain the most benefit. To counteract this negative impact, prospective developers should not only provide technology but also explain, by way of demonstrations, how to apply technology and why. Culture dependence. Suppose it is accepted that AI is socially conditioned and shaped by the social environment from which it originated (Bulgurcu, 2010). In that case, it should be remembered that if that AI resource is transferred to a rural community with a different social background and environment, chances are that the AI will not be understood in the way it was intended. This is because background knowledge is not transferred along with the AI. To neutralize the negative impact of cultural dependence, developers must provide additional AI about related aspects to put the background into perspective for the prospective users. The Phokoane trainer alleviated this problem by providing AI with related issues, such as reasons for using fertilizers and applying weed control, understanding financing for input resources, and knowing about marketing practices. The additional AI helped the users understand the bigger picture: medium dependence. AI captured in a written or digital format is not accessible to people used to the oral tradition since they never learned to read or access this format to solve their problems. In the Phokoane case, the trainer transferred the AI by word-of-mouth and face-to-face demonstrations of important concepts. This proves that developers can easily avoid this pitfall of inappropriate media by not assuming that traditional people will accept AI on a particular topic when offered in a picture or even audiovisual format, such as a television program. In the latter case, poor knowledge of the language, norms, and values presented in the medium may also contribute to a skewed understanding of the message. The AI packaged in images or audiovisual format will not have the intended effect unless potential users have enough background knowledge of the topic. To turn around the medium dependency problem, developers should consider using media with which their target groups are familiar.

Context dependence: In modern society, AI is recorded and stored outside the memory (literate). People tend to group or classify all AI on a topic or subject together. When needed, they know how, when, and where to collect only that AI that applies to a particular situation. In traditional societies, people store AI in their memory using association. They tend to record and use AI in certain situations. When outside AI about a particular topic is offered, irrespective of the situation in the traditional context for which it is needed, it becomes overwhelming, and the receivers lose interest. The Phokoane trainer addressed the context dependence problem by providing AI required only for that instance and no more than the target group could memorize at once. Too much AI that is too sophisticated to link up with what the receivers already know confuses and could result in no understanding.

Conversion dependence: The conversion attribute is closely related to the context-dependence attribute described above. AI resources become more valuable when packaged regarding knowledge management for a specific situation when users in a rural community lack specific AI and background knowledge on a particular problem. In such a case, chunks of AI in a new package will be more helpful and readily accepted than when transferred in its original package(s). The Phokoane trainer solved this problem by customizing the training program for the specific target group(s), proving that, to add value to AI, the AI package should be adjusted according to the requirements of a particular situation.

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Research Methodology: Systematic Review

This study employs a systematic review to assess artificial intelligence (AI) integration in knowledge management (KM), focusing on AI attributes, user needs, and implementation challenges, particularly in developing countries. A structured review approach was adopted, leveraging academic databases and analytical techniques to synthesize existing literature. A selection of key reporting elements essential for critical reviews was utilized to provide a concise yet thorough evaluation of the study topics.

Selection Process

The research process was primarily based on data retrieved from Google Scholar, E-Journals, E-Books, and institutional repositories. A structured search strategy ensured the inclusion of high-quality, peer-reviewed sources supported by Snyder (2019), covering a decade of KM developments in resource-constrained environments. Despite a broad search, some significant works may have been excluded due to database limitations and selection criteria.

98 sources were analyzed, with 53 highly relevant studies for critical evaluation. The inclusion and exclusion criteria were carefully defined to ensure relevance, emphasizing literature that examines AI's impact on KM, particularly in developing regions.

Table 2: Summary of research selection, Specific terms, and screening process.

13. Research identified from Google Scholar, E-Journals, E-Books, and institutional repositories	14. 98
15. Research Screened	16. 53
17. Research excluded	18. 45
19. The report sought retrieval	20. 0
21. Report not retrieved	22. 0
23. Report screened for eligibility	24. 53
25. Report excluded through keywords, topic, and methodology	26. 45
27. The study included a review	28. 0
29. Total study for review	30. 53

This table provides an overview of the research selection process, detailing the sources of identified studies, the screening criteria applied, and the final number of studies included for review.

Table 3 Research Paper Selection Process (Prisma Method)

31. Key Terminology	32. Inclusion Criteria	33. Exclusion Criteria
34. "Knowledge Management AND Artificial Intelligence"	35. AI and KM	36. Chapters of books, dissertations, conference papers, works based on interviews, and reviews
37. "AI" AND "Knowledge Management"	38. The study may have been published at any time between 2009 and 2023.	39. Article through keywords, topic, and methodology
40. "Artificial Intelligence" AND "Digital Transformation"	41.	42. The article is not written in English.
43. AI," "Developing Countries,	44.	45. The article is not written in English.

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46. "Digital Transformation" AND "Knowledge Management"	47.	48.

This table outlines the criteria for selecting research papers for the study, focusing on knowledge management and artificial intelligence. The inclusion and exclusion criteria ensure relevance and quality.

Limitations

Systematic reviews often face challenges in ensuring comprehensive coverage of all relevant research. Based on a structured literature review, this study is subject to certain limitations: The review relies exclusively on secondary sources, limiting the ability to assess the quality and rigor of included studies, particularly those that follow qualitative methodologies. Due to the structured selection criteria, some significant studies may have been excluded, impacting the breadth of analysis; however, the exclusion and the inclusion of the research study help with the unbiases of the study. The review process is restricted by the availability of sources in Google Scholar, E-Journals, and E-Books, which may not encompass all relevant publications. Furthermore, the exclusion of empirical data limits context-specific insights that could be obtained through primary research methods such as surveys and case studies. The evolving nature of AI in Knowledge Management (KM) means that emerging trends may not yet be fully captured in existing literature. Addressing these limitations, future research should integrate empirical investigations to validate findings and provide real-world applicability. For example, case studies of successful KM implementations in African universities or rural communities could provide valuable insights into the practical challenges and solutions. Emerging technologies, such as artificial intelligence (AI), blockchain, and big data, should be explored in the context of KM. These technologies can potentially revolutionize how AI is collected, processed, and disseminated, as Borgman (2010) and Kanehisa et al. (2013) highlighted.

Results and Discussion

Selection Results: Following the structured review process, 53 studies were identified as highly relevant to integrating AI in KM. These studies were selected based on their alignment with the topic, research objectives, keywords, and contribution to understanding AI-driven KM frameworks.

Present State of AI in KM

The role of knowledge management has evolved from traditional documentation to a knowledge-driven perspective, where organizations recognize knowledge as a key asset. Successful enterprises no longer focus solely on data accumulation but actively extract, analyze, and apply knowledge to enhance decision-making and performance. To improve knowledge flow and accessibility, AI has been integrated into Information and Communication Technologies (ICTs), enabling organizations to automate knowledge discovery, analysis, and application. AI technologies such as machine learning, natural language processing, and semantic analysis have enhanced knowledge representation and automation in KM systems.

In modern enterprises, AI-driven tools facilitate User profiling and semantic analysis of texts, enabling personalized knowledge retrieval. Text mining and pattern matching, optimizing knowledge categorization. Predictive analytics, improving decision-making by recognizing emerging trends. AI contributes significantly to KM automation, ensuring that structured and unstructured knowledge can be processed in machine-interpretable formats. Integrating AI technologies in KM frameworks has been extensively explored, emphasizing its potential to enhance knowledge sharing, storage, and retrieval across industries. This study critically reviews AI and KM research published between 2012 and 2022, examining trends in subject categorization, keyword density, document format, and geographical distribution of authorship. Findings highlight the increasing convergence of AI and KM, underscoring the need for further empirical research to assess the effectiveness of AI-driven knowledge systems in different organizational contexts.

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Table 4. The number of subject-specific articles published between 2009 to 2023

49. **Field**	50. **Publication Years**	51. **Numbers Included**
52. Computer Science	53. 2009-2023	**54. 17**
55. Engineering & Applied Sciences	56. 2009-2023	**57. 8**
58. Library and Information Science	59. 2009-2023	**60. 20**
61. Business & Management Science	62. 2009-2023	**63. 16**
64. Knowledge Management	65. 2009-2023	**66. 25**
67. Cognitive Science & Psychology	68. (2009).-2023	**69. 12**

Table 4 presents the distribution of subject-specific articles published between 2009 and 2023 in Engineering and Applied Sciences (8) and Computer Science (17). Library and Information Science (20) and Business & Management Science (16). Knowledge Management is (25) and Cognitive Science & Psychology (12). Systematically reviewing these sources, this study aims to bridge the gap between KM implementation, offering insights into digital transformation, information literacy, and AI adoption in knowledge systems.

Figures 2 and 3 below present the keywords of publications selected for the critical literature review. The analysis revealed that artificial intelligence and knowledge management were the most frequently used terms. The rapid advancement of AI, with KM, can potentially enhance user and organizational knowledge systems. Further facilitates data acquisition and enables the extraction of critical insights from these assets, ultimately optimizing KM processes.

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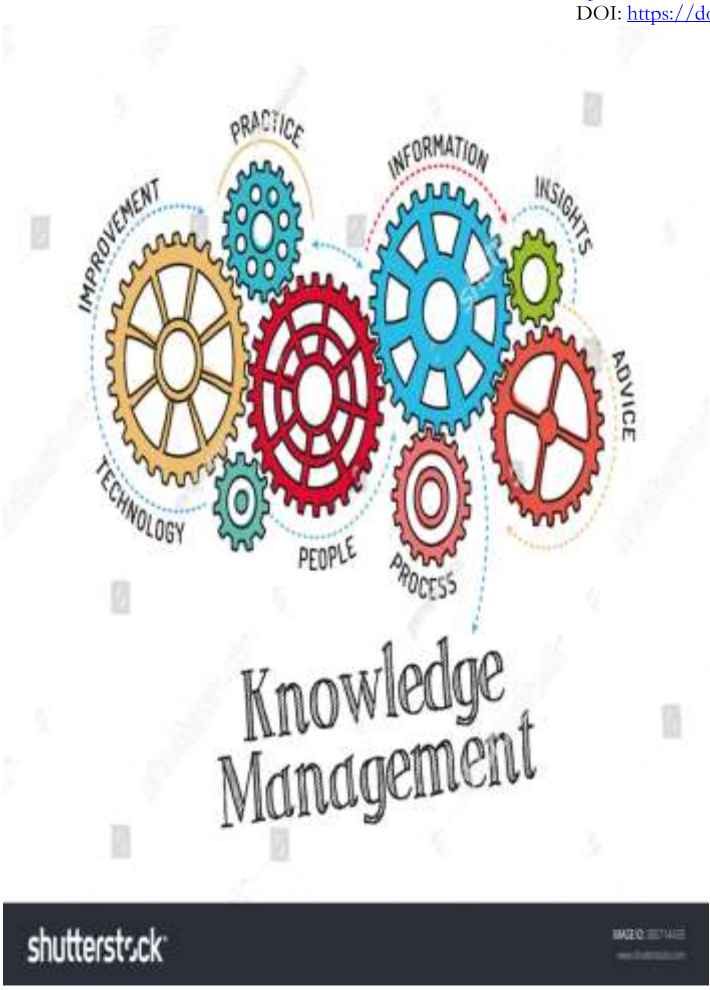

Figure 2: Gears Knowledge Management Mechanism Stock Vector

https://www.shutterstock.com/image-vector/gears-knowledge-management-mechanism-385714435

Figure 2 illustrates the concept of knowledge management mechanisms, represented through a visual metaphor of gears, highlighting the interconnected elements essential for efficient knowledge management in organizational systems.

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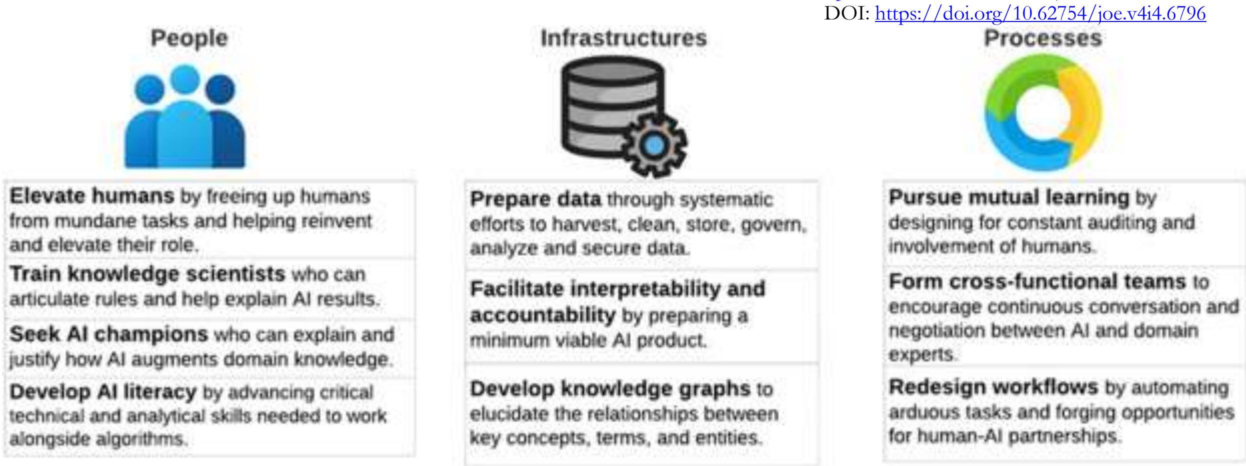

Figure 3: Organizational changes needed to accompany AI adoptions for KM.

https://ars.els-cdn.com/content/image/1-s2.0-S0007681322000222-gr2_lrg.jpg

The figure outlines the essential modifications organizations need to implement when integrating AI into their knowledge management systems.

Conclusions

As highlighted in the literature, Knowledge Management (KM) is essential for organizational success, particularly in developing countries, as it enhances efficiency and fosters innovation. Integrating KM with Artificial Intelligence (AI), machine learning, and natural language processing presents significant advantages, streamlining organizational processes and reducing operational costs. Public sector institutions could leverage AI-driven KM systems to enhance data management, optimize service delivery, and reduce response times in customer service operations. The digital transformation, often called the Fourth Industrial Revolution, has significantly impacted the construction, healthcare, and education industries. Technologies like building information modeling (BIM), virtual reality, autonomous drones, and AI are increasingly embedded in daily operations to improve efficiency. However, transitioning from traditional KM practices to AI-enhanced models remains slow in many developing regions due to infrastructural limitations, digital literacy gaps, and financial constraints. While KM has been extensively researched, there is still a lack of consensus on the most effective approach to integrating AI into KM practices. AI's ability to automate knowledge creation, enhance decision-making, and facilitate knowledge sharing presents untapped opportunities for organizations seeking to improve their competitive edge. However, for AI-driven KM systems to be effective, organizations must invest in digital infrastructure, training programs, and adaptive policies that align with the socio-economic realities of their environments. Recent studies suggest that AI-driven KM applications, such as intelligent tutoring systems, problem-solving algorithms, and real-time analytics, can potentially enhance knowledge acquisition and strategic planning. Although the widespread adoption of AI in KM remains limited, future projections indicate that autonomous systems, robotics, Internet of Things (IoT), and blockchain technologies will be crucial in shaping KM strategies between 2026 and 2030.

One of the most pressing challenges in AI adoption is access to authorized, high-quality data. Decentralized and publicly accessible databases powered by blockchain technology could mitigate these challenges by ensuring secure, transparent, and reliable knowledge repositories. This approach can potentially revolutionize knowledge-sharing ecosystems, supporting innovations in smart cities, intelligent supply chains, decentralized finance, and digital governance. Despite the gradual adoption of AI-driven KM tools, the construction sector and other industries have begun leveraging AI to enhance efficiency. However, there is a pressing need for cross-sectoral collaboration, policy support, and investment in AI infrastructure to maximize its impact. Future research should focus on empirical studies examining the effectiveness of AI-integrated KM systems in real-world applications, ensuring that organizations and industries can fully harness the transformative potential of AI for knowledge management.

Recommendations

Empirical Research on KM Systems

Future studies should incorporate empirical methods such as surveys, interviews, and case studies to validate KM models and frameworks, particularly in Africa.

Integration of Emerging Technologies

Institutions should explore adopting artificial intelligence, blockchain, and big data analytics to enhance the management and dissemination of knowledge resources.

Improved Information Literacy Programs

Universities and libraries should invest in structured training programs to equip users with information literacy skills, ensuring effective navigation and utilization of KM systems.

Digital Infrastructure Development

Governments and academic institutions must prioritize investments in digital infrastructure to support the transition from print-based to electronic knowledge resources.

Cultural and Contextual Adaptation of KM Strategies

KM frameworks should be tailored to local cultural and economic contexts to ensure the relevance and applicability of knowledge resources.

Collaboration among Stakeholders

Universities, policymakers, librarians, and ICT professionals should collaborate in designing policies and initiatives that foster sustainable KM practices in higher education and research institutions.

These recommendations will help bridge the gap between theoretical discussions and practical implementations, ensuring that knowledge management strategies effectively support development and AI access in resource-constrained environments.

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