

Artificial Intelligence: The key to Information and Knowledge Management Maturity in Organisations

Kagiso Mabe¹ and Kelvin Joseph Bwalya^{1,2}

¹The Department of Information and Knowledge Management, College of Business and Economics, University of Johannesburg, South Africa

²Research and Development, The Faculty of Computing and Information Technology, Sohar University, Oman

kmabe@uj.ac.za

Abstract: This study investigates the role of artificial intelligence (AI) as a catalyst for the maturity of information and knowledge management (IKM) within South African organisations. Positioned within the context of the Fourth Industrial Revolution (4IR), the research responds to the growing complexity of data environments characterised by big data, cloud computing, and advanced analytics. Traditional IKM approaches are increasingly inadequate for managing data variety, velocity, and volume, necessitating the integration of AI-driven capabilities such as machine learning (ML), natural language processing (NLP), and augmented analytics. Adopting an interpretivist paradigm, the study utilised a monomethod qualitative design. Semi-structured interviews were conducted with 12 strategically positioned IKM professionals across diverse functional areas, including knowledge management, business intelligence, records management, data governance, competitive intelligence, and social media management. Data were analysed using open, axial, and selective coding, supported by ATLAS.ti and thematic analysis. This approach enabled the development of an empirically grounded understanding of technology adoption patterns in IKM units, with a particular focus on AI adoption. The findings reveal that AI is widely perceived as central to achieving IKM maturity. Participants emphasised the importance of data analytics and visualisation platforms, many of which are enhanced by AI capabilities. AI-supported automation, predictive and prescriptive analytics, environmental scanning, anomaly detection, and generative content creation emerged as critical enablers of operational efficiency and strategic decision-making. Maturity was associated with process automation, infrastructure upgrades, enhanced data quality, and AI-driven system integration. While participants recognised AI as indispensable for competitiveness and innovation, concerns were raised regarding overreliance on AI, potential job displacement, and ethical implications. The study concludes that IKM units must strategically embed AI to remain relevant while balancing automation with human judgment and governance. By identifying foundational prerequisites for AI adoption, this research provides AI insights that can inform policy development, digital transformation strategies, and IKM's future positioning as a strategic organisational pillar.

Keywords: Technology adoption, AI, Knowledge management technologies, Artificial intelligence, Information and knowledge management

1. Introduction

Industries are becoming increasingly complex in the fourth industrial revolution (4IR), necessitating the implementation of advanced technologies to support information and knowledge management (IKM) functions that provide insights to facilitate swift decision-making in dynamic markets (Romero et al., 2021). IKM functions, such as business intelligence (BI), exist to assess past performance and identify past mistakes to predict future best practices and business demands, and to provide organisational benefits, including improved decision-making (Alqhatani et al., 2022). Additional benefits of IKM functions include assisting organisations in developing new business models, improving their reputation, product quality, and profitability (Bordeleau et al., 2018), as well as enhancing business performance (Bordeleau et al., 2019).

Traditional IKM techniques can no longer keep pace with the rapid development in data variety and the emergence of big data (BD). The large volume of data available makes it challenging to process in traditional ways (Hamad et al., 2022). The benefits of adopting artificial intelligence (AI) in IKM include automated analytics. For example, in traditional IKM tools, manually locating relationships between variables was required. In contrast, in the case of AI use, the relationships are automatically created and visualised for the user (Alghamdi and Al-Baity, 2022).

The integration of 4IR technology enables the collection and analysis of large volumes of data to produce high-quality business insights that support both strategic and operational functions (Romero et al., 2021). For example, when IKM and AI are combined, they create a new type of analytics capability referred to as augmented analytics (AA) (Alghamdi and Al-Baity, 2022). AA enable IKM practitioners to leverage the capabilities of machine learning (ML) and natural language processing (NLP), which are subsets of AI, to automate business analytics processes. AA also improves data analysis, preparation, and visualisation, framework development, and insight generation, while reducing time wastage (Alghamdi and Al-Baity, 2022).

AA deliver business advantages, including increased reporting accuracy, cost savings, enhanced decision-making, improved process efficiency, and refined strategies and plans, all of which contribute to increased profitability (Alghamdi and Al-Baity, 2022). When AI is used in IKM, it assists organisations in identifying business opportunities that would have been difficult to identify without the use of AI (Ratia, Myllärniemi and Helander, 2019). These technological developments motivated this study's aim: to investigate how IKM practitioners in South Africa utilise AI to enhance their work. The goal was to help IKM business units operate efficiently. Within the scope of this study, intelligent IKM refers to IKM teams utilising 4IR technologies to support organisations in making operational and strategic decisions, thereby enhancing business performance.

The study particularly focused on the following objectives:

- To determine whether AI is utilised in IKM business units in South Africa.
- To understand user perceptions of AI in IKM.

The technologies of the 4IR, such as the Internet of Things (IoT), cloud tools, and AI, can be combined to produce insights for enhanced intelligence creation (Kruger and Steyn, 2023). Employing cloud tools alleviates the challenge of technology obsolescence and reduces operational costs by minimising system maintenance and upgrade fees (Ahmad et al., 2020). For instance, TradeGecko offers a cloud-based IKM platform for inventory management, thereby enhancing online retail and shopping processes (Ahmad et al., 2020). Tools such as Decooda's AI engine assist with automated data preparation, restructuring, cleaning, transformation and anomaly sieving (Alghamdi and Al-Baity, 2022).

When IKM functions and AI come together, they increase IKM workers' productivity by enabling them to focus more on tasks that require human judgment while also supporting the performance of predictive and prescriptive analytics (Alghamdi and Al-Baity, 2022). This improvement in decision-making (Ratia et al., 2019) enhances IKM's overall performance. Employing AI enables automated, real-time data analysis, producing insights for enhanced decision-making (Hamad et al., 2022). AI assists with deep data analytics and the production of predictions about business strategies (Alqhatani et al., 2022). IKM processes automated by AI include data preparation, discovery, and data model creation and implementation (Alghamdi and Al-Baity, 2022).

Augmented IKM tools enable unskilled users to integrate, clean, and visualise data with ease, thereby enabling more effective analysis (Alghamdi and Al-Baity, 2022). For example, TIBCO Spotfire enables unskilled employees to analyse complex data stored across different data warehouses without assistance from an IT specialist (Ahmad et al., 2020). Qlik Technologies and Tableau have adopted AI, which provides suggestions on the type of visualisations to use to explain data (Alghamdi and Al-Baity, 2022; Ahmad et al., 2020). It is for these reasons that this study aimed to contribute to the increased adoption of AI for IKM purposes, helping to position IKM business units as essential contributors to organisational success. This effort aims to increase their recognition as organisational pillars in an environment where the IKM function can sometimes be overlooked.

2. Literature Review

2.1 The Impact of 4IR Technologies on Information and Knowledge Management

With the advancement of big data (BD), AI and cloud computing (CC), analytics has been propelled to the forefront, garnering significant attention (Abellera and Bulusu, 2017). The ever-growing volume of data and the availability of affordable technologies for generating it suggest that IKM tools must be continuously upgraded to harvest valuable, actionable insights from BD (Mehrotra, 2021). IKM has progressed over the years, from its infancy when insights would be shared with decision makers when they were no longer effective, to the use of extract, transform and load (ETL) tools, which are effective in delivering insights that give organisations a competitive advantage but still are not as efficient as desired when managing vast amounts of data and data types, especially BD. These techniques pale in comparison to modern IKM, which should rely heavily on AI, as without AI, it would have been humanly impossible to analyse BD (Abellera and Bulusu, 2017).

IKM systems need to be agile to manage BD and maintain data quality (Mehrotra, 2021). Fortunately, a new generation of IKM tools has emerged due to integration with AI, referred to by some as actionable intelligence (Abellera and Bulusu, 2017) or AA (Tcukanova, Yarskaya and Torosyan, 2022). To remain relevant, IKM systems must embed predictive mechanisms that enable big data analytics (BDA) and perform natural language processing (NLP) (Mehrotra, 2021). These capabilities enable IKM systems to perform analytics to new heights (Abellera and Bulusu, 2017). Trained IKM models can be utilised to deliver offline reports and key takeaways from data, and support predictive decision-making (Mehrotra, 2021).

AI enables IKM practitioners to generate actionable forecasts and prescriptive insights (Abellera and Bulusu, 2017). By providing prescriptive insights, AI enables users to perform in-depth data assessments, determine root causes and relationships within data, regardless of their skill level or domain knowledge (Tcukanova et al., 2022). AI can help organisations automatically detect anomalies, generating opportunities for revenue creation by identifying consumer patterns, forecasting, and enabling seamless reaction to unexpected events (Mehrotra, 2021). The primary aim of embedding ML into IKM systems is to provide recommendations by learning from changes in data patterns and making predictions, enabling instantaneous analytics and automated outlier detection (Abellera and Bulusu, 2017).

2.2 Information and Knowledge Management in the age of Artificial Intelligence

AI automatically cleans, transforms, categorises, analyses data, identifies outliers, and generates visualisations (Tcukanova et al., 2022) to support decision-making. By integrating AI into IKM systems, these systems can perform faster by automatically identifying data formats, detecting and correcting errors, and identifying relationships within data models (Tcukanova et al., 2022). With AI, outliers are easily identifiable, enabling organisations to forecast future events (Abellera and Bulusu, 2017). AI-supported clustering enables the identification of trends in data without requiring predefined data classifications (Mehrotra, 2021). Data will automatically be grouped based on their similarities and attributes (Jain et al., 2020). AI does not intend to replace data analysts, but rather to help them become more efficient and relieve them of routine work, such as gathering, preparing, and pre-processing data, leaving them more time for rich data analysis, insight generation, and intricate task resolution and performance (Ciccola et al., 2025). Additionally, NLP enables IKM systems to embed a search solution that allows users to access intelligence (Mehrotra, 2021) easily.

As a digital assistant, AI enables IKM solution users to query dashboarding tools using natural language and respond instantly via a chatbot (Tcukanova et al., 2022). When AI is embedded into IKM systems, it becomes a part of the system and thus accesses data faster and is scalable, meaning as the system grows, so does its capability for data management (DM) and ML (Mehrotra, 2021). When AI is integrated into an IKM system, the system can autonomously mine, extract, clean, and improve data quality, thereby increasing data reliability and accuracy (Jain et al., 2020). Ultimately, AI integration is the only future for IKM tools (Mehrotra, 2021).

Some data are challenging for humans to analyse and utilise optimally, requiring the use of ML to extract insights from them (Kyriakos and Vavalis, 2023). Finding useful patterns in BD that humans cannot process without the aid of supercomputers is the most compelling justification for employing ML (Abellera and Bulusu, 2017). ML enables IKM tools to establish rapid connections between data and their variables (Afsaruddin, Agrawal and Nayak, 2023). ML-based IKM systems can ask questions that humans failed to ask due to a lack of knowledge (Abellera and Bulusu, 2017). IKM capabilities have evolved from reporting on what occurred to understanding why it happened and what the future may hold, facilitated by the use of interactive dashboards (Hlaváč and Štefanovič, 2020). Figure 1 below illustrates the relationship between IKM, AI tools, and BD. This relationship is reciprocal: BD is used to produce IKM products through AI analysis, and the AI can create BD from IKM products, such as health records, which are then reanalysed to produce IKM solutions.



Figure 1: The integration of big data and information, and knowledge management through the application of artificial intelligence

3. Methodology

This section was designed with the guidance of Saunders, Lewis and Thornhill's research onion (Saunders, Lewis and Thornhill, 2012). Principles of grounded theory (GT) were also employed to ensure a systematic approach to data analysis, thereby strengthening the authenticity of the study results. The applicable research and philosophical paradigms clarified the researchers' epistemological, ontological and axiological positions. Empiricism and relativism were identified as the ontological positions adopted by the researchers as they sought to understand the phenomenon under study through subjective perceptions. The need to understand the experiences that comprise participants' realities led to the adoption of relational and subjective epistemologies.

Interpretivism was utilised to move from evidence to conclusions, using participants' subjective thoughts to develop qualitative findings. This approach required applying inductive logic to establish that AI is crucial to the maturity of IKM. The authors employed a monomethod qualitative approach, utilising semi-structured interviews to collect data. This method allowed for the use of an interview schedule to guide conversations, while also providing opportunities to ask follow-up questions. The need to follow the approach stemmed from the absence of prior framing of AI adoption in IKM business units from a South African context.

The interview participants were selected through judgment and expert sampling, as they held strategic and leadership positions in their IKM units. A total of 12 participants were included due to the broad nature of the IKM field; it was imperative that they worked in varied areas of IKM, including knowledge management, social media management, records management, business intelligence, competitive intelligence, and data governance. The participants were selected on the basis of their involvement in strategy development within their organisations and are thus in a position to provide a current and future IKM focus for the article. The authors opined that this approach was necessary to develop a comprehensive understanding of the technologies used in IKM. Furthermore, this approach was important, as the reality in South Africa is that some IKM business units may be behind others in terms of technology adoption, as evidenced by Mahlangu's (2023) report on poor RM practices in the country.

For data analysis, interpretive GT (IGT) was adopted, as evident in the use of open, axial, and selective coding. During open coding, the researchers generated as many codes as possible (McLeod, 2011). Axial coding was used to identify superthemes and subthemes; for example, participants would mention technology in a general sense. However, upon explanation, the researchers were able to delineate the types of technologies being referred to under the central theme of technology. For this study, it was prudent to identify when participants spoke to AI rather than other technologies. To complement the coding process, thematic analysis was also employed. At this point, selective coding was employed to identify the primary ideas presented by participants (Creswell, 2012). The codes were generated in ATLAS.ti version 24.1.1 (30840) were transferred to Microsoft (MS) Excel for thematic analysis. The results of the study are reliable as they are applicable in similar contexts (transferable), were developed strictly based on the collected data (confirmable), and could to a large extent be replicated if the same study were conducted multiple times (dependable).

This study was guided by four ethical principles: morality, deontology, fairness, and teleology. The authors ensured that participants were respected and their privacy was protected, and developed a study that makes a positive contribution to society. Additionally, ethical clearance was provided by the University [removed for anonymity]. Grammarly was also used strictly for proofreading to improve grammar and spelling. Judgment sampling enables access to the needed sample. However, it can limit the generalisability of one's results, as was seen in the selection of IKM unit managers and the study being conducted in South Africa. However, as discussed above, transferability was the primary aim of this study, as is often the case with qualitative studies. The results can thus be transferred to contextually similar business units and countries.

4. Presentation of Results and Discussion

The participants acknowledged that IKM business units need to contribute to innovation to achieve a return on investment after implementing technological solutions. The innovation referred to by participants was regarding the development of IKM products and solutions. This acknowledgement confirms what is found in literature, that technology's exponential growth rate requires staff who are tech-savvy, in order to have employees who can take advantage of new and emerging technological developments (Maceli and Burke, 2016). The inference from the findings is that the identified technologies assist with the delivery of IKM products.

The participants indicated that most technologies used enabled data analytics and visualisation. A reason could have been that analysing data yields insights that support decision-making (Bhatia, 2017). Data visualisation, on the other hand, refers to the use of snapshots and graphs to tell a story and help users understand the data's context (Sadiku et al., 2016). Participant 5 clarified that even though IKM practitioners may never be required to build dashboards, they need to understand how dashboards are built, given the foundational information flow and the need to comprehend how IT systems process work (Participant 7). The participants held this position because AI-enabled tools can build dashboards. Understanding the underlying information flow would then enable understanding how the dashboards were built or assessing their accuracy.

5. Perspectives on Artificial Intelligence in Information and Knowledge Management

Participant 1 highlighted that for IKM practitioners to use BD, which relies on advanced technologies for processing, *"the user has to calibrate KMS to capture what they need without necessarily destroying information and to filter it correctly"*. Participants had a keen focus on AI and business systems to digitalise IKM processes. It was stated that digital transformation will help drive organisational innovation, enabling organisations to remain competitive. Digital transformation is realised when significant alterations are made to processes through computerisation, including leveraging the cloud to enhance information use and communication (Mikalef and Parmiggiani, 2022). The deployment of information systems supports these IKM processes, which can then be matured through AI adoption.

Participant 11 touched on tech savviness and AI. The participant explicated that she uses AI to manage contracts. She added that AI's learning capability helps spot potential loopholes in contracts. Furthermore, the AI tool provides prescriptive responses based on previous interactions with the tool and thus *"we can reduce the number of errors and possible litigation using AI"*. Participants 3 and 4 stated that practitioners should have predictive and descriptive analytics skills and utilise AI.

The participants considered using AI-enabled technologies, ML for data and sentiment analysis, and cloud tools. The participants suggested that AI deployment and application were necessary because AI expedites the automation of processes. The participants added that organisations must be AI-driven and ensure the algorithms employed deliver accurate results. According to participants, the main aspects of maturity included process automation, the use of AI and ML tools, infrastructure upgrades, and enhanced data quality. This finding indicates that IKM units need to mature into 4IR technology-empowered units. Participant 1 added that maturity results in increasingly complex IKM processes, business requests, and solutions developed, which can be completed using AI (Korayim et al., 2025).

Based on participants' views, IKM maturity now relies on AI adoption. It was also added that AI modelling is a critical skill. In support, Bartneck et al. (2021) clarify that AI-enabled tools continuously learn and can thus rapidly adapt to changing business requirements, which means IKM tools will continue to improve while remaining fit for purpose. Hence, participants also noted that practitioners need to ensure their organisations are AI-driven. The implementation of AI tools was regarded as central to facilitating IKM automation. Therefore, in this study, automation is defined as the completion of IKM work without human assistance (Stoilov and Stoilova, 2006).

Participant 6 required IKM practitioners to know the role AI plays in IKM. Significant AI components to understand in relation to IKM include ML, algorithms, training algorithms, learning to use AI, and the ethics of using AI (Participant 7). It is imperative to note that the definition of AI changes over time as the technology keeps advancing; however, for this study, AI is defined as a system's capacity to appropriately comprehend data, learn from data, and utilise those learnings to fulfil specific (IKM-related) objectives and activities through agile adaptation (Bartneck et al., 2021).

AI was also proposed due to the need to utilise generative AI for content creation purposes. A participant's critique was that people are at risk of losing their jobs, and, as a result, the human touch would be lost. While this view contrasts with Ciccola's (2025) position that AI does not intend to replace data analysts, but rather to help them become more efficient by relieving them of routine work, leaving them more time for intricate task resolution and performance. The participant noted that she could also discern when an AI wrote something compared to a person. However, to buttress this view, another participant offered that people are still needed, particularly to perform AI modelling to instruct AI tools on the type of data to consume, to ensure the data collected is accurate, and to assess organisational contexts to determine the best AI tools to deploy in specific settings.

Bharadiya, Thomas and Ahmed (2023) aligned with the former statement, as they highlighted the widespread deployment of AI (automated intelligent responses to questions) by organisations to engage customers on SM. The AI tools can also analyse social media (SM) data to identify market opportunities. George and George (2020) emphasise the importance of factors such as human sustainability, highlighting the need for the fifth industrial revolution (5IR) to prioritise bringing people back to the workplace. However, the reality remains that people with technology skills are the ones who can effectively partner with the machines they employ. Figure 2 provides a synopsis of AI use in IKM.

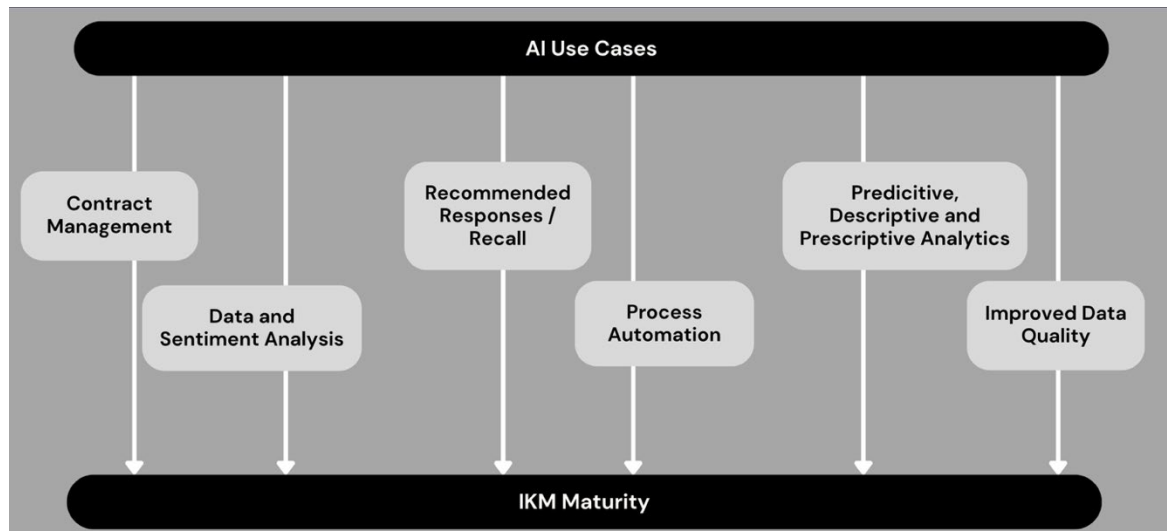


Figure 2: Artificial intelligence uses in information and knowledge management

Ethics declaration: From an ethical standpoint, the authors provided participants with a letter of informed consent that detailed the study's purpose, confidentiality clause, and benefits of participation, among other relevant details. Additionally, before any data was collected, the study received ethical clearance from the University of Johannesburg's College of Business and Economics Research Ethics Committee. The ethical clearance code is 2020SciS51.

AI declaration: AI was used in the development of this article. Grammarly was also utilised only to improve grammar and correct spelling errors, while ChatGPT was used to write the abstract.

6. Conclusions and Implications

In achieving the first objective, the participants expressed, without mincing words, that they had to adopt AI-driven systems. In connection with the second objective, a key finding was that AI should be central to any decisions around technology adoption. These findings imply that IKM business units must adopt AI to remain relevant, as this will deliver optimal business value. The practical implication for IKM practitioners is that they need to assess how best to leverage emerging and disruptive technologies. The study results can help advance IKM practitioners as lead AI consultants who can ensure the development of contextually fit AI-enabled business systems.

One participant raised concerns about overreliance on AI, as she felt the technology was eliminating human workers from their jobs, which she viewed as a negative development. She noted that she could distinguish between content created by AI and that created by humans. This point contributes to a broader discussion of the ethical use of AI and how higher education institutions can prevent AI brain drain by addressing students' overuse and excessive reliance on AI. From an employability standpoint, this concern suggests that future research should examine how the 5IR plans to ensure human sustainability and the roles organisations will play in this movement. The study's limitations included the use of purposive sampling, which reduced the generalisability of the results. However, the study aimed to achieve transferability, enabling the results to be used by organisations with similar contexts. Future research must address the need to develop higher education standards to support AI use and prevent the loss of critical thinking skills, as well as explore how emerging technologies can be utilised alongside human resources, as outlined in 5IR efforts.

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