Impact of Artificial Intelligence on Knowledge Management: An investigation on the Public Sector in Saudi Arabia

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Abstract: In an era where knowledge has become a key component of government operations, artificial intelligence represents a powerful tool for the public sector. When implemented strategically and ethically, artificial intelligence can help the public sector deliver more efficient, responsive and citizen-focused services, contributing to overall well-being and prosperity. Accordingly, this paper empirically investigates the impact of artificial intelligence on knowledge management. The paper took employees in the Saudi public sector, especially the ministries, as a population to implement the investigation. A convenience sample was obtained through a cross-sectional design consisting of 226 respondents constituting a response percentage of 73.5%. Structural equation modeling, an analytical approach, was used to test hypotheses and extract validity and reliability indicators. The paper concluded that the dimensions of artificial intelligence had a positive impact on knowledge management, except machine learning, which did not affect knowledge management in the Saudi public sector. As a result, the paper recommended the need to develop a comprehensive AI strategy that aligns with the goals and priorities of the public sector in Saudi Arabia and ensures that AI initiatives are integrated into the broader knowledge management strategy.

Keywords: Artificial Intelligence, Knowledge Management, Public Sector, Ministries, Saudi Arabia.

1 Introduction

In today's rapidly evolving, knowledge-based economy, knowledge management is a core strategy for organizations looking to excel and remain agile amidst constant challenges and opportunities. Chopra et al. (2021) described knowledge management as more than just technology, as it focuses more on developing a culture of knowledge sharing, continuous learning and cooperation. Knowledge management is a holistic approach that plays a pivotal role in the success of organizations. It includes a set of processes, strategies and practices designed to identify, capture, store, organize, access and share knowledge assets within an organization (Cillo et al., 2022). The strategic goal of knowledge management, according to Bratianu et al. (2021), is to harness the organization's intellectual capital, which includes explicit knowledge, i.e. tangible and documented information, and tacit knowledge, i.e. unwritten and experiential insights and experiences. By effectively managing knowledge assets, organizations can enhance decision-making (Agrawal, 2021), stimulate innovation (Gürlek & Cemberci, 2020), and improve overall performance (Urban & Matela, 2022).

The recent development of artificial intelligence has led to the proliferation of its applications in various aspects of our daily lives, from virtual assistants such as Siri and Alexa to self-driving cars, healthcare diagnosis, and financial analysis. Artificial Intelligence is a transformative and interdisciplinary field at the intersection of computer science, mathematics, and cognitive science (Zhang & Lu, 2021). It is based on algorithms and mathematical models harnessed to process massive amounts of data to extract patterns and relationships for use in predictions and informed decision-making (Bullock et al., 2020, Alghanemi & Al Mubarak, 2022). Artificial intelligence technologies have the potential to revolutionize many industries, from healthcare and public services to manufacturing and entertainment (Loureiro et al., 2021). Kaplan & Haenlein (2020) stated that its impact on society is profound, as it provides opportunities for automation and improved decision-making. However, artificial intelligence has produced multiple ethical and societal challenges, such as privacy concerns, cybersecurity breaches, and the potential for job displacement (Kelly et al., 2019).

In the context of the KSA, the rapid adoption of artificial intelligence technologies in the public sector presents both opportunities and challenges for knowledge management. While artificial intelligence has the potential to revolutionize knowledge management processes, there is a critical need to understand and address its implications, particularly regarding how artificial intelligence affects the creation, organization, sharing, and utilization of knowledge within government agencies. As artificial intelligence technologies are increasingly integrated into various public sector functions, the problem at hand is to investigate the impact of artificial intelligence on knowledge management practices, including knowledge creation, retrieval, sharing, and decision-making processes in KSA's public sector. This research aims to identify the challenges, opportunities, and best practices associated with artificial intelligence-driven knowledge management, ultimately facilitating the development of strategies that optimize knowledge management practices in the era of artificial intelligence and contribute to the efficient and effective functioning of public sector organizations in Saudi Arabia.

This problem statement highlights the significance of the issue and the need for research and analysis to better understand the specific challenges and opportunities that artificial intelligence presents in the context of knowledge management within the public sector of KSA. It sets the stage for further exploration and investigation to guide policymakers, government agencies, and researchers in addressing these critical concerns and leveraging artificial intelligence for improved knowledge management in the public sector.

2 Literature Review

2.1 Artificial intelligence

In the denouement of the 1980s and the nascent phase of the 1990s, Artificial Intelligence (AI) evolved into a multifaceted domain of inquiry, encompassing diverse subfields such as virtual reality, neural networks, expert systems, voice recognition, natural language processing, and robotics. Defining the concept of artificial intelligence accurately is difficult at present, as it is a dynamic concept and in the process of development. According to the American Association for Artificial Intelligence (AAAI), it is the systematic understanding and realization of the mechanisms behind intelligent thought and behavior and their embodiment in machines (Mintz & Brodie, 2019). Saghiri et al. (2022) considered that artificial intelligence is a branch of computer science that deals with the simulation of intelligent human behavior in computers and machines. They are systems that engage in intelligent, human-like behavior by analyzing their environment and taking actions, with a certain degree of autonomy, to achieve specific goals (Mikalef & Gupta, 2021). Likewise, Haenlein and Kaplan (2019) stated that artificial intelligence is the art of creating machines that perform functions that require intelligence when performed by humans.

In the denouement of the 1980s and the nascent phase of the 1990s, Artificial Intelligence (AI) evolved into a multifaceted domain of inquiry, encompassing diverse subfields such as virtual reality, neural networks, expert systems, voice recognition, natural language processing, and robotics (Taherdoost & Madanchian, 2023). According to Qasaimeh and Jaradeh (2022), artificial intelligence is based on a set of technologies that contribute to mimicking human functions (Qasaimeh & Jaradeh, 2022). (1) Machine learning focuses on developing algorithms and statistical models that enable computers to learn, predict, or make decisions without being explicitly programmed. In essence, it is a data analysis method that automates analytical model building (Zhou et al., 2020). (2) Expert systems, also known as knowledge-based systems, mimic the decision-making capabilities of a human expert in a given domain. Janjanam et al. (2021) pointed out that these systems use a knowledge base, containing a huge amount of domain-specific information and rules, to solve complex problems and make decisions. (3) Natural language processing refers to the interaction between computers and human language. It enables machines to understand, interpret and generate human language in a way that is meaningful and contextually relevant. (4) Computer vision enables machines to interpret and understand the visual world, just as humans do (Bullock et al., 2020). It involves developing algorithms and technologies that allow computers to process and analyze visual information from images or videos, understand the content and derive meaningful insights.

2.2 Knowledge management

Researchers and research bodies have provided multiple definitions of knowledge management. Urban and Matela (2022) believed that knowledge management is represented by the strategies and processes used to identify, capture, and structure an organization's intellectual assets to benefit from them in enhancing its performance. The International Organization for Standardization (ISO) defines it as “the deliberate organization of information and expertise to achieve the goals of the organization” (Saeed et al., 2023). Knowledge management is a systematic process that aims to obtain the information necessary to make decisions, organize it, and make it available to the right people at the right time (Singh et al., 2023). Similarly, Gürlek and Cemberci (2020) stated that knowledge management is based on the process through which value is generated by relying on the organization's intellectual and knowledge-based assets.

The three-dimensional model was relied upon to measure knowledge management in accordance with the recommendations of Sahibzada et al. (2023). (1) Knowledge creation is a fundamental process within knowledge management that involves generating new insights, ideas, and information within an organization or an individual's cognitive domain. It is the transformation of data and existing knowledge into new, valuable knowledge. (2) Knowledge dissemination focuses on the effective distribution of information, insights, and expertise to individuals, teams, and stakeholders within an organization or beyond its boundaries. The goal of knowledge dissemination is to ensure that knowledge is shared, accessible, and utilized in a way that benefits the organization and its decision-making processes. Bratianu et al. (2021) reported that it plays a vital role in turning knowledge into actionable insights and informed decisions. (3) Knowledge exploitation involves using existing knowledge and information to create value, solve problems, make informed decisions, and drive innovation within an organization. It goes beyond simply acquiring and storing knowledge and focuses on actively leveraging that knowledge to achieve specific goals and objectives (Qhal, 2023).

3 Theoretical Model and Hypotheses

Artificial Intelligence technologies have the potential to transform the traditional approach of an organization acquiring knowledge, disseminating it within the units, and storing it into a more advanced approach. However, it is important to recognize the challenges of applying these technologies, including cyber security and the ethical use of artificial Intelligence. Anshari et al. (2023) stated that machine learning enables self-automation of data analysis and building analytical models, which in turn leads to improved organizational knowledge management. Zhou et al. (2020) emphasized that the capacity of organizational innovation and industrial development in engineering consulting institutions depends mainly on knowledge management models that are supported by machine learning techniques. Terán-Bustamante et al. (2021) sought to study and analyze the impact of Bayesian networks and machine learning techniques in knowledge management on correct management in Mexico City. Additionally, Jarrahi et al. (2023) explored the potential role of AI in knowledge management (KM) and proposed ways to build a partnership between humans and AI in supporting KM activities. They discussed the implementation of emerging AI systems for KM, focusing on the creation, storage and retrieval, sharing, and application of knowledge. Empirical evidence has shown that the most important factors for adequate knowledge management are information management, relational capital, intellectual capital, quality and risk management, and technology absorption. Organizations that effectively integrate machine learning into their knowledge management processes can benefit from improved decision-making, increased efficiency, and better use of their knowledge assets. Therefore, the following hypothesis was proposed:

Hypothesis 1 (H1): The application of machine learning has a positive impact on knowledge management of the public sector in Saudi Arabia.

The papers collectively suggest that expert systems have a positive impact on knowledge management. Qhal (2023) highlighted the role of robots and expert systems in enhancing knowledge management performance using a systematic strategy based on a genetic algorithm, as the results confirmed the pivotal role of these technologies in improving the organization’s ability to manage its knowledge assets. Janjanam et al. (2021) considered that expert system architectures, including the backward chaining method, the forward chaining method, and the value approach, play a positive role in solving complex problems and improving knowledge management processes. According to Buccieri et al. (2020), expert systems build permanent institutional memory, which ensures that the required knowledge

can be accessed even when human experts are not available. Expert systems facilitate the decision-making process and improve the use of employee expertise by providing answers and making comparisons and inferences that contribute to obtaining accurate and reliable knowledge. In general, expert systems play a critical role in knowledge management by enhancing productivity, supporting decision-making, and preserving organizational knowledge. Therefore, the first hypothesis was proposed as follows:

Hypothesis 2 (H2): The application of expert systems has a positive impact on knowledge management of the public sector in Saudi Arabia.

Natural language processing techniques are significantly used in extracting, capturing, sharing and applying knowledge in various fields (Arnarsson et al., 2021). Idris and Alsultan (2023) focused on identifying the potential of natural language processing to support the knowledge management process in healthcare through a comprehensive survey. The study concluded that these techniques support knowledge management extraction and capture processes, thus a conceptual model for these processes was proposed. Furthermore, Basyal et al. (2020) pointed out that natural language processing algorithms can be applied to unstructured data, such as free text, to accurately retrieve relevant documents and create labelled collections that enhance an organization's knowledge assets. According to Maksutov et al. (2020), natural language processing facilitates the semantic processing of linguistic knowledge, allowing users to understand meaning and scope and use related techniques and algorithms. Natural language processing is particularly valuable for managing unstructured textual data, which often makes up a significant portion of an organization's knowledge resources. As a result, the third research hypothesis can be formulated as follows:

Hypothesis 3 (H3): The application of natural language processing has a positive impact on knowledge management of the public sector in Saudi Arabia.

Studies indicate that computer vision has the potential to enhance knowledge management through various applications and considerations. Zhong et al. (2019) argued through a bibliometric analysis the role of computer vision in producing information and improving managerial decision-making to enhance engineering project management processes. Opiła (2019) attempted to delve deeper into understanding the relationship between computer visualization and knowledge exchange pathways in the tourism and agriculture sector. The results indicated that computer visualization is an important part of the data analysis and knowledge transfer process, as hybrid visualization styles improve information density but potentially reduce clarity. Computer vision enhances knowledge management by providing powerful tools to manipulate and manage visual knowledge assets, from classification and search to automation and knowledge discovery. This is especially valuable in industries and applications where visual information is essential and can streamline operations, improve decision-making, and promote effective knowledge sharing. Accordingly, the fourth hypothesis was proposed as follows:

Hypothesis 4 (H4): The application of computer vision has a positive impact on knowledge management of the public sector in Saudi Arabia.

Figure 1 serves as a visual representation of the research model proposed in this study, providing an insightful and structured overview of the impact of artificial intelligence on knowledge management. This graphical depiction encapsulates the fundamental framework guiding the research's objectives, presenting a comprehensive map of the study's core elements.

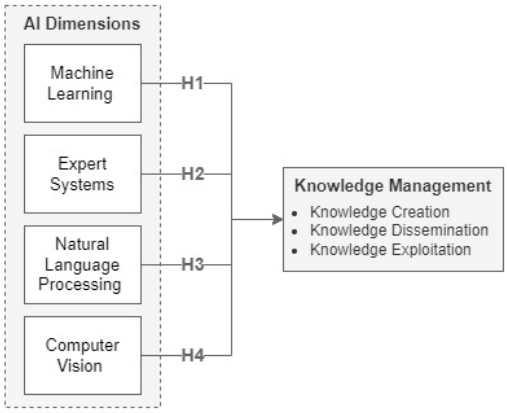

Figure 1. Research Model.

4 Methodology

4.1 Participants

The research population included employees in the Saudi public sector, specifically emerged ministries such as the Ministry of Tourism, the Ministry of Sports, the Ministry of Investment, and the Ministry of Industry and Mineral Resources. These government bodies are considered among the catalysts for the development approach adopted by Saudi Arabia and the main supporters of the NEOM project. The large target population and research restrictions prompted the application of a sampling method instead of a comprehensive survey. Convenience sampling was used with a minimum of 200 valid responses as reported by Bougie and Sekaran (2019). To achieve sufficiency in sampling, the instrument was sent to 300 employees at various administrative levels in these ministries. 247 responses were received, including 21 incomplete responses or their answers were stereotyped, and thus were removed from the research sample. Consequently, the final research sample was composed of 226 responses representing 73.5% as a response percentage.

According to an analysis of the demographic factors of the participants, it was found that the majority 77.9% were male compared to 22.1% of females. 50.4% of participants were in the age group "30-40", followed by 25.7% in the age group "41-50", then 17.7% in the age group "less than 30", and finally 6.2% in the age group "more than 50". Moreover, the responses received were consistent with the organizational hierarchy in the ministries, as 59.3% of the sample was within the operational administrative level, 35.4% within the middle administrative level, and 5.3% within the high administrative level. On the other hand, the results showed that 47.8 of the respondents have job experience less than 10 years, followed by 45.1% who have job experience between 10 and 15 years, then 7.1% who have job experience higher than 15 years.

4.2 Instrument

The research utilized a self-administered questionnaire as the main instrument to collect data on the role of artificial intelligence in knowledge management. The questionnaire items were formulated according to the relevant literature. These items were translated into Arabic, then returned to English and included in the research according to back translation procedures (Klotz et al., 2023). The data collection process continued between September 28 and November 2, 2023. Use the electronic design of the questionnaire through Google Foam and send the link via social media platforms and email to the relevant ministries. The questionnaire

consisted of two main sections and an introduction that emphasized the voluntary participation of respondents and the preservation of the confidentiality of their data. The first section of the questionnaire included demographic factors, including gender, age group, administrative level, and job experience, which were categorical variables. The second section was devoted to the basic research variables of ordinal type as respondents were asked to rate their items according to a five-point Likert scale, with a minimum (1) of "strongly disagree" and a maximum (5) of "strongly agree".

Artificial intelligence was the predictor variable in this research, which included 16 items drawn from Qasaimeh and Jaradeh (2022). Artificial intelligence included four first-order constructs used to evaluate the technology used in this field through four items each. Machine learning focuses on developing algorithms and statistical models that enable computer systems to learn, predict, or make decisions without being explicitly programmed. Expert systems mimic the decision-making abilities of a human expert in a specific domain. Natural Language Processing (NLP) expresses the interaction between computers and human language. It involves the development of algorithms and models to enable computers to understand, interpret, and generate human language in a way that is both meaningful and useful. Computer vision depends on enabling computers and machines to interpret, understand, and process visual information from the world, primarily in the form of images and videos.

Knowledge management was the predicted variable in this research, which included 14 items corresponding to Sahibzada et al. (2023). Knowledge management includes three first-order constructs that were used to measure each process of knowledge management. Knowledge creation is the process of generating new information, insights, or understanding that was previously unknown or unarticulated. Knowledge dissemination refers to the distribution and sharing of information, insights, and knowledge with a wider audience or target group. Knowledge exploitation refers to the intentional and strategic utilization of existing knowledge assets to create value, solve problems, drive innovation, and achieve specific objectives.

4.3 Analytical approach

The research was based on a cross-sectional design with quantitative data to investigate the impact of artificial intelligence on knowledge management in the Saudi public sector. Therefore, an analytical approach using structural equation modeling (SEM) was followed in accordance with the recommendations of (Lutfi et al., 2023; Yousefi & Tosarkani, 2022). According to this approach, the measurement model is initially evaluated to ascertain the validity and reliability levels of the instrument through confirmatory factor analysis (CFA). Moreover, the application and investment levels of variables were evaluated according to the opinions of the respondents' using indicators of central tendency and dispersion, i.e., the mean and standard deviation. The linear relationship between the variables was evaluated through the Pearson correlation matrix, as was the multicollinearity between the dimensions of the predictor variable. Finally, SEM was evaluated through goodness-of-fit indicators, based on the results of which standardized and non-standardized impact coefficients were extracted.

5 Results

5.1 Measurement model

The model for measuring the impact of artificial intelligence on knowledge management in the Saudi public sector was evaluated using confirmatory factor analysis (CFA). According to Baharum et al. (2023), the goal of measurement model evaluation is to determine the degree

of fit of the research measures, that is, the latent constructs and observed variables, with the empirical data and the theoretical model. This step is essential to promote accurate interpretation of the relationship between variables. Table 1 depicts the results of evaluating the measurement model used to investigate the impact of artificial intelligence in knowledge management.

Table 1. Results of measurement model assessment.

Constructs	Items	Loadings	AVE	MSV	√AVE	CR
Machine Learning	ML1	0.706	0.556	0.304	0.745	0.833
	ML2	0.729				
	ML3	0.788				
	ML4	0.756				
Expert Systems	ES1	0.736	0.593	0.272	0.770	0.853
	ES2	0.766				
	ES3	0.819				
	ES4	0.756				
Natural Language Processing	NLP1	0.726	0.569	0.278	0.755	0.841
	NLP2	0.815				
	NLP3	0.731				
	NLP4	0.733				
Computer Vision	CV1	0.801	0.626	0.304	0.791	0.870
	CV2	0.778				
	CV3	0.758				
	CV4	0.725				
Knowledge Creation	KC1	0.745	0.563	0.241	0.751	0.866
	KC2	0.749				
	KC3	0.745				
	KC4	0.718				
	KC5	0.794				
Knowledge Dissemination	KD1	0.730	0.553	0.278	0.744	0.832
	KD2	0.703				
	KD3	0.760				
	KD4	0.780				
Knowledge Exploitation	KE1	0.731	0.590	0.272	0.768	0.877
	KE2	0.767				
	KE3	0.726				
	KE4	0.737				
	KE5	0.870				

The results of Table 1 indicated a high relation between the latent constructs and their observed variables, as the factor loadings were between 0.703 and 0.870, which supports their retention within the measurement model since they exceeded the minimum threshold of 0.50 (McNeish & Wolf, 2023). The values of the average variance extracted (AVE) were between 0.553 and 0.626, which calls for the measurement model to be considered to have convergent validity since these values exceeded the threshold of 0.50 (Shrestha, 2021). Regarding discriminant validity, the results demonstrated that AVE was greater than the maximum shared variance (MSV), as well as the square root values of AVE were higher than 0.70 and the correlation values between the constructs. Rönkkö and Cho (2022) emphasized that this result is considered evidence that the measurement model is characterized by discriminant validity. In another context, the composite reliability (CR) of the measurement model was verified using McDonald's Omega coefficients. The results elucidated that the CR values were

between 0.832 and 0.877, which is considered an indicator of the measurement model reliability, given that it exceeds the minimum of 0.70 (Kalkbrenner, 2023).

5.2 Inferential statistics

Inferential statistics contribute to drawing valuable conclusions drawn from the research sample about the application degree of the variables, i.e., artificial intelligence and knowledge management, in their institutions. Moreover, it allows the determination of multicollinearity between independent constructs to ensure their independence and their expression of different but complementary concepts. Table 2 lists the results of the inferential statistics used in this research.

Table 2. Mean, standard deviation, and correlation.

Constructs	M	SD	ML	ES	NLP	CV	KC	KD	KE
Machine Learning	3.65	0.659	1						
Expert Systems	3.81	0.707	0.400	1					
Natural Language Processing	3.74	0.695	0.374	0.335	1				
Computer Vision	3.69	0.753	0.464	0.272	0.436	1			
Knowledge Creation	3.66	0.635	0.310	0.348	0.408	0.425	1		
Knowledge Dissemination	3.60	0.681	0.355	0.313	0.411	0.414	0.324	1	
Knowledge Exploitation	3.62	0.685	0.433	0.469	0.405	0.418	0.316	0.433	1

The results of Table 2 indicated that the adoption level of artificial intelligence variables in the Saudi public sector was high, except for machine education (M= 3.65, SD= 0.659), which was at a moderate level and achieved the last rank. Expert systems (M= 3.81, SD= 0.707) ranked first, followed by natural language processing (M= 3.74, SD= 0.695) in second place, and computer vision (M= 3.69, SD= 0.753) in third place. In contrast, knowledge management processes in the Saudi public sector were at a moderate level. The results confirmed that knowledge creation (M= 3.66, SD= 0.635) ranked first, followed by knowledge exploitation (M= 3.62, SD= 0.685) in second place, then knowledge dissemination (M= 3.60, SD= 0.681) in third place.

Furthermore, a linear correlation between the research constructs was assessed. The results manifested that the correlation coefficients between the artificial intelligence constructs and the knowledge management constructs were between r= 0.310 and r= 0.469, which means that they were at a moderate corre;ated level. Similarly, correlation coefficients between artificial intelligence constructs ranged between r= 0.272 and r= 0.464. This result indicates that the independent variable constructs were free from multicollinearity as the correlation coefficients did not reach the upper threshold of 0.80 as reported by Kyriazos and Poga (2023).

5.3 Structural model

Structural equation modeling (SEM) capabilities through AMOS v25 were exploited to evaluate the structural model and determine the impact between artificial intelligence and knowledge management in the Saudi public sector. Structural model evaluation focuses on identifying the overall suitability and validity of structural relationships between latent constructs (Collier, 2020). This process is based on two steps: extracting goodness-of-fit indicators and evaluating the impact coefficients between the constructs. Figure 1 exhibits the results of the goodness of fit indicators for the model testing the impact of artificial intelligence in knowledge management.

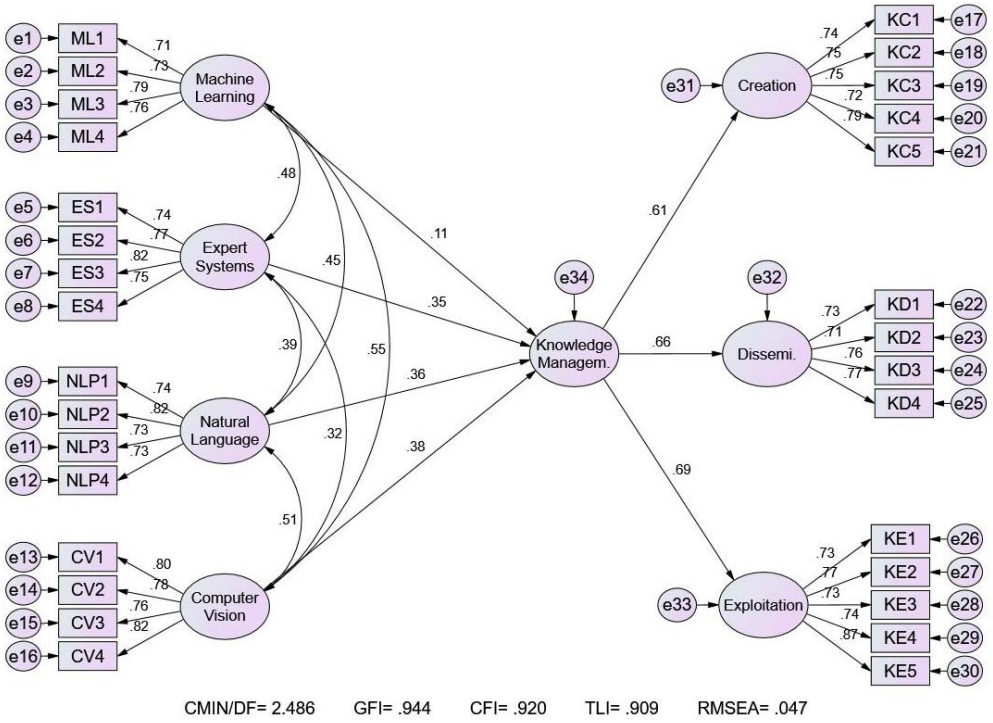

Figure 2. SEM for the impact of artificial intelligence on knowledge management.

The results of Figure 2 presented that the chi-square to degrees of freedom (CMIN/DF) was 2.486, which indicates that it did not reach the upper threshold of the indicator, which is 3 according to West et al. (2023). The values of the goodness of fit index (GFI), the comparative fit index (CFI), and the Tucker-Lewis index (TLI) were 0.944, 0.920, and 0.909, respectively. This result confirms that these indicators achieved acceptable levels as they exceeded the minimum level of 0.90 (Sahoo, 2019). Moreover, the root mean square error of approximation (RMSEA) was 0.047 which indicates that it is within the permissible limit of less than 0.08 (Shi et al., 2022). According to the results of the indicators, the structural model was considered appropriate and provides reliable readings, as Table 3 reveals the results of the path coefficients and testing of hypotheses related to the impact of artificial intelligence in knowledge management.

Table 3. Path coefficients for hypotheses testing.

Constructs			B	S.E.	Beta	T	P	R^2
Machine Learning	→	Knowledge Management	0.070	0.060	0.109	1.176	0.240	0.857
Expert Systems	→	Knowledge Management	0.227	0.058	0.355	3.954	0.000	
Natural Language Processing	→	Knowledge Management	0.223	0.058	0.365	3.864	0.000	
Computer Vision	→	Knowledge Management	0.202	0.053	0.375	3.844	0.000	

Table 3 promoted that artificial intelligence had a significant impact on knowledge management, as the Interpretation coefficient reached (R2) was 0.857, which indicates that approximately 86% of the knowledge management variance could explained by the artificial intelligence constructs. Moreover, the artificial intelligence constructs showed a noticeable difference in their impact on knowledge management, except for machine learning (β= 0.109,

t= 1.176, p> 0.05), which did not significantly affect knowledge management. Despite this, the rest of the constructs had an impact on knowledge management, where natural language processing (β= 0.365, t= 3.864, p< 0.001) had the greatest impact, followed by expert systems (β= 0.355, t= 3.954, p< 0.001), and then computer vision (β= 0.375, t= 3.844, p< 0.001). Accordingly, the research hypotheses H2, H3, and H4 were accepted and the hypothesis H1 was rejected.

6 Discussion

Artificial Intelligence has the potential to have many positive impacts on knowledge management in the public sector in Saudi Arabia. Artificial intelligence tools contribute to the efficient collection, classification, and organization of large amounts of data and documents, which helps facilitate the knowledge management process. Moreover, artificial intelligence techniques can provide valuable insights and predictions based on data analysis, according to (Basyal et al., 2020; Al Mansoori et al., 2020). These predictions help public sector officials make informed decisions based on broad and complex data sets, along with improving the allocation of organizational resources. On the other hand, artificial intelligence supports the automation of routine administrative tasks, freeing human resources to focus on higher-value tasks. Opiła (2019) stated that this efficiency improves productivity and allows employees to devote more time to knowledge creation and strategic thinking.

Artificial Intelligence can improve the accuracy and speed of information retrieval through advanced search algorithms, making it easier for public sector employees to access the knowledge they need when they need it. It has an essential role to play in enhancing data security by detecting and preventing security breaches and ensuring compliance with data protection regulations according to Anshari et al. (2023). In the public sector, where data privacy is paramount, this is extremely important. In addition, artificial Intelligence-powered collaboration tools facilitate the process of sharing knowledge between public sector employees and collaborating on projects more effectively, even across different departments and regions. In a similar context, chatbots and virtual assistants that rely on artificial intelligence have a role in providing immediate and around-the-clock support to citizens and answering common questions and inquiries efficiently, which enhances the organization’s intellectual capital, according to Zhong et al. (2019). In sectors such as infrastructure and public utilities, AI can be used for predictive maintenance, ensuring public assets and services are maintained efficiently and disruptions are minimized.

7 Recommendations

Here are some recommendations for effectively implementing artificial intelligence in the public sector in the KSA to enhance knowledge management. First, develop a comprehensive artificial intelligence strategy that aligns with the goals and priorities of the KSA's public sector and ensure that artificial intelligence initiatives are integrated into the broader knowledge management strategy. Second, establish robust data governance practices to ensure the quality, privacy, security, and ethical use of data through establishing a clear framework for data collection, storage, and sharing. Third, invest in artificial intelligence training and education programs for public sector employees to build in-house AI expertise. Last but not least, foster collaboration between various government departments and agencies to share knowledge and best practices related to AI implementation and knowledge management.

8 Conclusion

The integration of artificial intelligence into the knowledge management practices of the public sector in the Kingdom of Saudi Arabia (KSA) holds immense promise for improving efficiency, decision-making, and citizen services. Artificial intelligence technologies offer the ability to transform how knowledge is created, stored, disseminated, and exploited within government agencies. By harnessing artificial intelligence, the public sector in KSA can enhance its capabilities in numerous ways. Artificial intelligence can streamline data management, facilitate informed decision-making, automate routine tasks, and provide valuable insights from vast datasets. The positive impacts of artificial intelligence extend to knowledge dissemination, making information more accessible and personalized for citizens. Additionally, artificial intelligence-powered chatbots and virtual assistants can provide around-the-clock support and engagement.

9 Limitations and Future Directions

While the integration of artificial intelligence into the knowledge management practices of the public sector in the KSA offers numerous benefits, it also presents several limitations and challenges. The most significant one revolved around that artificial intelligence systems rely on data, and there are concerns related to data privacy and security. Hence, future research should explore frameworks and governance models that ensure ethical and responsible AI use in the public sector. Second, artificial intelligence algorithms may inherit biases present in the data they are trained on. Therefore, studies could investigate how AI can improve decision support systems for government officials, offering insights and recommendations while maintaining human oversight.

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