A Quantitative Study of Artificial Intelligence's Role in Knowledge Management: Evidence from Industry Experts

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Abstract: Knowledge management (KM) is considered the lifeblood of growth and sustainability in modern organizations. The emergence of various information technology-based solutions has thoroughly transformed the KM system by making it efficient, swift, and robust. Artificial intelligence is one such IT evolution. The study has considered experts from different industries like IT and ITEs, research, banking, FinTech, and retail. The data were collected from 217 industry experts through a structured questionnaire containing a five-point Likert scale for measurement, containing 20 items as independent variables and one as the dependent variable. Data analysis was done through 'exploratory factor analysis (EFA)' and multiple regression analysis. The most important factor contributing to knowledge management was found to be 'knowledge distribution' with an effect size of standardized beta (.806), followed by 'amplifying efficiency' (0.307), real-time engagement and collaboration (0.108), and 'AI as an artificial neural network' (0.080).

Keywords: *knowledge management; artificial intelligence; knowledge distribution; artificial neural network; ANN; real-time engagement.*

1 Introduction

Knowledge is an essential resource to maintain a competitive advantage. The process of gathering, sharing, and effectively using knowledge is termed knowledge management (KM). The knowledge-sharing mechanisms are vital to the growth and development of organizations. It is also called Situational Awareness (De Bruyn et al., 2020). First, acquiring, storing, and sharing knowledge had to be given a proper name, and then it was decided that KM would best fit. McKinsey was where the term started being defined and used in 1987 (Gehl, 2015). The first time it was used in a study extensively based on internal records management and for some surveys taken on the same forum. At the same time, McKinsey recorded the fundamental standards of the subject of KM and published its guidelines and procedures to other enterprises for internal usage across several sectors (Donate and De Pablo, 2015).

People already liked acquiring knowledge and sharing; however, they were thrilled when they learned about a proper system. Then the need for managing knowledge just as a resource was given due importance, and the professionals optimized the systems for the long-term success of the organizations they worked for. The information acquired in an organization by the executives is to find meaningful outcomes that serve the purpose of strategic planning (López-Robles et al., 2019).

KM is a rising topic of interest, acquiring the attention of both industry and the government. As everyone is pushing toward creating a knowledge-oriented industry, business leaders have started emphasising the need to transform basic individual information into something hierarchical and functional, as seen from a bigger lens for the organisation's benefit (Hsieh et al., 2019). There are most commonly six strategic functions given by the American Productivity and Quality Center, especially those used for formulating businesses and selecting the chief knowledge officer, for that matter (Hollenbeck and Jamieson, 2015). These strategies help concentrate on the fundamental exploitation of the knowledge base, the critical information prevailing in an organisation, or any form of information that the public administration bodies have shared. Various activities occur in an organisation, such as human resources, supply chain management, and product development in the market. A crucial area is customer relationship, commonly known as CRM (Tarigan and Ivandianto, 2020).

The first and foremost thing during problem-solving is assessing the internal and external environment. It provides a picture of the adversities and risks that might fall beyond while brainstorming to find the correct answer. Thus, to a scholar's notice, situational awareness was a critical phrase coined in business long ago. However, it got much more weightage when it became an inclusive part of KM. Business leaders need to be alert while taking a risk and be aware of the situation to make the right decisions at the right moment (Mizintseva and Gerbina, 2018). The most critical aspect while dealing with KM is considering the intelligent systems that would help capture knowledge and help individuals share their knowledge in the teams or even in the cross-functional teams. This process will be advantageous at individual levels and from an organisational perspective.

1.1 Relevance of knowledge and KM

Knowledge is an excellent input that one can provide in a space where it is most required. The extant literature confirms that knowledge differentiates one from another in terms of understanding, intellectual capacity, and leveraging the resources to create the best out of what is available. Organisations understand that KM is critical in the current scenario (Paulin and Suneson, 2015). Businesses prioritise all these activities as proper implementation of knowledge and wisdom in business go hand in hand. KM is a vast domain inclusive of acquiring and presenting a knowledge base to one and all present in the organisation and shall be handy for the more significant developments focused on growing the firm (Hallinger and Suriyankietkaew, 2018). The knowledge flowing across the departments is rich. To utilise this knowledge, complete, open communication, operation, and accessibility are required. It is evident now that organisations need to ensure effective communication to make knowledge more powerful. The continuous inflow of knowledge is equally important because the transparency of knowledge provides a multitude of scopes that automatically line up when there are readily available options (Landy et al., 2020). A very famous saying put forth by Peter Drucker is that a pharma company does not sell pills; the essential thing it sells is information. The moral that comes out here is a need for internal and external communication, which can only be satiated by the right amount of knowledge flowing within the organisation. Businesses have evolved, and from an industrial viewpoint, they shifted their focus to knowledge and defined knowledge as a significant asset for an organisation (Lahti et al., 2018).

1.2 Employees' participation in KM

An organisation's employees have various experiences during their work hours and even outside of work. These experiences generate the immense possibility of gaining knowledge that can be used in any field, professional or personal. The enterprises have determined the importance of effectively using knowledge and, henceforth, finding ways to spread the message in the industry (Ardolino et al., 2018). 'Knowledge socialisation', 'externalisation' and 'internalisation' have positive relationships with stakeholders' aspects in organisational performance (Moftian et al., 2022). A study in the context of the role of KM in the Virtual Knowledge Environment found that with the emergence and inclusion of new technologies, knowledge creation has become the most critical aspect of KM Practices in the case of Learning Management systems (Wahdan et al., 2021). The internally created dashboards, presentations, reports, and policies, are shared among the employees in an organisation through the intranet. Even though this is an old and well-adopted practice, many new tools under the umbrella of KM are utilised to implement the same (Sengupta and Ray, 2017). The employees in organisations create various reports and documents shared for daily business activities. The idea and phrasing of the term KM were popular for years and grew inside the counseling or consultation firms specialising in managing several organisations (Mahdi et al., 2019).

1.3 Technology and KM

The new paradigms in KM are constantly being studied, giving scholars more avenues to further base their studies (Tzortzaki and Mihiotis, 2014). Furthermore, the availability of the internet made the firms realise the opportunity to set up an internal medium of transferring or presenting information for the benefit of the end-users in the company. Therefore, an internal part of the internet was deployed within the premises so different reports, databases, and other documents or multimedia could be put up for different cross-functional departments (Fernandes et al., 2014). The professionals discovered that they had generated big data. Therefore, the strategies, especially the dashboards or the benchmarked processes, were segregated as essential features and contributed hugely to the KM system (Santoro et al., 2018).

The second level of KM is its implementation of virtual information sharing, which many organisations maintain. Some widespread instances are online journals, periodicals, wikis, reports, and interpersonal interaction locales. At the same time, the specialist in any association ought to principally arrange one's insight. Although organisations are now empowering themselves with better knowledge-sharing approaches, innovation and technological advances have empowered new structures, including circulated information and knowledge capacities (Sousa et al., 2010; Bharadwaj et al., 2015).

It is often viewed that expertise is lost when an employee who is trained and educated about a particular function leaves the organisation. He takes his knowledge along with him. There is a void in the organisation that takes time to fill up again. To overcome this problem, organisations use software solutions known as KM systems (Cerchione and Esposito, 2017). The knowledge acquired from experts can be preserved for a more extended period in well-built knowledge systems. It can be disseminated to existing and future employees as and when required. KM was an unknown term around 1990; however, disappointment was associated with it because the software solutions linked to KM were not correctly implemented, so the results were not up to the mark (Capano and Howlett, 2020).

1.4 Major changes and developments in the recent past

In the last few years, KM, digital transformation (DT), and Industry 4.0 have become the new buzzwords. KM contributes to the innovative ecosystem, frontier technology, and decision-making (De Bem Machado et al., 2021). In the context of educational institutions, it was found that KM is not only a mechanism for coordinating information but also enables a knowledge ecosystem in the organisation (Gupta et al., 2020). Similarly, in education, AI-enabled online education products and strategies help operators reconcile the experiences and needs of the users (Lin et al., 2022). In the healthcare sector, AI contributes to policy improvements, greater investment in R&D activities, and effective governance (Chatterjee et al., 2022). In addition to this, AI helps in predicting the future of the fashion industry. Banerjee et al. (2021) developed a model in the fashion industry that may help create products, improve margins, minimise inventory, and enhance business results. Chowdhury et al. (2023) developed an AI capability framework based on the integrated resource-based view and knowledge-based view theories, which enable the self-assessment of how much an organisation is ready and able to develop the strategies to implement AI-enabled HRM.

2 Literature review

2.1 Artificial intelligence in KM

Artificial intelligence (AI) recognises the pattern, or the algorithms and logic and heuristics captured in the search bar and ultimately understand the pattern to give results as humans do in each situation. KM has been gaining popularity because of the AI technologies associated with managing these systems (Duan et al., 2019). AI has proved to be a beneficial tool in providing the right amount of ease with which knowledge sharing can be done (Almeida and Soares, 2014). AI in KM examples are genetic algorithms, neural networks, and other intelligent agents, which provide specific techniques or tools for analysing the semantic text matching the patterns, text mining, and so on (AlGhanem et al., 2020). KM heavily depends on analysing the information present in the organisation to produce better results, and AI makes the job easier for these systems. AI helps make better decisions by interpreting the patterns in historical information. These automatically generated conclusions are then applied wherever required (Stone et al., 2020). Goonetillake et al. (2021) proposed a model with a hybrid approach in which database and ontology were used for effective KM practices. The model was tested with the data, and the results were accurate. In a study by Crowder et al. (2019), a solid logical 'ontology-based KM systems' framework was provided for AI, reflecting the role and relevance of AI in practical KM.

Various individuals might have gathered much data and experience while walking through their problems within the industry. These people are often called experts, and those new to any form of work may seek help from these stalwarts. However, the experts may not be in a particular area where few might seek help. Therefore, AI tools would be the best detector to find the appropriate expert whom the knowledge seeker can contact.

These AI-based arrangements are called expertise location systems (Ellwart et al., 2014). Organisations all over the globe are putting resources into information through their representatives. They archive their business processes, articulate their standard working methods, document their records, index their goods or services, and catch all data connected with their administration conveyance. Accordingly, information base programming is imperative to the information the executives' program of an association. The board device's highlights of decent information ought to enable the association to catch, share, find, and keep up with their authoritative information. The rise of AI is set to provide an aid of information to the executives, especially in helping the enterprises to consider the maintenance of data and knowledge built upon the information available, joint effort, and ultimately cares for the customers (Pan and Zhang, 2021).

2.2 Impact of AI on KM

2.2.1 *Amplifying efficiency*

The approaches which AI uses vary in different circumstances. KM processes significantly influence innovation, business success, competitive advantage, efficiency, and performance outcomes. Intelligent Agents can duplicate patterns and make decisions in the same circumstances. Associations are broadening their conventional co-found work to virtual ones. The circumstance with scattered specialists' increments requests on correspondence and coordinated effort frameworks, attributing the focal job to association with ICT. In such associations, information must be moved across four limits: culture, time, space, and associations. There is much in the same way as information mining and looking on the web (Ortigosa et al., 2014).

However, one thing to ponder in KM is that it is specific to the datasets, databases, reports, and other types of information record specific to the organisation. Thus, the meaning of KM was limited to only certain areas, but now it is becoming a more significant concept accepted by one and all. The fundamental way to manage knowledge is to manage content first. The flow of data is related to all sorts of functions and components in the organisation. It is most preferred for enterprise content management (Oztaysi, 2014). The data is set up graphically and is showcased online to be available for individuals to scroll through. It became evident that knowledge takes the front seat to deal with such processes in an organisation. KM is a very sophisticated and diversified area that helps with different functions such as marketing, human resource management, provider network management, etc. It also helps with the organisation's decision-making process efficiently. KM in an organisation is necessary not only to help improve the efficiency or the performance of an organisation but also to exploit the intellectual capital. It helps optimise the resources to deal with the risk and use the opportunities that are in line for a better competitive advantage over others in the industry (Girard and Girard, 2015). Globally, organisations are succeeding at an incredible pace because they can determine, monitor, and develop knowledge as a resource in a more practical manner. Knowledge is backed up by information and technology and is used to communicate this information from one corner of the world to the other. Automation is helping the traditional KM system touch skies in unimaginable ways. The collection of information is the first step of KM, and henceforth the data collected is analysed in different ways to be perceived by different individuals and groups according to the needs of the enterprise. AI tools support information and communication technology for optimising technology to its best (Li et al., 2017a). Based on the inputs from the studies included here the following hypothesis was formulated:

H1 AI significantly and positively continuities in amplifying efficiency of the KM.

2.2.2 AI as artificial neural network

AI has proved to be a boon in KM because it is a broad area that cannot be dealt with manually. Hence the major categories of AI in sync with KM are intelligent agents, expert systems, and artificial neural networks (ANNs). The expert systems are closely linked to the KM system because both focus on the impact of knowledge. It is a program that covers a large part of knowledge but in a very restricted area and, at the same time, uses complicated reasoning methods to carry on the activities which probably an expert would be able to do. The second one is the ANN which is of immense potential because, in KM, it can link specific other allergies with the brain's functioning. ANN's huge benefit is that even if the system captures incomplete data, it can generate complete information with the existing data (Bibault et al., 2016). Therefore, ANN could be incorporated within the KM system to distribute and share information. However, ANN encapsulates a slight drawback: it can only work with numeric data, contrasting with KM (Evans et al., 2015). The third form is the intelligent agent, which is exceptionally autonomous and can achieve its goals only with knowledge. Therefore, intelligent agents can be placed in the KM system to retrieve tenant information and then combine it to develop new knowledge forms that could be used across departments in the system. The discussion leads to the formulation of the second hypothesis:

H2 AI as ANN significantly and positively contributes to KM.

2.2.3 Knowledge distribution

As the information base of an enterprise develops, search is a crucial part of bringing applicable substance when representatives search utilising not many catchphrases. An AI device can use natural language processing (NLP) and diagram-based calculations to bring significant substance to the view of catchphrases (Jany Shabu et al., 2020). Moreover, the evaluation and analysis of the text can naturally produce applicable labels for every information base substance, which intensifies AI-based web indexes to bring essential substances to the forefront. This engages every individual to observe the ideal data at the ideal time as the information base develops. This upgrades the operational efficiency of an organisation. If an AI calculation cannot observe relevant articles considering search terms, then, at that point, it can proactively make content makers aware of filling in the information hole. This methodology prompts rapidly tending to information hole regions guaranteeing all corporate information keeps awake to date with advancing business. Content creation is the centre action to be attempted utilising AI tools. An AI can consequently address errors and fixes linguistic missteps. AI can likewise present ideas to develop the meaningfulness of the substance, further considering semantic rules. An AI can likewise recommend the correct business glossary terms to ensure business-client consistency, which creates a mutual perspective among all representatives inside an association, prompting authoritative versatility. An AI calculation can also assist with measuring the effect of an informative article by totaling information from numerous sources, for instance, Google Analytics (Agbehadji et al., 2020).

For instance, a client does not have to know hierarchical metaphysics or even the scientific categorisation of how the information base is coordinated; instead, an AI chatbot conveys suitable substance to the clients because of their inquiries. Moreover, an AI can assist the subject just like the subject matter experts do in such a case. This would help team up viably by uniting them progressively for information creation and sharing. An AI can work by joining different cooperative apparatuses. AI also guarantees a broad content reach that will inspire hierarchical information on all workers. This will help representative fulfilment and maintenance (Li et al., 2017a). An AI calculation can push representatives into getting new abilities considering their present mastery and what information content they read or share or use in any given condition. An AI calculation will tackle the force of information by incorporating distinctive hierarchical frameworks to assist the employees with refreshing their range of abilities. For instance, assuming a representative is perusing a ton of articles on information examination, then, at that point, AI can push a worker to take another seminar on the information presented by the association's learning the board framework. This shall be helpful for the employees as it would enhance their abilities and empower them to be broadly educated. This contributes to the agility that an enterprise could build over a period of time. An AI tool will present ideas on content partaking in the right stage to boost the market. For instance, information gathered from different systems or departments will help AI tailor the suitable substance to be partaken in the right stage to boost client commitment to the given substance.

Essential experiences created by knowledge systems can be utilised to upgrade the substance and achieve the highest quality level in improving the information acquired. Similarly, an AI calculation can make pertinent partners aware of audits and occasionally change content to guarantee modern information. Keeping the information base sound gives immense business dexterity to the whole organisation along its success path. An AI chatbot is another tool that would arrange all the information collected from the range across the association in various information archives. A chatbot can talk with individual employees to give the right solutions to questions (Flanagan and Walker, 2021). This lifts the client experience of employees working within the company and the external clients while having any kind of formal and significant discussions. The discussion of extant literature has led to the formulation of the following hypotheses:

H3 AI contributes significantly and positively to the distribution of knowledge in the KM.

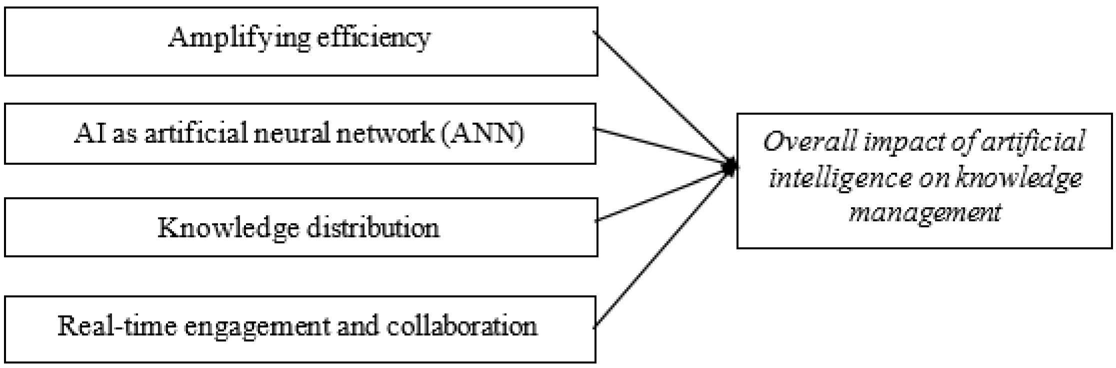
2.2.4 Overall impact of AI on KM

The most crucial aspect of developing knowledge systems entirely for organisational success is transforming individual data into organisational data. This can be used for strategy building in the long run and will heavily depend on AI. This provides an edge over other techniques since AI-based technology is equipped with features that can be helpful in KM in a much more expansive manner (Zhong et al., 2017). AI was prevalent in the Business World before KM carved a niche. AI has been deployed in various fields and disciplines; whether it can do the same magic for KM is a question posed by various individuals and groups (Bates et al., 2020).

2.3 Research gaps and conceptual framework of the study

Many studies discuss the context, relevance, and role of AI in KM in contemporary literature. However, most studies are theoretical and miss the empirical aspect in the form of the opinion and experiences of professionals using them in real-life settings. AI in KM has been discussed theoretically in computer science research, wherein the efficiency of AI-based KM systems was technically measured. The present study has explored this concept in-depth. An attempt has been made to empirically test the various AI constructs that contribute to the practical KM system and practice.
Figure 1 focuses on establishing the impact of AI on KM. The extant literature studied AI and its role in KM has mainly indicated the four significant aspects – amplifying efficiency, AI as an ANN, knowledge distribution, and real-time engagement and collaboration. Therefore, the above four aspects have been considered predictors (independent variables) for the 'Overall impact of AI in KM as the dependent variable.

Figure 1 Conceptual framework of the study



3 Methodology

3.1 Research design

This study is descriptive, in which the primary data were collected from industry professionals through a structured questionnaire. Like a typical descriptive study with cross-sectional data, the relationships among the manifest variables have been established in this study. Such research design is highly suitable in the case of empirical studies based on primary data wherein the variables can be extracted from the literature review (Malhotra, 2007; Chawla and Sondhi, 2011).

3.2 Scope of the study and origin of data

The theoretical scope of the study is confined to the study of different factor that determines the role of AI and its impact on KM. The collected data includes experts from different industries such as IT and ITEs, research, banking, FinTech, and retail, where AI is used for KM.

3.3 Sample size

According to Green (1991), the minimum sample size in multiple regression should be multiple regression or N ≥ 104 + m, where m = number of predictors. In the present study, there are four predictors (after précising by factor analysis); hence the minimum sample size required is 104+4 = 108 (Burmeister and Aitken, 2012). The data were collected from 217 industry experts through a structured questionnaire containing a five-point Likert scale for measurement.

3.4 Instrument development

The survey instrument was developed in two phases. The items were extracted from the extant literature in the first phase, and a 28-item measurement scale was prepared. These draft items were sent to the experts for their opinion on whether they could measure what they were meant for. This method was recommended by Polit and Beck (2006). Ten experts were chosen from the field of AI and KM (The experts were asked to rate the item as 'suitable' and 'not suitable'. Only those items kept, which got 80% of the experts' score on the 'content validity index'. Finally, 8 out of 28 items were dropped, and the final questionnaire contained 20 items and one statement as dependent variable – overall role of AI in KM.

3.5 Techniques for data analysis

A two-step data analysis approach was applied. Firstly, for a precise understanding of the data, 'exploratory factor analysis (EFA)' was applied to all 20 items and was taken into consideration, and subsequently, the reliability was measured. Then, based on the item-to-total correlation criterion, one item was dropped with an item to a total correlation of below 0.3 (Nunnally, 1978).

In this study, the independent and dependent both kinds of variables have been measured on an Interval scale; hence, multiple regression analysis has been applied to determine the cause-and-effect relationship (Field, 2017). Multiple regression was applied to determine the causal effect. The measurement of independent variables was based on the 'factor scores' obtained from the EFA process. The dependent variable was 'the overall impact of AI in KM'. The set of variables, along with their denotation, has been presented in Table 1.

Table 1 Details of the dependent and independent variables

Variables	*Type of the variable*	*Denotation*
Amplifying efficiency	ADV	□1
AI as ANN	ADV	□2
Knowledge distribution	ADV	□3
Real-time engagement and collaboration	ADV	□4
Impact of AI on KM	DV	Y
Constant		□

1.1 *Multiple regression equations proposed*

Y □ □(Constant) □ □* (*X*) □ □* (*X*) □ □* (*X*) □ □* (*X*)□ □
1 1 2 2 3 3 4 4

Y dependent variable

□ constant or intercept

$□_1$ to $□_4$ parameters to be estimated

□ error term or residual.

3.6 Data analysis and interpretation

Table 2 shows the demographic profile of the respondents. A total of 217 people were surveyed; among them, the percentage of males was 55.8, and females contributed
44.2 percent. 28.1% of them are from the age group of 35–38 years, 44.7% belong to the age group 38–42 years, and the rest, 27.2%, are above 42 years of age. 25.8% of the respondents are Postgraduates and below, 45.6% have Advanced Degrees, and 28.6% are with their professional Degrees. 40.1% of the respondents are experts from the IT and ITEs industry, 14.7% from the research industry, 12.4% from the banking industry, 19.6% from FinTech, and the rest, 13.3% are experts from the Retail industry.

3.7 Exploratory factor analysis

EFA is a technique based on correlation, which puts together the highlighted correlated variables (manifest) in the form of constructs (latent) and makes the data fit for establishing causal relationships. Table 3 shows the results of 'KMO and Bartlett's test'. KMO value is more than the recommended value of 0.6 (Kim and Muller, 1978), determining that the sample is adequate to perform the factor analysis. The significance value is 0.000, which shows that the correlation matrix is not an identity matrix. Hence, the data fulfils the initial diagnostics of the EFA.

Table 2 Demographic profiling

Categories		*Percentage*
Gender	Male	55.8
Female		44.2
Total		100
Age profile	35–38 years	28.1
38–42 years		44.7
Above 42 years		27.2
Total		100
Educational qualification	Postgraduates and below	25.8
Advanced degrees		45.6
Professional degrees		28.6
Total		100
Industry type	IT and ITEs	40.1
Research		14.7
Banking		12.4
FinTech		19.6
Retail		13.3
Total		100

Table 3 KMO and Bartlett's test

KMO		0.884
Bartlett's test of sphericity	Approx. chi-square	3,121.421
	df	190
	Sig.	0.000

Table 4 presents the number of factors derived from the corresponding variation. Four factors were extracted, explaining a total variance of 70.691 percent. The obtained factors were labelled as amplifying efficiency, AI as an ANN, knowledge distribution, and real-time engagement and collaborations, depicted in Table 3.

3.8 Factor 1: amplifying efficiency

The factor includes variables like AI helps in boosting KM, AI provides intelligence for efficient use of infrastructure, AI helps to overcome past issues that had dealt with a colossal amount of data and was challenging to maintain, AI enables the knowledge workers to see the advantages in the usage of KM tools. AI can handle big data decentralised blockchain data storages. It reveals the maximum Variance among all four factors (20.508%).

3.9 Factor 2: AI as ANN

The factor consists of variables such as AI as ANN can handle big data, ANN helps decentralize blockchain data storage, ANN incorporates with a KM system to distribute the knowledge and share the Information, ANN is helpful when the system captures incomplete data to generate complete information with the existing data and AI linked to the KM system to focus on the impact of knowledge to cover a large part of knowledge and uses complex reasoning methods to carry on the activities as the expert. The factor explains the 17.801% variance.

3.10 Factor 3: knowledge distribution

The constituents of the factor are an AI-based search engine that helps to bring in relevant content with the correct Information; AI helps in making better decisions by interpreting the patterns of history and generating the conclusion automatically, Retrieving and tenant the information to develop a new form of knowledge, AI provides easy access to information shared by others. AI delivers knowledge to make decision-making process fast, efficient, and accurate. The Variance explained by the factor is 17.428%.

3.11 Factor 4: real-time engagement and collaboration

The factor includes variables like AI strengthens the collaboration between the employees, AI chatbot helps to curate knowledge content for different knowledge repositories, AI collects, stores, and sharing knowledge for better employee engagement and collaboration, AI helps to put up reports, databases and other documents or multimedia for different departments and AI works as an internal medium that transfer and present the information to benefit the end-user. This factor explains the 14.954% variance.

4 Regression analysis

This study measures the impact of all four constructs – amplifying efficiency, AI as an ANN, knowledge distribution, and real-time engagement and collaboration on the 'overall impact of AI in knowledge management', multiple regression was applied. As a result, the model explained more than 76% of the variance (R square = 0.762); hence the model can be termed a good fit.

Table 4 ANNOVA

Model		*Sum of squares*	*df*	*Mean square*	*F*	*Sig.*
1	Regression	153.875	4	38.469	169.753	0.000
	Residual	48.042	212	0.227		
	Total	201.917	216			

Notes: DV: overall impact of AI in KM.

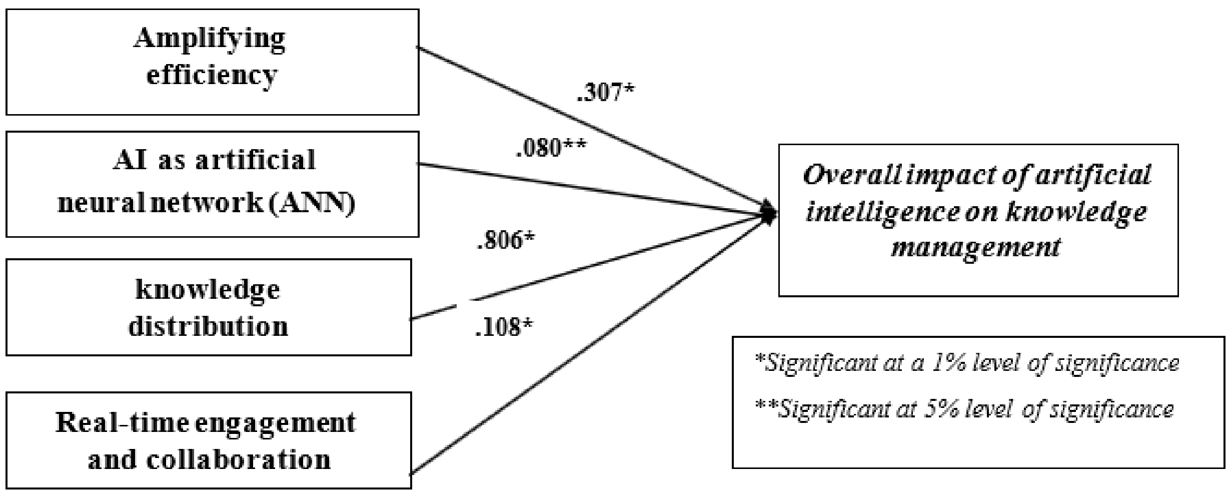
Predictors: (constant), amplifying efficiency, AI as an ANN, knowledge distribution, and real-time engagement and collaboration.

Table 5 Role of AI on the overall impact of AI in KM

Model	*Unstandardised coefficients*	*Standardised coefficients*	*Sig.*
Constant	3.604	----	0.000
Amplifying efficiency	0.297	0.307	0.000
AI as ANN	0.077	0.080	0.018
Knowledge distribution	0.780	0.806	0.000
Real-time engagement and collaboration	0.104	0.108	0.002

Table 4 (ANOVA) shows whether the IDVs significantly impact the DVs. The significance value is less than 0.05 (0.000), reflecting that one or more of the IDVs significantly influence the DV.
Table 5 shows that all four variables, namely amplifying efficiency, AI as an ANN, knowledge distribution, and real-time engagement and collaboration, significantly impact AI on KM. All the hypotheses proposed in the study were supported. Furthermore, it has been found that all the relationships are significant; the independent variables significantly influence the dependent variable positively. To conclude, amplifying efficiency, AI as an ANN, knowledge distribution, and real-time engagement and collaboration influence the overall impact of AI in KM (Figure 2).

Figure 2 Role of artificial intelligence on overall impact of AI in KM



5 Discussion and conclusions

The study considers the various ways in which KM systems can be efficiently worked out in organisations. It is evident from this study that knowledge in an organisation is vast and cannot be articulated, monitored, and managed simultaneously by a single Technology. Therefore, there are various methods by which knowledge can be managed and distributed to the stakeholders at the right time and proportion. KM, basically, and there are plenty of activities. Therefore, there is a need to accumulate all the critical information available in an organisation with the help of Sound Technology equipped with AI and its features to drive efficient results for the users (Kumar et al., 2019). This study has highlighted the role of AI in dealing with the activities that KM covers. It is also pertinent to understand that the resources available in an organisation must be optimised and not wasted by developing something that does not yield positive results. Therefore, implementing AI-based systems in KM also becomes essential.

The study concludes that Amplifying efficiency, AI as an ANN, knowledge distribution, and real-time engagement and collaboration are the factors that determine the role of AI in KM. The most important and unique contribution of this study is that it has collated the four important constructs predicting the overall role of AI in KM. There have been many studies on KM and AI separately; however, very few studies empirically test the convergence of these constructs from the viewpoint of people implementing them. The study enlightens the path for future researchers proposing a scale for measuring AI in KM. This study puts together the essential components of AI and KM and connects them to the overall contribution of AI in KM.

The present study shows satisfaction by presenting AI’s critical role and impact on KM. AI for industry KM can be implemented effectively by adopting the latest technologies. It is vital to provide proper training to the workforce, providing technical support to concerned departments of the industry. The study has some important implications for heads of departments and the company’s workforce. The person responsible for implementing different technologies in the company needs to know about the different roles of AI and its impact on KM. The employees and workforce of different industries need to be motivated and encouraged to learn the latest technology and undergo training programs to learn the use of AI.

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