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ABSTRACT

This paper analyses Artificial Intelligence (AI) and Knowledge Management (KM) and focuses primarily on examining to what degree AI can help companies in their efforts to handle information and manage knowledge effectively. A search was carried out for relevant electronic bibliographic databases and reference lists of relevant review articles. Articles were screened and the eligibility was based on participants, procedures, comparisons, outcomes (PICO) model, and criteria for PRISMA (Preferred Reporting Items for Systematic Reviews). The results reveal that knowledge management and AI are interrelated fields as both are intensely connected to knowledge; the difference reflects in how – while AI offers machines the ability to learn, KM offers a platform to better understand knowledge. The research findings further point out that communication, trust, information systems, incentives or rewards, and the structure of an organization; are related to knowledge sharing in organizations. This systematic literature review is the first to throw light on KM practices & the knowledge cycle and how the integration of AI aids knowledge management systems, enterprise performance & distribution of knowledge within the organization. The outcomes offer a better understanding of efficient and effective knowledge resource management for organizational advantage. Future research is necessary on smart assistant systems thus providing social benefits that strengthen competitive advantage. This study indicates that organizations must take note of definite KM leadership traits and organizational arrangements to achieve stable performance through KM.

1. Introduction

We are currently on the brink of a fourth industrial revolution that will radically change the way we connect with each other, work, and live. AI's opportunities and

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advantages are overwhelming and beyond what we can even fathom. It is stated that just as the second industrial revolution caused the invent of electrification, the fourth revolution will turn out to be 'Cognification' (Lei & Wang, 2020). We are inching closer to a world powered by data and insight, and it would be critical at this juncture to test the link between Artificial Intelligence and Knowledge Management to leverage AI more meaningfully. While identifying the relationship between KM and AI, it is critical to first recognize what precisely businesses do with knowledge (Pereira & Santos, 2013). Organizations carry out numerous obligations; the accomplishment and competitiveness of which relies upon maturity in performing critical tasks, in addition to where they stand regarding the industry.KM and AI are extensively all about 'knowledge' (Liebowitz, 2000). AI offers tools & mechanisms to make learning possible for computers or machines where it enables machines to learn, interpret and employ information to execute tasks along with assessment of knowledge that can be transmitted to individuals to upgrade decision-making (Liebowitz, 2000). KM facilitates knowledge to be well understood, while AI provides the ability to enlarge, make use of, create and unlock knowledge in ways beyond imagination (Goncharova & Murach, 2020). Artificial intelligence is overlooked by many KM practitioners and theoreticians and is one of the essential keys to constructing blocks for the development, improvement, furtherance, and advancement of Knowledge Management (Wu & Hu, 2018). As a discipline in education, artificial intelligence (AI) was initiated earlier than KM, has been grounded and balanced in the computing discipline over decades, and is implemented extensively in several domains (Sanzogni et al., 2017). By definition, 'knowledge is acquired and memorised facts and relationships between them, it is information which within itself includes values, attitudes and ideals; knowledge and skills that have an influence on human behaviour and are subject to changes' (p. 834) (Litvaj & Stancekova, 2015). 'It is the way we assimilate information that leads to knowledge creation. The industrial age automated humdrum manual tasks using machines and left humans to perform knowledge work of higher value'. The scientific age seeks to eliminate the burden of information and knowledge from human beings as well, leaving them with creative work and other intelligence. Artificial Intelligence and Machine Learning, including the analysis of organizational networks and the development of industry networks, are proving to be essential business tools (Chen & Liu, 2016). Knowledge management appears to have reached a higher level during the twenty-first century (Lei & Wang, 2020). AI & Blockchain have come into play and transformed again, how knowledge within organizations is captured, developed, shared, and used effectively (Qi & Zhu, 2021). The capabilities of AI are highlighted in recognizing context, concepts and meaning which are emerging up with exciting new collaborative paths between knowledge workers and machines. How can AI power KM sustainably? The irony today is, given the overuse of digital tools to get simple things done, we are less productive and more distracted. This paper makes an honest attempt to synthesize the literature on Artificial Intelligence (AI) and Knowledge Management (KM) and focuses primarily on examining to what degree artificial intelligence (AI) can help companies in their efforts to handle information and manage knowledge effectively. This systematic literature review will answer the research question by providing data on KM practices

& knowledge cycle and how the integration of AI aids knowledge management systems, enterprise performance & distribution of knowledge within the organization. The outcomes improve the understanding of effective and efficient knowledge resource management for organizational advantage. An elaborate review of past literature brings the birth and evolution of knowledge management to light. This evidential synthesis incorporates PICO model and criteria for PRISMA to underline the deep-seated relationship between Artificial Intelligence and Knowledge Management while a bibliometric analysis presents an overview of the literature that supports the study. Further on, a comprehensive discussion broaches the important elements that are required to implement a knowledge management process while offering insights on the future holds when a robust KM model is applied in a set-up. On a conclusive note, we shed light upon the current state of Knowledge Management, the influence of AI on KM and the need to apply KM in a contemporary business model to understand the operational efficiency of KM in specific areas.

2. Literature review

One of the important key building blocks for the development and advancement of knowledge management is artificial intelligence, which has been overlooked by several knowledge management practitioners and theorists (Liebowitz, 2001). Knowledge management attempts to combine various concepts disciplines like artificial intelligence, organizational behaviour, human resources management, and information technology (Bai & Li, 2020). Machines can improve human competencies and create new experts (Busch, 2008). Companies would have to redesign and update the flows, expertise, and tasks of knowledge workers, to completely use AI to their advantage (Bai & Li, 2020).

Knowledge takes several forms of which tacit knowledge is 'the knowledge of the subconscious which is something done automatically without almost thinking' (Bhardwaj & Monin, 2006). This type of knowledge is difficult to extract and elicit due to the knowledge engineering paradox (Obrenovic et al., 2015). The earlier implementations of KM could not be beneficial since they were highly preoccupied with converting tacit to explicit and then rendering the explicit, discoverable and reusable, through search driven repositories and fora (Raquel Merlo, 2017). The idea of 'converting' tacit into explicit knowledge has been strongly criticized (Nonaka & Takeuchi, 1996) as it has been argued that 'Tacit-explicit' transformations are the greatest shortcomings of any effort at information or knowledge management (Burnett, 2012). The skills of the workplace are articulable, while language, awareness, emotions, and feelings are un-articulable (Busch, 2008). In addition, codifying it in the true sense is either very difficult or impossible. This puts an unnecessary strain of externalization on people who are either unmotivated, organized, disciplined or capable of doing so. These attempts to codify result either in poor articulation and therefore poor assimilation of knowledge by users or failure to hold the codified information up to date (Obrenovic et al., 2015).

Knowledge workers are people who use non-routine cognitive processes to think, resonate, create, evaluate, and apply insights to a given situation. The ongoing

objective of Artificial Intelligence (AI) is to improve it to the extent where it matches the capabilities of the human mind, and in certain cases (computation and memory), to exceed the proficiencies of the human mind (Pereira & Santos, 2013). Currently, the global discussion is about the possibility of pursuing and achieving such a goal. AI also aims to solve past problems of coping with large quantities of data, which have been considered cumbersome and hard to manage (Wu & Hu, 2018). Modern AI-based systems can manage big data with a certain degree of security using new forms of data storage such as HDFS, NoSQL, and decentralized blockchain data storage (Djenouri et al., 2021). AI tools are rapidly maturing and are due to make a quantum leap in the decade to come as initiatives are underway to offer machines free will, emotions, and consciousness. Engineers and pioneers across disciplines are developing AI so that experts can train and test it more easily and integrate their highly useful and often scarce expertise.

To start exploring these new possibilities, companies will need to distribute their spending on AI accordingly as they would have to reimagine how experts and computer systems communicate or interact, to get the best value out of both – their systems and their knowledge workers (Yeşil & Hırlak, 2019). Much like the machine learning systems of today advance the abilities of ordinary employees, the systems of tomorrow will boost the efficiency and performance of skilled workers to previously unattainable levels of consistent excellence (Gao, 2021).

The world deserves tireless renewed attempts to lift the bar from enterprise software vendors. Time is ripe for enterprise software to tap intelligence to make customers' workflows relevant, leaner, easier, and high on ROIs. Strategy, process-centric methods, inter-organizational dimensions of decision-making support, research work on emerging technologies, and academic ventures in this arena will continue to provide insights into how we process and manage big data to enhance decision-making and productiveness.

3. Methodology

The review accompanies the guiding principles for systematic review of business research and management. Eligibility and screening evaluation observed participants, interventions, comparisons, outcomes (PICO) and the suggestions of PRISMA (Preferred Reporting Items for Systematic reviews) (Moher et al., 2015). PRISMA guidelines include a 27-object specification and a four-phase flow diagram that suggests items most crucial for the translucent reporting of a review.

By aiding researchers to record a deductive roadmap in their systematic evaluation, it offers a checklist with reference to the various rationale, certain protocol, specific objectives and registration, eligibility standards, source of information, search, and selection of the study, data collection technique, data objects, the risk of bias in individual research, précis measures, synthesis of outcomes and the threat of bias throughout the research studies (Shetty & Basri, 2018). It additionally fosters to provide a precise declaration engendering information on the PICO model. This study has particularly concentrated analytical questions with a specific research approach for the present review. After defining the research query it is elaborated in the initial

segment, while search strategy encompassing inclusion criterion, identification of the database, and search phrases are furnished as follows: Inclusion criteria: Intervention – object of the study: integrating artificial intelligence for knowledge management; outcome: enhanced effectiveness of knowledge management systems in the organization; nature of the study: cross-sectional/longitudinal study; publication: academic journals; population: Organizations (into KM) looking to explore the benefits of AI; Period: 1990 to present; Language: English. Search approach: Few search techniques were used to look up research articles, searches in several digital databases on iterative references and internet of articles retrieved, and hand searches that have added to the uniqueness of this systematic evidence synthesis (Ankitha & Basri, 2019). The database consists of Emerald Insight, Scopus, Springer LINK, JSTOR, Sage, ScienceDirect (Elsevier), SSRN and EBSCO. These databases are specially considered as standard databases which are well established with maximum coverage of highly ranked peer-reviewed journals. The search strategy involved a preliminary search with the use of phrases, namely: knowledge management and artificial intelligence, knowledge management and technology, artificial intelligence, and its relationship with knowledge management, integrating knowledge management and artificial intelligence, the state of knowledge management in 2020 and beyond. Totally nine research papers fulfilled the inclusion standards of the studies, wherein researchers chose a combination of quantitative analysis (via quantitative surveys) and qualitative approach (via semi-structured interviews) to gain a deeper understanding of the topic of the study.

3.1. Bibliometric analysis

This study aims to present a comprehensive review on Artificial Intelligence (AI) and Knowledge Management (KM), primarily focusing on examining its magnitude where AI can help companies in their efforts to handle information and manage knowledge effectively. A need arises for an overview of KM practices & the knowledge cycle. Hence a bibliometric analysis is appropriate to find out how the integration of AI aids knowledge management systems, enterprise performance & distribution of knowledge within the organization.

Initially, we commenced by conducting a document search on the Scopus database. The search string consisted of a combination of compound keywords concatenated with the AND/OR operators. By using 'All Fields' we ran a search with keywords emphasizing 'knowledge management' OR 'KM' AND 'artificial intelligence' OR 'AI' AND 'information technology' AND 'relationship between KM & AI' AND 'knowledge sharing' AND 'knowledge repositories'.

The database was limited to Scopus hence authors fail to claim that an exhaustive list of data was collected for this bibliometric analysis. There is a possibility of missing out on data from other databases Scopus covers a large number of articles and provides higher records in terms of citations. Consequently, we claim that sufficient data to outline the scientific landscape, research hotspots, and other analysis conducted in this study was retrieved.

This Systematic literature employed bibliometrix R-package software which is open-source software that provides a set of tools for conducting quantitative research in bibliometrics. R-package was developed by Aria and Cuccurullo and written in the R language that has the main algorithms for conducting statistical and science mapping analysis. We have used the recent versions of the bibliometrix R-package (i.e., 2.0 upwards) containing a web interface app (Biblioshiny) to present an overview of the integration of AI leading to knowledge management systems.

The total number of documents were N = 958 on Scopus where the search was created to get an overview of the same. The author's keywords (DE) refer to a specific list of keywords authors of a publication must describe what their study dwelt upon as used in the full-text N = 3248. In contrast, keyword plus (ID) refers to extended keywords and phrases generated by Scopus system where N = 5260. In addition, authors per document refer to the mean number of authors per document, while co-author per document is the mean number of authors' appearances per document—both authors per document and co-author per document measure authors' collaboration. The average years from publication was 0.45 and the average citations was 4.547. The co-authors per document were 4.57 and the collaboration index was 4.28.

3.2. Results and discussions

Results and discussion of findings are depicted in this section to reflect (i) growth and trends artificial intelligence research in terms of publication output, distribution, source, and citations; (ii) prolific scholars, affiliations, and social networks; (iii) thematic focus of the field of smart learning environments.

3.3. Most relevant sources

The findings of the top 20 most relevant sources that have focused on publishing research articles on the Knowledge management is portrayed in Figure 1. The result
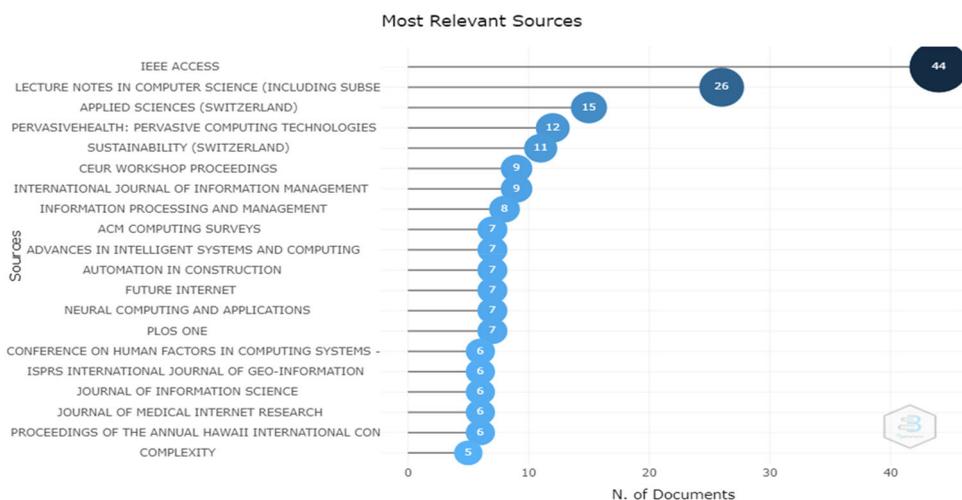
Figure 1. Most relevant sources.
Source: Bibliometric Analysis (Biblioshiny).

is based on the Scopus data Scopus retrieved in the year 2020 and beyond. It is mentioned that IEEE Access is the topmost relevant source. Other relevant sources include Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and that of Bioinformatics), Applied Sciences, Pervasive health: Pervasive computing technologies, Sustainability, Workshop proceedings, International Journal of Information Management. Aside from mentioned sources, other dedicated journals depicted by the present study analysis include Information processing and Management, ACM computing surveys, and so on.

Among these top 20 relevant sources, further investigation shows that Automation in Construction is the most locally cited source. Next, the most locally cited source is Information Integration which has been highly ranked for global citations with N = 71. Foundation trends for machine learning has the highest normalized global citation of 11.08 whereas Automation in Construction and Information Integration has the highest normalized local citation of 42.38.

3.4. Three field plot

A clear visualized and precise representation of prolific scholars along with their countries and the areas of interests depicted with keywords in the field of knowledge management and artificial intelligence is shown in Figure 2. A three-field plot of article contributions by countries, authors, and themes within the field of knowledge management is portrayed.

The left column is a representation of countries, the middlemost column showcases the names of the researchers in contributing, and the right column is a representation of the most used keywords by these authors. The number of occurrences of the keywords forms is referred to as 'themes. The height of the boxes along with the
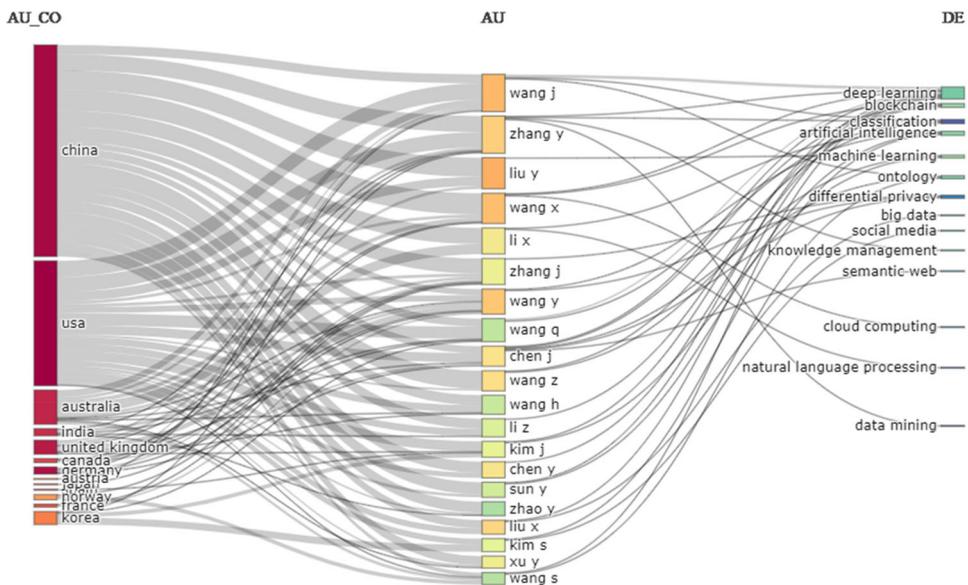
Figure 2. Three field plot.
Source: Bibliometric Analysis (Biblioshiny).

thickness of the connecting lines intensifies the relationship and the connectivity on the side of countries. China has the highest authors' affiliations followed by United States. In the same order, Australia has the next higher volume of authors, followed by India and the United Kingdom. It is observed that the thickness of the line leading from the countries to authors, the giant contributors are Wang J, Zhang Y, and Liu Y from China. Similarly, Wang Y Wang Q and Chen J are prolific authors who have contributed to the field of knowledge management, artificial intelligence, and machine learning from the United States. Besides, the knowledge management field received interest and publications Wang Z. and Wang H. as leading authors.

3.5. Thematic map

The thematic analysis takes clusters of authors' keywords and their interconnections to obtain themes. These themes are characterized by properties (density and centrality). The density is represented in the vertical axis, while centrality takes the horizontal axis. These properties measure the relevancy of the topics and differentiate them as important and not important. The higher the number of relations a node has with others in the thematic network, the higher the centrality and importance, and it lies within the essential position in the network. Similarly, cohesiveness among a node, which represents the density of a research field delineates its capability to develop and sustain itself. In Figure 3, the thematic map of knowledge management and artificial intelligence is depicted that divides itself into four quadrants (Q1 to Q4). The upper right quadrant (Q1) depicts the driving themes, the lower right quadrant (Q4) portrays underlying themes, the upper left quadrant (Q2) is the much-specialized themes, and the lower left quadrant (Q3) is emerging themes.

Themes such as artificial intelligence and machine learning seen in Q4 are the basics and are very important for the field's development. Themes in Q2 have developed internal bonds but are still of marginal contribution to the development of the
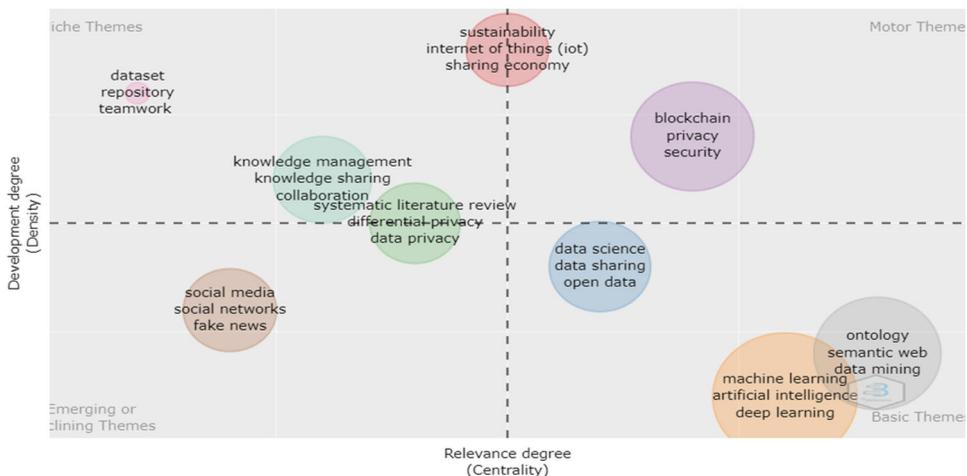
Figure 3. Thematic map.
Source: Bibliometric Analysis (Biblioshiny).

field of knowledge management. This finding suggests that themes in Q2 such as the most potential which encompasses dataset repository, knowledge management, and knowledge sharing. The lower left quadrant (Q3) takes up social media and social networks.

The clusters of 'knowledge management' and 'Artificial intelligence' has a Callon centrality of 1.260639694 and 2.354461498 and a Callon density of 48.74587302 and 64.01647427 with rank centrality and density of 3 and 6, respectively.

3.6. Word cloud and co-occurrence network

The study also investigated the keywords co-occurrence network (KCN) to gain further insights into the trends of knowledge management. This analysis presents the link between keywords, which contributes to the field's knowledge structure.

The results showcase that apart from identifying the frequent keywords in the word cloud a co-occurrence network helps to reveal the connections between them. Analysis of keywords incorporated by authors in publications is an essential tool for investigating trending topics and scholars' focus in the field. Word cloud analysis enables to identification of the topic and focus of that publication quickly with the help of the most frequent keywords used (Figure 4).

A few keywords have a greater impact on the co-occurrence network. A close examination of these keywords from its colour code suggests that a bigger keyword represented by their width is cohesively connected to other smaller keywords. For instance, artificial intelligence is connected to information management and
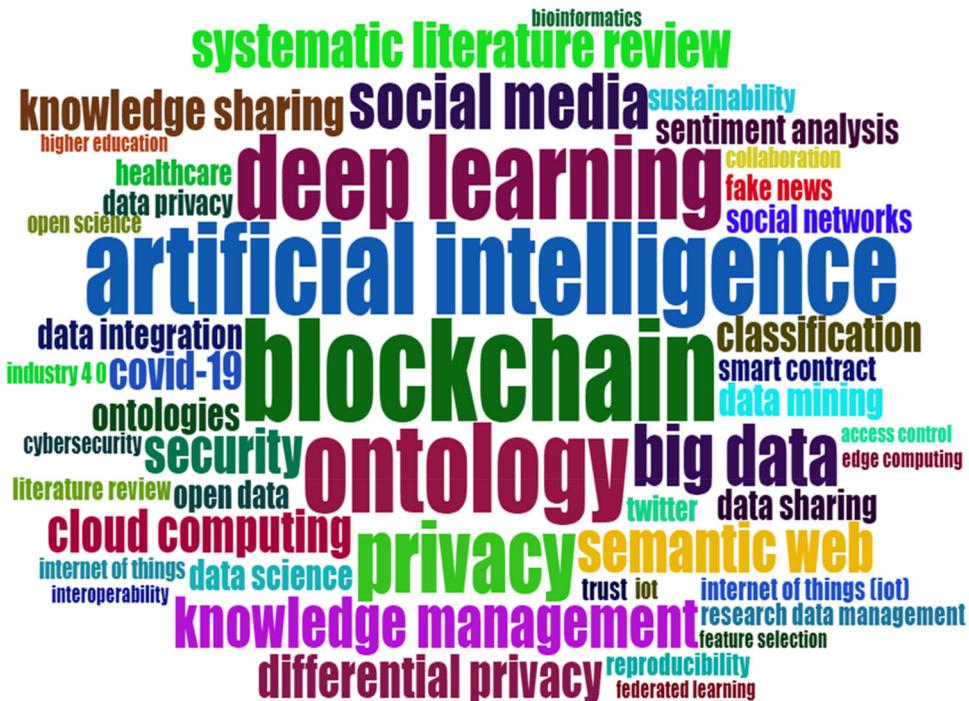
Figure 4. Word cloud.
Source: Bibliometric Analysis (Biblioshiny).

Figure 5. Co-occurrence network.
Source: Bibliometric Analysis (Biblioshiny).

knowledge management followed by knowledge sharing that belongs to other clusters. The cluster indicated in green and in red is the most relevant one to get a clear overview of the present keywords in the study. The construction of a co-occurrence network in Figure 5, permits us to scout and explore the conceptual structure of the scrutinized research domain.

3.7. Conceptual structure

The conceptual structure map visualizes the substantial structure of the words that appeared often in journals and papers on the topic of knowledge management by mapping to connection of the words to each other through regional mapping. Words are placed according to Dim1 20.68% and Dim2 being 18.01% Dim being diminutive particle. It is a scientific term in the science of bibliometrics, which creates a relation word that do not differ much from each other. The map shown below is divided into two parts, the blue area, and the red area, and contains words related to one another. As shown below, the red area consisted of a bigger variety and number of words, which showed the relation between that many research papers based on the words used. The words used most often were mainly about artificial intelligence. The words placed close to each other are closely related to each other and are mentioned in the papers together whereby the words away from each other are less related to each other. The closeness and the nearness of the words reflect the mapping and the relation towards each other frequently used by the researchers in their study (Figure 6).

Figure 6. Conceptual structure map.
Source: Bibliometric Analysis (Biblioshiny).

3.8. Country collaboration network

The country collaboration network has been segmented into 3 clusters showing how closely they are related to each other. These clusters show the betweenness and the closeness amidst each other. In cluster 1, United Kingdom has the highest betweenness and in Cluster 2, USA followed by China has the highest betweenness. Cluster 3 showcases the highest betweenness with Malaysia. Hence these countries have greater betweenness in the collaboration (Figure 7).

However, it is not advisable to solely rely on these results, but a mechanistic process of investigation alongside would have high yielding outcome benefits. Therefore, the abovementioned findings and results are for preliminary consideration that is to be developed further by righteousness and rectitude of an in-depth investigation of the research papers from the dataset where the results are shown and justified through the systematic literature evidence.

4. Results

Learning from errors across different companies and industries can minimize similar errors in an organization. Reading a shared error report across industries is a time-consuming process which hinders the learning process. Perhaps, a better knowledge management technique could be to automate the entire process of error report management using artificial intelligence with minimum human intervention. The paper also demonstrated an approach to classifying text reported as per older error reports by human experts and cases were discussed on how data across different industries can be coded into machines with the help of artificial intelligence and serve as an efficient cross-discipline knowledge transfer.
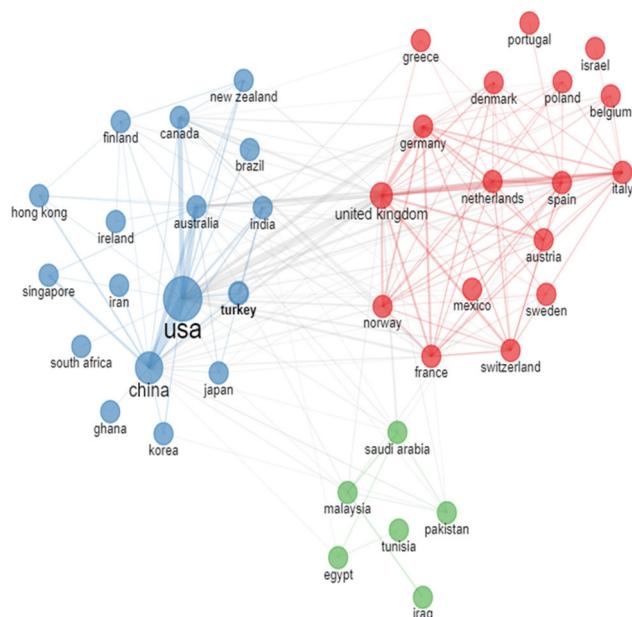
Figure 7. Country collaboration network.
Source: Bibliometric Analysis (Biblioshiny).

Knowledge sharing can help to minimize bias in the recruitment process based on artificial intelligence (Soleimani et al, 2022). A collective approach to knowledge management using big data analytics is useful for decision-making processes in unpredictable environments. The validity of managerial approaches and old business models is being questioned by the ever-changing fluidity of social and business configurations. Hence, an approach that integrates big data and artificial intelligence will help make better business decisions. There has been an exponential increase in knowledge growth with the increase in content-based platforms such as blogs and media. Traditional knowledge management methods involve knowledge sharing within an organization but with the advent of content-based platforms, organizations can trace the employee footprint across the internet with the help of artificial intelligence-based knowledge mapping systems (Al Hakim et al., 2020). A study on organizations' coordination between human learning and machine learning to learn effectively as a whole, i.e., organizational learning found that organizational learning in the presence of machine learning can aid effectively in reallocating scarce resources (Sturm et al., 2021).

Artificial intelligence-based IT support systems are no longer an option for organizations' operations but an imperative for innovation, efficiency, and effectiveness goals. A consistent automation framework for the needed infrastructure, data, IT assets, and life cycle management is highly related to sustainability, security, compatibility, compliance, and legal regulations. The biggest challenge remains the continuous progress in both infrastructure and software advancements (Stanciu et al., 2021). The paper addresses the challenges of modern businesses' digitalization, states, and demonstrates the solution through flexible, consumption-based information technology services in a knowledge-based sharing platform.

Figure 8. The knowledge cycle value chain.
Source: self-developed by authors.

Internet of Vehicles is a highly collaborative data environment. To enhance the security and privacy of knowledge sharing among the vehicles, Hierarchical block-chain framework and hierarchical federated learning algorithm are used for knowledge sharing of vehicles' environmental data through machine learning methods. Knowledge sharing is then modelled as a trading market process to stimulate sharing behaviours and the trading process is formulated as a multi-leader and multi-player market (Chai et al., 2020). Knowledge management is a necessity in all fields of science including architecture. An increase in software usage with various functions to solve architectural problems shows the increase in data volume and the complex nature of design processes for architectural problems (Safarnezhad et al., 2021). The result of this research presented a simulated model of knowledge management in architecture and modelling of the process of building an automated design intelligence. According to the obtained results, the introduction of artificial intelligence to design the facade of buildings can provide the process of data management, information, and knowledge in architecture to achieve the multifactorial design.

An approach that can integrate human and machine interaction using a framework developed by Mohapatra (2021) to make the interaction a sustainable implementation. In the study, Explicit knowledge management, both symbolic and geometric, proved to be instrumental to richer and more natural human-robot interactions by pushing for pervasive, human-level semantics within the robot's deliberative system.

Knowledge employees have useful experience which if shared properly can increase the operational efficiency of an organization but since they have time pressures and deadlines, artificial intelligence systems can act as an assistant to do the knowledge sharing. Artificial Intelligence-based systems (AIS) possess the capacity to aid human workers in knowledge-intensive work. Providing a domain-specific language, contextual and situational awareness as well as their process embedding can be specified, which enables the management of human and AIS to ease knowledge transfer in a way that processing time, cost and quality are improved significantly (Grum et al., 2021).

The knowledge cycle

Transformation of raw data into awareness involves much more than simply looking for a few phrases or words. Alternatively, the procedure may be divided right into a four-stage cycle (as indicated in Figure 8).

- Find: Sources and records in a timely manner, providing the requisite raw material. This may additionally encompass general queries consisting of a full-text search for large collections of documents or a search into structured catalogues and directories that lead to organization of sources and document files into predetermined beneficial categories.
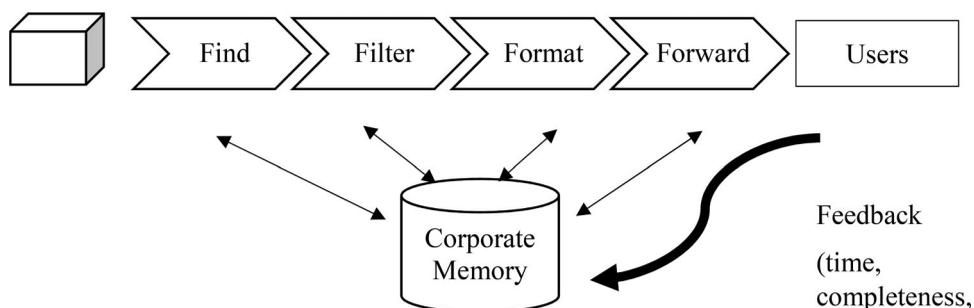
Figure 9. Continuous improvement in the knowledge cycle.
Source: self-developed by authors.

- Filter: Information availed from various sources as well as documents to retrieve only what is more appropriate to the knowledge task. This can involve making use of greater rigorous pertinence tests to whole documents, grading them, categorizing them, etc. This can encompass the use of natural-language processing strategies for the extraction of details for textual documents (Hobbs, 1993).
- Format: Filtered data for an effective communication. This may include gathering information from across various documents, 'data-cleansing' as well as standardization of information from various sources, and the appropriate presentation of outcomes through textual content formatting, summarization, graphics, charts, spreadsheets, multimedia, etc. (Larkin & Simon, 1987).
- Forward: The outcomes are coded to the individual or group of individuals who can utilize it at its best. This involves deciding on who deserves to receive and deliver the information via a variety of media – email summaries, personal databases, attachments, faxes, phone numbers, pagers, etc. (Krulwich et al., 1996).

While an organization earns experience in the transformation of information into knowledge, it can province more impactfully and efficiently as futuristic prospects for knowledge erupt. Since the collection of sources of information and requirements for knowledge is complex and constantly evolving, it is difficult to predict all the processing that will be needed by a given organization. A fifth stage; *feedback*, may additionally offer the possibility to alter the primary four stages, to new circumstances. Feedback assesses the success of the preceding phases of performance metrics consisting of the ones defined above.

The 5 processes work collectively on the corporate memory, as visible in Figure 9.

To effectively manage and organize knowledge, businesses need to recognize their knowledge-based activities of the highest value, and that they need to recognize and resolve the principal bottlenecks in the information process (knowledge cycle) for those tasks. Some of these bottlenecks may be bureaucratic or organizational; and restructuring, retraining, company policy, etc., will fix them.

Admittedly, the comprehensive task analysis and support needed for automation of the information chain can be strenuous and is only worthwhile to pursue very high-value applications. Nevertheless, corporations investing in effective knowledge management AI technologies – sorting, extraction of information, intelligent search,

end-user profiling & content or document forwarding, and so on – can earn substantial returns, for wisely selected applications.

Technology and knowledge-based organisations: AI and its link to KM

Technology holds a fundamental position, in the domain of acquiring and constructing of knowledge, and is evident to be the potential contributor and facilitator to knowledge accretion and management procedures (Champy & Hammer 2001; Davenport & Beers, 1995; Kock et al., 1996; Davenport, 1997) Thus, while the prevalence of human capital as the inventor and creator of information is substantially defined in the principle of KM (Harrigan & Dalmia, 1991; John, 1998; Swan & Scarbrough, 2019), the function and interaction of technology must also necessarily be considered.

Recent hardware supported with deep learning developments has paved way to a proliferation of deployed AI systems. AI is not limited to the lab anymore but has now become an omnipresent part of the modern world (Bennett & Lanning, 2007; Berk, 2012). We depend on AI systems to help us make decisions as easy as which movie to watch next or which restaurant to pick for dinner as well as more complicated and decisions with high stakes such as who is more deserving of a loan be it a big or small amount. We regularly engage with social media bots, share the roads with autonomous vehicles, and today, algorithmic trading dominates the financial markets (Bonnefon et al., 2016; Ferrara et al.,2016).

An artificial neural network is a kind of artificial intelligence that attempts, through its architecture, to simulate the biological structure of the human mind and nervous system (R. Gupta et al., 2006). These artificial indicators may be altered in similarity to the physical modifications that arise in neural synapses (Pradhan et al., 2010). Some neural network applications include speech synthesis, medicine, diagnostic issues, business and finance, processing signals, robotic control, controlling mitigation processes, computer vision, and biomedical applications (Takagi, 1997; Chua & Yang, 1988; Fu, 1998).

Neural networks provide advantages that are absent from computer applications such as the conventional KBES, in that they can function with data which is incomplete to generalize, abstract, probably by demonstrating perceivable intuitiveness (Wasserman, 1989l; Sharda, 1994; Kasabov, 1996). The core objective of the system is to generate results, e.g., decisions that are deemed to be good or to be better than the equivalent, an expert person would have made while coming across the similar collection of input data. This is accomplished by recurring learning cycles that have input sets and related established outputs are applied to the system. The intensity or weightings connected with links between nodes are then gradually modified through optimization routines implanted in the system, which gradually diminish the error arising between the 'ideal response' and the neural network response presently generated. This cycle is then repeated with numerous training data sets until output performance is regarded to be precise and persistently reliable.

Case-Based Reasoning (CBR) is not at its infancy in the field of engineering. Artificial Intelligence (AI) methodology is used to aid reasoning ability and learn advanced decision-making systems (Aamodt & Nygård, 1995 The drawbacks with

such systems inclusive of the excessive administrative burden that could give birth and the dependence on human infrastructure (as with alternative forms of AI).

One of the highly interesting and fascinating trends in technology this year is the utilization of AI in concurrence with KM. One type of KM, for example, information is offered to consumers who carry unique concerns about an organization in which they are running a business. Over and again, this included an online knowledge source, a collection of web pages detailing their products and services, or even a Frequently Asked Questions (FAQ) page, and if such documents fail to include a response, consumers were provided with an email address that could be used to query a customer support representative from the organization. A level of commitment is required along with persistence on the side of the customer, as well as a lengthy back and forth communication process (Liebowitz & Wilcox, 1997).

A common goal is considered by the professionals in knowledge which focuses on disseminating knowledge towards an organization's employee or more who is actively gaining information and data. (Nethravathi et al., 2020) A general approach to exchange this sort of data is through resources like an internal intranet, Sharepoint or wiki and contextual warnings and messages with the help of collaboration software applications like Slack or Microsoft Teams. Knowledge management has started to evolve into a collaboration of which is a process where group interactions are structured to facilitate knowledge sharing and problem-solving.

5. Discussion

Important elements needed to implement such a knowledge management process:

1) Strategy Through Senior Leadership and Active Involvement: One of the most relevant elements of the progress of KM is the implementation of an all-encompassing enterprise-wide KM strategy for the organization, assisted by senior, morally, and financially responsible leadership. This strategy of KM can implement different forms. One strategy could include focusing initially on a specific core proficiency of the organization (that can have a 'graying' staff basis), to harness expertise internally in the best possible way within the organization, i.e., employee base as well as externally to clients.

It is suggested that KM Project Offices within the organization, could be utilized as a strategy. KM projects of four different types and related activities have been identified: knowledge repository, transfer of knowledge, knowledge asset management, and the development of infrastructure.

Another tactic is to provide employees across the company with the framework, the knowledge repository ontology, and knowledge management resources to allow their departments or groups to originate their own knowledge repositories. The World Bank uses this approach, investing approximately $50–60 million for less developed countries, in 76 knowledge sectors to create infrastructure and knowledge-based support desks.

2) Knowledge Management Infrastructure and The Need for A 'Cko' Or Equivalent: The second important element in know-how control is a necessity for a CKO (Chief Knowledge Officer) or equivalent (Head of KM, Intellectual Capital Director, etc.)

and an organizational know-how management infrastructure. Forty-one of the Fortune 500 companies have a Chief Knowledge Officer or an equivalent, in conjunction with the Arthur D. Little research report. It is evident within the Big Five and major consultancy corporations. The CKO must be the father of facts, know-how, and gaining knowledge. This is especially useful if the CKO has capabilities in reengineering business, knowledge & change management, and innovative IT.

3) *Need for Information Ontologies and Knowledge Repositories*: Ontologies; enclosed in the context of knowledge management, are discourse specifications in the state of a vocabulary that is shared. They furnish the structural framework, vocabulary, along with the relationships required to build and enhance the repositories of information. Such knowledge ontologies need to be developed by organizations to ensure the standardization and integrity of repository creation & development and to encourage the preservation and controlled growth of these repositories.

In order to build these repositories of knowledge, the methods may take several forms that may be a mixture of active/passive knowledge compilation and distribution versus active/passive knowledge interpretation and circulation or dissemination. The passive compilation and passive analysis/dissemination are in the form of utilizing a knowledge repository as a record or archive that is accessed as necessary—i.e., individual workers input their learned lessons, and these lessons acquired are not systematically analyzed or disseminated (i.e., no active study or lesson distribution takes place). Another approach is active compilation but passive review/distribution in which the organization actively tries to build and develop a knowledge repository. The last method, known as the information pump, is the active collection and active evaluation/dissemination.

4) *Systems and Tools for Knowledge Management*: Knowledge repositories defined in the preceding segment are a part of these knowledge management structures. Issues in the user interface design need to be closely looked into. MATA- D is a Multi-attribute Technological Accidents Dataset that uses a classification focussed on the relationship between human errors and the influencing factors such as cognitive functions, organizational and technological factors (Morais et al., 2022). Some of those knowledge management systems use methods such as Lotus Notes, Infofinder (by Arthur Andersen – a smart agent which gains an understanding about the information needs of a user in a document repository), GrapeVine, Autonomy, Topic, Open Text, Magic Solutions, Perspecta, and InXight. Lotus Notes resembles a tool that is primarily based on groupware. Search tools encompass Infofinder, Autonomy, Topic, Open Text, and Magic Solutions; and Visualisation tools include InXigh and Perspecta. Such resources are not the management of knowledge by itself which should be a key to remember. These methods help develop and improve processes & tools for knowledge management. Managing knowledge is not just 'technology.' It requires a blend and combination of individuals, culture, and technology to create a 'framework' of knowledge management.

5) *Encouraging Knowledge Sharing Through Incentives*: Incentives are inevitable to promote the initial deployment of such systems, to ensure that knowledge management systems get used within the Organization. Buckman Labs (Memphis, Tennessee,) initially provided cash incentives for the use of its information

management program. Through time, the usage has become part of the 'intelligence community' of the company. As part of their annual work performance analysis, organizations such as Andersen Consulting (now Accenture in Chicago, Illinois, USA) and Lotus assess their workers on the quality as well as quantity of knowledge that they contribute towards various knowledge repositories and how that knowledge has been applied from those repositories.

6) Building A Culture of Support: In the opinion of, 70-80 percent of the learning is carried out using 'informal' methods versus 'formal' approaches (reading books and documents, etc.). To promote a casual employee to employee activities and encourage knowledge-sharing, organizations such as Johnson and Johnson, the World Bank developed 'knowledge exchanges' also known as 'knowledge fairs'. There is a need that technology of culture and knowledge both, should work together. Ways of assessing and measuring and evaluating the progress of these knowledge management systems also need to be taken into consideration.

It serves to provide as a mechanism to promote as well as facilitate an organization's Knowledge Management to act as a facilitator of interaction between people which is predominantly the primary and basic source of creating knowledge. Accordingly, it is acknowledged that AI can build ways to collect, retrieve and transmit the data in a more effective way, impactfully and rapidly. It can manipulate raw data and generate higher information, which potentially contributes to new and effective ways of developing and exploiting knowledge. Alternatively, the development of hybrid systems consisting of a combination of a rule-based expert system and a neural network is likely to provide access to embedded information and empower it to operate in the partial absence of a particular data. These systems are likely to demonstrate their capability to learn over a period and enrich their performance.

In addition to this, the knowledge base can provide examples from documented experience that illustrate the CBR approach. It could further extend and expand the capabilities of the system and alleviate the question of bottleneck acquisition in association with classical KBES. It can be especially useful in promoting applications wherein there is less than a substantive theoretical foundation. Ultimately, the argument that such innovations are not mutually exclusive and could have a great deal to offer in suitably combined hybrid forms, is a point worth reinforcing.

5.1. Future implications

The implementation of Knowledge Management (KM) as a business strategy provides a competitive edge for companies to perform better than their competitors. Upon successful application, KM carries the potential to increase revenues, decrease resource exploitation, increase savings and a visible surge in user acceptance (Fakhar Manesh et al., 2020). KM facilitates the creation of an environment of educating and learning, both of which as tagged as assets to a company since employees are motivated and often incentivized to continuously educate themselves, upskill themselves and take up leadership roles. Organizations need to make fundamental changes to their strategic map to cater better to the needs of the local market to compete better. KM, when incorporated into the strategic configuration, helps in understanding the

local environment by differentiating upon varying institutions, needs of entities and identifying consumers' tastes and preferences. (Kot et al., 2021) The global economies today are transitioning at a pace faster than imagined. In a dynamic atmosphere, be it on local grounds or global, organizations need employees who are trained with precision to identify vital information and knowledge. Therefore, companies can improve their output through the strategic implementation of KM. (Bencsik, 2021)

5.2. Limitations

Lack of adoption of AI and KM tools in this digitalization world creates a great hindrance in the progress of organizations. Few AI tools are implemented that encompass machine, human, and cloud interaction where it is evident that AI is slow on its approach towards lending support for KM within industries. Furthermore, there can be better uses for AI in terms of KM which can majorly impact and benefit organizations and businesses. Therefore, this paper has explored and reported the use of integrating AI and KM concerning personnel and distributed knowledge. It is asserted that AI-based technology alone does not try to offer a specific solution to KM's organizational needs. AI also does not act as a substitute to human intelligence and has the limited magnitude to embark the tacit knowledge issue.

6. Conclusion

The most difficult business decision is to implement the right KM strategy. The strategy inculcates a robust way of capturing, sharing, and transferring knowledge. Most of the organizations have implemented some sort of AI systems within projects and organizations by combining AI systems into Common Data Environments that will assist the employees in finding documents easier with a unique ID or referenced words. Being a key part of business best practices KM facilitates and allows future projects to learn from successes/mistakes and share with others. Managing knowledge should be a core precept of the philosophy of an enterprise as we prepare ourselves for the Information Age. The upsurge of KM is real, and it will have enormous value-added benefits if implemented properly thus creating upliftment of the enterprise. As Tom Stewart of Fortune and Karl-Erik Sveiby of Australia suggest, intangible assets and which are not just measurable ones, shall form the new wealth of the organization. With AI incorporated into the system, it fosters an efficient pathway for employees to access knowledge and information at a faster pace.

It is however concluded that AI systems can be framed and utilized to assist along with the KM processes that have been already implemented by businesses. Through this study, we try to come to throw light on despite AI not been adopted in several organizations due to strong reasons like heavy investments at the start, hesitation as they are unaware of its full benefits, and how it could boost KM within the organization.

KM is not undergoing a revolutionary change in 2020 and albeit that, it is still collaborative in an increasingly digitized workspace and is a vital part of growing business organizations for its survival in times of crisis. Through learning, to use all

available teamwork, communication methodologies, and project management more effectively, apart from that there is limited utilization of meagre emerging technologies like AI, knowledge workers and visual display of data is continuing to play a significant role in an organization.

Finally, there remains considerable space for future research and development, most importantly paving way for a novel range of intelligent assistant systems that entirely embody the various processes and the criteria outlined in the definition of the extended value-cycle of knowledge. This gives prominence to KM in building a structure for the technological approach that has historically underpinned an expanse of AI. Such work is likely to take the form of qualitative research to evaluate the level and the category of AI that is currently or potentially used in the application of KM, with the ability of the EKVAC model to capture that use. Such studies may also be adversely extended to a quantitative level to look at managerial alternatives and estimates of time, price, and profit that is associated along with the concerning levels of the know-how cost-cycle.

Future research should focus more on the conceptualization being worthwhile for most of the organizations as a framework for further debate for those who would want to apply and expand these ideas in broader empirical contexts can be considered. Also, **i**t could be helpful if a model canvas of implementing AI to benefit KM within organizations is facilitated for identifying the difference between the business processes without AI for KM and with AI being used to assist KM and also finding the relationship between the two. To gain more insight after a literature synthesis and bibliometric analysis as presented in the current study, it would be beneficial to explore the implementation of AI in a few organizations as a case study to establish the results of barriers and benefits on the use of AI to support KM within that organization. This will allow rich and deeper insights within the field areas.

Disclosure statement

No potential conflict of interest was reported by the authors.

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