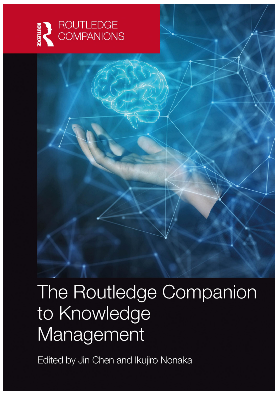

The Routledge Companion to Knowledge Management

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Artificial Intelligence-Enabled Knowledge Management

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ARTIFICIAL INTELLIGENCE-ENABLED KNOWLEDGE MANAGEMENT

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Introduction

Due to human-like thought and action, AI technologies have made tremendous changes in all aspects of production and life, including knowledge management (KM). KM is widely acknowledged by various organizations around the world, as a kind of activity to explore the principles of knowledge activities within or between organizations, which helps to comprehensively manage organizational knowledge (Alavi & Leidner, 2001; Nonaka & Peltokorpi, 2006). With the development of AI technologies, it seems to be very accessible to acquire knowledge, control knowledge activities, and even identify potential needs (Faraj et al., 2018; Faraj et al., 2016). Besides, AI technologies help process data, such as text, images, and videos, enabling which to share and exchange knowledge without interruption and hindrance (Yan et al., 2018). AI can also adapt to new situations, detect and infer models.

There is significant meaning in paying attention to AI-enabled KM. For example, there is much unstructured data with high value in the digital age, which is difficult to identify in traditional KM (Khan & Vorley, 2017). With the breakthrough of AI, organizations can even quantify accurately the various stages of knowledge creation (KC), so as to deeply analyse the current situation of organizational KC and prepare for the future in advance. In addition, AI has the abilities of learning, reasoning, memory, and decision-making (Andersen & Ingram Bogusz, 2019; Leicht-Deobald et al., 2019). It will expand the knowledge reuse and innovation in the process of KM (Huang & Zhang, 2016).

This chapter is organized as follows: First, we describe the relevant background of AI and KM, including the related concepts of AI, the development stage of KM and new phenomenon of AI-enabled KM. Second, we explain the dual influence of AI on KM, including positive and negative effects of AI on KM. Next, we point out the future research trends of AI-enabled KM, including the study of new questions, new technologies/mechanisms, and new theories. The final section comprises the conclusion of this chapter.

AI and KM

AI and Algorithm Technologies

The conception of AI was first proposed in 1955, which means, all aspects of learning or any other characteristics of intelligence can in principle be accurately described, so that machines

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can be made to simulate it (McCarthy et al., 2006). Nowadays, massive amounts of data from enterprises, governments, and society make data available everywhere; the self-learning capabilities of machines (such as deep learning) are constantly increasing, and as a result, the capabilities of AI are also constantly being improved. These three forces promote each other and promote the rapid development of AI (Anthes, 2017).

AI is an interdisciplinary scientific field that intersects with psychology, linguistics, mathematical methods, and computer science (Bobrow & Stefik, 1986; Sokolov, 2019). Therefore, AI has different definitions in different subject areas. For example, in management research, AI is regarded as a new generation of technology that can interact with the environment in the following ways: (a) collect information from outside (including natural language) or other computer systems; (b) interpret information, recognize patterns, summarize rules, or predict events; (c) produce results, answer questions, or issue instructions to other systems; (d) evaluate the results of their actions and improve their decision-making systems to achieve specific goals (Ferras-Hernandez, 2018). Since the environment that stimulates functions of AI is usually highly complex and partially random, the behaviour of AI is uncertain and complex, and has multiple levels (Glikson & Woolley, 2020). The decision-making process of AI is usually opaque (Danks & London, 2017). It means that decisions made by AI may be difficult to predict, and the logic behind each decision is often difficult to understand.

There are three ways of AI presented to humans, which are AI-enabled robots, AI-enabled virtual agents, and embedded AI (Glikson & Woolley, 2020). First of all, AI-enabled robots may have multiple functions with different mechanical or human-like representations. And they can perform social-oriented mechanical tasks orderly. Second, an AI-enabled virtual agent is a representation is one in the AI does not exist in physical form but in a unique identity, such as a chatbot (Ben Mimoun, Poncin, & Garnier, 2012). This virtual representation can exist on any electronic device and can have features, such as face, body, voice, or text capabilities. Besides, this type of AI is used commercially today, and there are lots of empirical researches on interface design. At last, embedded AI is invisible to the user, which means it has no visual representation or unique identity. It can be embedded in different types of applications, such as search engines or GPS maps, and people may not be aware of its existence.

Development Tendency of KM

At present, the three stages of the KM development process and their comparisons are shown in Table 11.1.

According to Table 11.1, in the KM1.0 era, knowledge resources were abundant for most organizations, so the focus of KM was mainly on how to effectively manage it and promote KC (Nonaka, 1994). With the rapid development of Internet technology and globalization, KM entered the era of 2.0. It was no longer sufficient to only focus on KM within the organizations. It's also necessary to use Internet technology to effectively utilize global knowledge outside the organizations (Bell & Loane, 2010; Provost & Fawcett, 2013). In recent years, big data has brought new trends in the global economy, which is digital transformation. Traditional knowledge and innovation activities have undergone major changes, and KM has been in the 3.0 era. With the development of AI technologies, acquiring and using the knowledge implicit in different types of data began to become research hotspots (Jin et al., 2015). There are a lot of uncertainties in the KM 3.0 era, for example, the uncertainty of the process of KC, the uncertainty of knowledge acquisition channels, the uncertainty of knowledge partners and mechanisms (Wang et al., 2020). The emergence of AI will match

Table 11.1 Development tendency of KM 1.0, KM 2.0, and KM 3.0

The development process of KM	*Characteristics*	*Background*	*Research focus*
KM1.0	Knowledge management within the organizations	Knowledge creation theories of famous companies in Europe, US, and Japan	Knowledge creation, sharing, and storage process within organizations
KM2.0	Global knowledge transferring	Internet and globalization	Improve the efficiency of global knowledge transfer and cooperation through information technologies
KM3.0	Artificial intelligence (AI)-enabled knowledge management	Digital transformation; reverse globalization trends	Deep mining and micro mechanisms of the knowledge creation process driven by AI

Source: Adapted from Wang et al. (2020).

the best modern technologies to the KM process and assist its development (Ordóñez de Pablos & Lytras, 2018). Therefore, the main characteristic of this era is AI-enabled KM.

Specifically, AI brings huge possibilities to solve the problems faced by the KM 3.0 era (Wang et al., 2020), as follows:

AI drives knowledge creation process. In this stage of KM, people have to constantly search the knowledge they want, as simply sharing the existing knowledge resource management may no longer meet the needs of KM. Only combining the advanced AI technical methods, various process of KC can be effectively predicted and managed.

AI promotes rich knowledge acquisition platforms. In the era of KM 3.0, the trend of reverse globalization has made knowledge transfer between multinational companies more difficult (Kuang et al., 2019). Yet on the flip side, AI technologies promote the use of a large number of open communities and communication platforms by people, and provide rich knowledge acquisition platforms (Eseryel, 2014). The developing countries in the world, especially China, have begun to consider vigorously developing crowdsourcing or other open innovation models to stimulate knowledge innovation in the future.

AI helps build knowledge cooperation mechanism and identify knowledge partners. In the KM 3.0 era, it is crucial to find accurately the knowledge partners distributed all over the world. However, most small and micro enterprises cannot obtain the necessary information support, which prevents them from accurately matching knowledge partners and not merely conducive to their further development. Due to the low-cost characteristics of AI technologies, it can help establish good and efficient models for these disadvantaged companies to carry out knowledge sharing activities (Teodoridis, 2018).

AI accelerates digital transformation. The emergence of big data technology has effectively improved the status quo of enterprise KM. But enterprises are still facing many inevitable problems at present, such as the slowdown of overall economic growth, more personalized customer demand, and intensified industry competition (Wang et al., 2020). Digital transformation can effectively alleviate these thorny problems (Bharadwaj et al., 2013; Khanagha et al., 2014). The essence of digital transformation is that enterprises need to carry out business transformation according to their own equipment, capital, and other conditions (Vial, 2019). AI can help enterprises become intelligent and have the core competitiveness against other enterprises in the context of big data, thereby achieving the acceleration of digital transformation (Magistretti et al., 2019).

New Phenomena in AI-Enabled KM

Many new phenomena are generated in AI-enabled KM. For example, not only does the traditional KM scene change within the organization, but also new knowledge scenes are generated outside the organizations (Chae, 2019). With the advent of the AI age, many companies are following the strategy of digital transformation, simultaneously proposing numerous AI platforms such as digital communities, intelligent talent management systems, and intelligent recruitment systems (Yablonsky, 2020). Many intelligent systems and AI technologies have changed the internal environment of the organizations. It will have huge impacts on the process and effects of KM. In the digital age, the knowledge within the organizations is rich in the characteristics of big data. There is a large amount of organizational knowledge, and the growth of data is exponential. Moreover, there are various forms of organizational knowledge, such as semi-structured and unstructured text and images. The change of organizational knowledge is rapid, and the generation of new knowledge can be completed in a very short time. Through enhancing firms' knowledge search and knowledge reuse, AI-enabled KM benefit firms' innovation performance (Ruan & Chen, 2017).

In the age of AI, many advanced information and communication technologies have been developed outside the enterprises, forming many new virtual interactive communities, such as social Q&A sites, digital enterprise social media, and online communities with AI functions (Barker, 2015; Kaba & Ramaiah, 2017). These online communities may contain high-quality group tacit knowledge. Once they are converted into organizational knowledge, it will be beneficial to the development of organizations (Erden et al., 2008). In a specific dynamic environment, knowledge can be created and refined into wisdom (Nonaka & Toyama, 2007; Nonaka et al., 2018). And the stronger the resource integration ability, the more opportunities organizations have to gain a core competitive advantage (Nonaka et al., 1996). Under the influence of these new interactive activities, KC will have a certain degree of change.

Knowledge creation has been the main topic of concern in AI-enabled KM research due to its significant impact, yet there are still gaps in AI-enabled KC (Alavi & Leidner, 2001; Eseryel, 2014; Kane et al., 2014; Nonaka & Peltokorpi, 2006). For example, the theoretical understanding of KM empowered by AI needs to be improved. After Nonaka put forward the KC theory-SECI model, he proposed the concept of the KC scene – 'Ba'. He believes that tacit knowledge needs to be continuously interacted in a specific social scene to create new knowledge (Corno et al., 1999; Nonaka & Konno, 1998; Nonaka et al., 2000; Peltokorpi et al., 2007). Later, some scholars discovered that 'Ba' can exist in a virtual team or community, providing a social scene for KC (Martin-Niemi & Greatbanks, 2010). However, the KC process may be different in different social scenarios (Nonaka et al., 2014; Nonaka & Krogh, 2009; Nonaka et al., 2006; Zhao et al., 2018). However, current research has not extended to the change of the KC theory yet, and the understanding of KM enabled by AI needs to be improved. The current KM practice that focuses on managing explicit data and information technology is not enough, and tacit knowledge, such as subjective insights or emotions, must also be considered (Nonaka et al., 1998). However, it is difficult to achieve it through traditional manual ways and simple management systems in the organization. Thus some scholars turned to new situations such as community-based KC or learning in open source communities (Hemetsberger & Reinhardt, 2006; Lee & Cole, 2003). From the perspective of participants, scholars also studied the influence of communication behaviour, individual characteristics, feedback characteristics, and many other behaviours such as turnover on KC in virtual environments (Majchrzak & Malhotra, 2016; Ransbotham & Kane, 2011). Nevertheless, these studies only reveal the sociality and the re-practice of KC in the virtual environment, and there are still gaps in explaining specific KC processes in AI environments.

Dual Influence of AI on KM

AI has a dual influence on KM. On the one hand, due to the maturity of data mining and neural network technology based on big data, AI can help people search for knowledge more effectively and improve the efficiency of KM. For example, Starbucks has developed a smartphone app which is essentially a question answering robot, which can effectively improve the efficiency of counter service staff and improve customers' satisfaction with the company by saving on their wait time (Warnick, 2020). On the other hand, since most of the algorithm systems involved in AI are regarded as proprietary technology property rights, AI is unexplainable and not transparent, which further brings puzzling moral and ethical issues. For instance, ProPublica (an authoritative and nonprofit newsroom in the US) once analysed a system that can predict the possibility of criminals committing a crime again, but found that the system discriminated against blacks while helping judges make more correct judgements (Larson et al., 2016).

AI Improves the Efficacy of KM

AI can integrate explicit knowledge effectively and improve the utilization of knowledge. It is because AI can not only accurately identify static features, such as text and pictures, but also accurately identify and capture dynamic features, such as body language. Through data mining technology, people can find and effectively integrate their related explicit knowledge (Dick Stenmark, 2015). And AI technologies, such as machine learning, can process and analyse explicit knowledge efficiently and generate new knowledge (Peltokorpi et al., 2007).

AI can also help analyse large-scale and multi-dimensional data to mine potential knowledge. After acquiring data, the main problem people face is how to analyse these massive amounts of data and obtain results to assist decision-making. Thus the accuracy and timeliness of the entire process are crucial. Traditional data analysis technologies can no longer meet the huge data volume analysis requirements. Yet, natural language processing, deep learning, or other AI-related technologies can simplify data efficiently process data from multiple dimensions and perform predictive analysis on data. AI turns data into information and then knowledge, which becomes an essential core competence of an organization (Hu et al., 2018). In other words, AI improves the possibility and efficiency of discovering tacit knowledge, lays the knowledge foundation for KM, constructs multiple knowledge acquisition channels, and ultimately promotes knowledge exchange between organizations. For example, expert systems based on neural networks and other AI technologies can effectively transform tacit knowledge into explicit knowledge (Tan et al., 2010).

Social and Ethical Issues Related to AI-Enabled KM

While AI improves efficiency and effectiveness, it also eliminates the transparency, interpretability, predictability, teachability, and auditability of machine behaviour, and hides it in opaque and unexplainable methods (van der Waa et al., 2020). Not only the participants do not know the logic of programs, but even the creators of the programs do not know it. When people and algorithms participate in the KM process as different decision-making bodies, algorithms must also comply with some moral rules as the decision-making body (Martin, 2019). Ethics refers to the philosophy of dealing with human values, right and wrong behaviour, and good or bad motivations (Leicht-Deobald et al., 2019). Management ethics refers to the active fulfilment of obligations and responsibilities to stakeholders, such as investors, employees, customers, governments, and society, with regard to the operations of the management in high compatibility with social ethics (Woods & Lamond, 2011). The ethical risks of AI and algorithm technologies are mainly reflected in the fact that while AI improves efficiency and improves results, it also raises privacy and interpretative questions (Mujtaba & Mahapatra, 2019). As AI and algorithm technologies make more and more important decisions for humans, the transparency and predictability of decision-making is likely to become difficult. In addition, intelligent machines based on data-driven learning algorithms are prone to biased and discriminatory decision-making, which violates human ethics and values (Leicht-Deobald et al., 2019). Therefore, once humans lose control of AI, the consequences will be serious, such as large-scale social problems (Mujtaba & Mahapatra, 2019).

Future Research Tendency of AI-Enabled KM

Based on the above introduction and discussion of AI-enabled KM, this section outlines possible future research trends. First, we put forward the questions that require urgent attention in three aspects: tacit KM, knowledge network, and personalized knowledge. Second, we describe several new technologies or mechanisms, to respond to these questions from a technical point of view. Finally, we put forward new theoretical directions and try to study these issues from the heuristic perspective of theories. That is, Human-AI collaborative knowledge management systems (KMSs) should be established from a technical perspective and AI-enabled KC theories should be built from a management perspective.

New Research Questions

Question 1: How to facilitate tacit KM?

Explicit knowledge refers to the knowledge fully expressed by human beings (such as language, mathematical formula). People know their tacit knowledge, but it is not easy to describe it through personal experience (Q. Huang et al., 2011; P. M. Leonardi & Bailey, 2008). In the past, the focus with regard to knowledge in enterprises was on explicit knowledge. Actually, tacit knowledge plays an important role in maintaining competitive advantage and continuous KC of enterprises (Chen et al., 2021). According to the SECI theory, the mutual conversion of tacit knowledge and explicit knowledge can create new knowledge (Nonaka, 1994). And it can be transformed into valuable knowledge assets through appropriate management and leadership approaches (von Krogh et al., 2012). Many literatures emphasize that tacit knowledge can not only make innovation successful, but also bring new scientific discoveries to support strategic decision-making (Nonaka & von Krogh, 2009). Therefore, how to accurately acquire knowledge and convert tacit knowledge for use in organizations is a key challenge (Kawamura and Nonaka, 2016).

How to use the advantages of AI to process and analyse information to identify and mine tacit knowledge is an important issue. Tacit knowledge is difficult to be captured, so some scholars believe that only by showing it can we better discover, preserve, and spread it (Erden et al., 2008; Nonaka & von Krogh, 2009). But the possibility of failure in this process is very high and it is not easy to achieve. Nonaka and Takeuchi (2011) believe that through analogy and metaphor in social interaction, tacit knowledge can be gradually familiarized by people through the process of externalization. Tacit knowledge can only be used after this process, and experimental cooperation among designers is usually related to the emergence and dissemination of it (Nonaka, 1994). In the digital age, knowledge within organizations is rich in the characteristics of big data. There is a large amount of organizational knowledge, and the growth of data is exponential (Ruan & Chen, 2017). Thus, the externalization of tacit knowledge in AI environments becomes obvious, and the types of knowledge continue to increase and appear on various digital platforms, etc. For example, when people find experts with professional knowledge in specific fields within or among organizations, AI technologies can record the experience and ideas of these experts, thereby forming a knowledge base. And the next time people encounter similar problems, AI technologies can use corresponding solutions to solve problems faster. Thus, tacit knowledge is transformed into explicit knowledge and can be managed easily.

Question 2: How to Build an Intelligent Knowledge Network?

Nonaka's SECI theory interprets the process of how to integrate internal knowledge resources from the perspective of creating information and knowledge (Corno et al., 1999; Krogh et al., 1997; Nonaka & Yamanouchi, 1989). This kind of knowledge can be understood as the category of domain knowledge. There is another kind of knowledge, which also plays an important role in KM, which is meta-knowledge (Engelbrecht et al., 2019). Early research has not formed a unified definition of meta-knowledge, but it is generally believed that meta-knowledge is the knowledge about knowledge, which describes the content, structure, and general characteristics of known knowledge. Meta-knowledge is the memory with location and tag information about other members (Ren et al., 2011). Later, according to Leonardi (2015), meta-knowledge is defined as the accuracy of who knows who and who knows what. Since then, the definition of meta-knowledge has gradually become clear, and its connotation and extension are basically determined.

Meta-knowledge is a very important knowledge structure for individuals (Engelbrecht et al., 2019). Many studies have shown that the meta-knowledge of individuals like professional managers is usually incomplete (Foss & Jensen, 2019). The increase of meta-knowledge can help enhance their understanding of team members' knowledge and skills, thereby assigning tasks to team members in a more reasonable way. So team members can perform their respective responsibilities and improve the efficiency of remote office and collaborative learning.

In the AI environments, social network extensions are greatly improved. Thus, knowledge networks have become intersected, fragmented, and complicated, and the identification and measurement of meta-knowledge become more difficult. Many companies encourage workers to use online social platforms when they are not easily in contact with others, which can enhance mutual understanding among employees (Engelbrecht et al., 2019). Interactions with people of various knowledge capabilities can enhance the capacity of individuals to define a situation or problem, and apply their own knowledge to the required action and specifically solve problems (Ikujiro Nonaka et al., 2006). Besides, the use of AI technologies can capture the trajectory of people's use on digital social platforms, and identify and improve meta-knowledge networks by mining communication networks between people. Thereby, it will help manage people's fragmented knowledge and build effective knowledge networks.

Question 3: How to Design Personalized Knowledge Recommendation Systems?

Differentiated knowledge refers to the specialized knowledge possessed by individuals or organizations (Barley et al., 2018). The main goal of maintaining differentiated knowledge in the organizations is to enable organizations to retain broader knowledge and protect different forms of knowledge to provide them with a competitive advantage. It can promote important organizational processes, such as coordinating actions, supporting organizational learning and adaptation, and stimulating innovation (Barley et al., 2018). The process of creating differentiated knowledge is also the process in which an organization highlights its particularity and specialization. Differentiated knowledge that belongs to organizations or individuals are extracted from the knowledge shared by organizations to complete specific tasks. Individuals or organizational units will use this knowledge in novel ways to apply or develop in order to engage in other specific tasks, namely the production of new knowledge and the creation of value. So, the creation of differentiated knowledge is the ultimate goal of KM (Barley et al., 2018).

In the past, with regard to enterprises, the management process of differentiated knowledge focuses on dealing with the conflict of individual knowledge among employees (Barley et al., 2018; Faraj & Xiao, 2006). Although there are many kinds of knowledge in enterprises, the discovery of differentiated knowledge is lacking. And it is difficult to achieve the efficient use of differentiated knowledge. However, differentiated knowledge becomes measurable in AI environments. It's closely related to the appearance and wide application of a personalized knowledge recommendation system. This kind of system has the characteristics of initiative and timeliness, involving a variety of technologies, among which the data mining technology and collaborative filtering technology are relatively more applied. For example, this kind of system will be developed according to collaborative filtering technology and content-based technology, which can not only provide users with matching documents but also establish close contact with relevant knowledge owners, so as to achieve long-term progress (Wang & Chang, 2007). Personalized knowledge recommendation system can not only collect individual performance, individual characteristics, and other knowledge, but also adjust recommendations according to these data, so as to achieve efficient KM. For enterprises, the management of differentiated knowledge not only has to deal with the conflicts of individual knowledge, that is, to meet the needs of the individual; it also needs to be considered from an organizational level, such as organizational strategic goals. Therefore, how to make personalized knowledge recommendation from the perspective of multi-agent needs is an important issue (Wang et al., 2020).

New Technologies and Mechanisms

New Technologies – Knowledge Tracing

Initially, knowledge tracing refers to a technology that models the learners' knowledge mastery based on learners' past answering conditions, so as to obtain the current knowledge state of the students (Corbett & Anderson, 1994). It aims at predicting accurately the learners' mastery of various knowledge concepts and the performance of learners' learning behaviour in the future. In a further abstract expression, knowledge tracing refers to an empirical statistical model based on past behaviours (Romer, 1990). Through extensive training of the model, it can clearly show the current state of the subject, thereby providing part of the basis for predicting specific classification content and inferring future performance behaviour. What's more, it's a process of dynamic interaction. The model obtains information from the subject and composes its own prediction mechanism, and then infers the subject's development status through this prediction mechanism. This kind of model composed of information from the same object can produce future predictions after analysing existing information to influence the source of the information.

Knowledge tracing can help improve tacit knowledge and differentiated knowledge. For instance, it is difficult to track the knowledge status of each learner in the face of a growing group of learners. That is, for the knowledge supplier, it is impossible to determine the demand status of the knowledge demander. So there are difficulties in providing knowledge training and guidance. Knowledge tracing is currently widely used in online learning systems to accurately predict learners' performance and assess ability levels. Similarly, this technique can be applied to employee training. This is an important part of employees' personal KM.

In organizations, when training employees with the help of KMS, such as digital online learning platforms, knowledge tracing technologies can be used to evaluate employees' learning and ability levels, thereby improving the level of employees' differentiated knowledge. In other words, AI-based knowledge tracing technologies can automatically trace the learner's knowledge mastery, and trace the real-time status and changes of the learner's tacit knowledge. This will then dig out the learning rules and make it better to provide personalized knowledge recommendations. On the one hand, it can provide an analysis of the knowledge mastery based on model construction, so that the education provider or the system itself has a more comprehensive understanding of each learner. Thereby they can judge the learner's knowledge weaknesses based on this analysis, and provide more efficient feedback on learning path and resources. On the other hand, learners can also train the system in a targeted manner, so as to deeply mine the resource library, fully schedule the resources in the system, and realize the special knowledge needs of learners.

New Technologies: Knowledge Graph

Knowledge graph was first formally proposed as a concept in 2012, aiming at improving the functions of search engines (Nickel, Murphy, et al., 2016). Although the definition is controversial, knowledge graph can be regarded as a knowledge network constructed based on the semantic database of entities (Qi et al., 2017). And the semantic database is essentially a graph-based data structure for storing knowledge.

Compared with the earlier semantic network, knowledge graph has its own characteristics (Nickel, Rosasco, et al., 2016; Qi et al., 2017). Above all, the knowledge graph focuses on the relationship between entities and their attribute values. First, knowledge graphs have conceptual hierarchical relationships, but the number of these relationships is much smaller than the number of relationships between entities. Second, an important source of knowledge graph is encyclopedia, especially the semi-structured data extraction in encyclopedia. Encyclopedia acquires high-value knowledge as kernel knowledge, using knowledge mining tools to quickly build a large-scale, high-value knowledge graph. Third, the construction of the knowledge graph focuses on solving the knowledge fusion and data cleaning technology from different sources.

Taking advantage of knowledge graph technologies can help extract fragmented knowledge, tap tacit knowledge, and discover connections between various sources of knowledge. Based on the above characteristics, knowledge graph can refine knowledge from heterogeneous multi-layer structure data and information by using AI technologies, such as machine learning, to build a graphical knowledge base (Nickel, Murphy, et al., 2016). It can be seen that an important value of knowledge graphs is to extract useful information from massive amounts of data, and aggregate scattered information fragments, and organize them together in the form of graphs to become relatively reference information and insightful knowledge to aid decision-making. Therefore, for KM, knowledge graph technology can better dig out the explicit and implicit value of knowledge. For example, it can be used in knowledge search, knowledge question and answer, knowledge recommendation, etc.

New Mechanisms – Knowledge Spillover

Knowledge spillover was a way of knowledge diffusion (Feldman & Kelley, 2006). Romer (1990) proposed a knowledge spillover model, which is used to explain the knowledge produced by any manufacturer can increase the productivity of the whole society. It is manifested that the change of any individual knowledge increases the scale of the overall knowledge, which is realized through the influence of the knowledge of a certain unit on the knowledge change of the surrounding unit body. In a broader way, knowledge spillover can be expressed as a product's own output leading to changes in the surrounding environment, and this environmental change is reflected in the corresponding increase in the output of other similar products in the environment, that is, product promote changes in the scale of products of the same species and different genera. Jaffe (1986) originally introduced the process of knowledge spillover into the knowledge process, and linked this process with the impact that corporate knowledge may have on its industry. Knowledge spillover contributes to the diffusion and re-creation of knowledge.

Knowledge spillover has a high spontaneity in daily life, so it does not need to be promoted by related parties to a greater extent. But to deconstruct this effect, it can be found that the knowledge spillover effect is essentially an indirect promotion under the influence of the environment. The following examples can help understand the process of knowledge spillover. Governments in some regions may set up R&D subsidies to encourage companies in different industries in the market to promote their own R&D, enhance market vitality, and speed up technological progress. When some companies have won awards, other companies that have not received funding in the industry have also increased their own funds from other sources (Feldman & Kelley, 2006). These funds are the performance of companies seeking breakthroughs, and at the same time, they make the R&D projects of these companies classified as environmental more feasible. In other words, companies that receive government subsidies have knowledge spillover effects on other companies in the industry. It can be seen that knowledge spillover not only promotes the diffusion of knowledge, but also helps promote the development of organizational innovation activities.

The development of AI technologies makes the knowledge spillover effect more obvious and measurable. As large-scale social networks are becoming more common, the scale of knowledge networks has also expanded. In this case, the knowledge spillover effect will become more obvious. In addition, due to the development of virtual AI, such as robots, the carrier of knowledge spillover is no longer limited to communication between people, but can also be spread through explicit machine language (Gu & Li, 2020). What's more, AI can accelerate enterprise KC and technology spillover, improve organizational learning and knowledge absorption capabilities, and bring technological innovation to enterprises (Liu et al., 2020). Therefore, even if AI is applied in a few companies, it will undoubtedly promote the KM level of the entire industry.

New Theories

Technical Perspective: Human-Machine Collaborative KMS

From a technical perspective, in order to better promote tacit knowledge, build intelligent knowledge networks, and promote differentiated knowledge, human-machine collaborative KMS can be built. Enterprises usually use KMS to mine and manage user knowledge and the emergence of AI makes KMS more intelligent. It can transfer information between human and machine intelligence through logical algorithm, and transform knowledge (Alavi & Leidner, 2001). This kind of human-machine collaborative KMS can not only store a large amount of data, but also perform efficient calculations, logical predictions, adjustments, and optimization decisions, and meet the requirements of current KM. However, in the digital age, the design of KMS has become more and more complicated. Due to the opacity and other characteristics of AI, the system can easily exceed human reasoning and analysis capabilities and lose control. For example, there is an algorithmic ethics problem. Therefore, how to establish a KMS based on human-machine collaboration from the perspective of design science has become very important.

The goal of design science is to improve the human condition by shaping IS solutions (Gregor & Hevner, 2013). The application of AI in the design of socio-technical systems often creates complex (opaque) solutions to important research challenges. Intelligent control means knowing all levels of system behaviour in all use cases. Therefore, it is necessary to design the rules of human-machine common behaviour in KMS not only according to the development law and evolution characteristics of AI, but also to meet the needs of humans and society. In addition, after discovering system problems and deficiencies, it is necessary to continuously iteratively update, so as to effectively design a KMS based on human-machine collaboration.

Management Perspective: AI-Enabled Knowledge Creation Theory

From a management perspective, new theories can be built to further explore the questions discussed above, for AI is changing the variables, mechanisms, and boundaries of KC (Avdeenko et al., 2016; Fowler, 2000; Pee et al., 2019). In the era of AI, tacit knowledge is no longer just a concept, it may also become variables that can be identified and measured, and it is constantly being explored and expanded. The essence of the KC process is the mutual transformation of different kinds of knowledge when people interact with others (Nonaka & Toyama, 2003). The rapid advancement of algorithm technologies undoubtedly provides excellent tools for mining deep-level information in data and efficiently using knowledge. As mentioned above, tacit knowledge can be visualized through knowledge graph technologies, and real-time changes of tacit knowledge can be measured through knowledge tracing. The research of Stenmark (2000) who attempted to exploit tacit knowledge using recommender systems is a good example. Meta-knowledge can also reflect the level of tacit knowledge to a certain extent. Therefore, it can be further explored in the direction of measurement and visualization of tacit knowledge constructs.

Second, new mechanisms can be explored to build the process of AI-enabled KC. Given the process of KC will become more rapid and even predictable, its development may have a state of leaps and mutations. For example, the ubiquitous social network makes every stage of KC have a social characteristic. With the help of algorithm tools, we can accurately identify the various information, quantify the various stages of KC, and better grasp the process of KC. For example, AI technologies can accelerate the process of KC through reconstructing the knowledge network, thus achieving a breakthrough in innovation (Kneeland et al., 2020).

Finally, it is possible to explore the boundaries of KC in different scenarios, for the reason that the boundaries of KC have become blurred, due to the creation of multiple AI-enabled knowledge scenarios. For example, some open innovation platforms with large-scale users are using digital technologies to gather collective wisdom to realize KC and innovation (Germonprez et al., 2017; Yan et al., 2018). In other words, large-scale KC has become possible. Besides, digital transformation has made the organizations more virtual, and the boundaries of KC within the organizations have also become blurred due to the introduction of AI. It makes the KM process a dynamic process, which matches the creative and adaptive aspects of dynamic capabilities, including knowledge that is constantly updated over time (Nonaka et al., 2016). Therefore, future research can also explore the process of organizational KC in new scenarios such as digitalization.

Conclusion

This chapter reviews the background of AI and KM, and elaborates what happens in the KM process under the influence of AI. The future research direction of AI-enabled KM has also been elaborated. It can be seen that KM has undergone tremendous changes due to the influence of AI technologies. It means that the role of AI in KM should not be ignored, whether in the practice or research of KM. And AI-enabled KM will become a focus of KM research in the future.

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