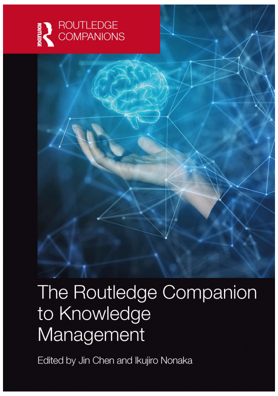

The Routledge Companion to Knowledge Management

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Knowledge Management in the Digital Economy Era

Publication details
https://test.routledgehandbooks.com/doi/10.4324/9781003112150-10
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Published online on: 23 May 2022

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KNOWLEDGE MANAGEMENT IN THE DIGITAL ECONOMY ERA

Challenges and Trends

Xiaoying Dong and Yan Yu

Tapscott (1996) initially proposed the concept of digital economy in 1996. In the late 1990s, the analyses were mainly concerned with the adoption of the Internet and early thinking about its economic impacts (with reference to the "Internet economy") (Brynjolfsson and Kahin, 2002). The recent discussion on digital economy focuses on "digitalization", which is defined as the transition of businesses through the use of digital technologies, products, and services (Brennen and Kreiss, 2014). In the United States, it is believed that digital economy relies on the e-commerce and information technology (IT) industries, which are composed of infrastructure, e-commerce process, and e-commerce trade (Henry et al., 1999). On the G20 Summit held in 2016, the Chinese government highlighted digital economy and considered it as the most important driver for innovation and economic growth in China (NSILG office, 2016). "Digital economy" was referred to as a system that uses digital knowledge and information as key production factors, information network as an important carrier, and effective use of information and communication technology (ICT) as an important driving force for efficiency improvement and economic structure optimization of economic activities. The definition of the digital economy has evolved, reflecting the rapidly changing nature of technology and its use by enterprises and consumers (Barefoot et al., 2018).

With the advancement of ICT, digital economy has become a new economic form after agricultural economy and industrial economy. Digital economy is a new engine of economic growth, which greatly reduces the cost of information search and information sharing in the transaction activities of social members and improves the output efficiency. In the new form of digital economy, knowledge will continue to be a key competitive differentiator when it comes to driving organizational performance. Figuring out how to effectively produce and manage knowledge in the digital economy era brings forth new challenges for both researchers and practitioners.

According to the UNCTAD report on digital economy in 2019, the digital economy continues to evolve at a breakneck speed, driven by the ability to collect, use, and analyze massive amounts of machine-readable information (digital data) about practically everything. These digital data arise from the digital footprints of personal, social, and business activities taking place on various digital platforms. This has been accompanied by an expansion of big data analytics, artificial intelligence (AI), cloud computing, and new business models (e.g., digital platforms). With more devices accessing the Internet, an ever-increasing

DOI: 10.4324/9781003112150-10

number of people using digital services and more value chains being digitally connected, the role of digital data and technologies is set to expand further. As a result, access to data and the ability to transform data into digital intelligence have become crucial for organizations to gain and sustain their competitiveness.

The expansion of the digital economy creates many new economic opportunities. Digital data can be used for development purposes and for solving societal problems, including those related to the SDGs (Sustainable Development Goals). Thus, data can help improve economic and social outcomes, and be a force for innovation and productivity growth. Platforms facilitate transactions and networking as well as information exchange. From a business perspective, the transformation of all sectors and markets through digitalization can foster the production of higher quality goods and services at reduced costs. Furthermore, digitalization is transforming value chains in different ways, and opening up new channels for value addition and broader structural change.

In the digital and hyperconnected era, organizations are collecting and generating a tsunami of data, but few are able to capitalize on its full potential. Technology has also spawned new ways of working that make the knowledge management (KM) transformation become more urgent. With the explosion of workforce conversations on digital collaboration tools, knowledge no longer sits in databases waiting to be accessed but flows dynamically across the digital communications channels that now define working relationships. To fit to these changes, organizations need to redefine how they promote KM to help maximize human potential at work. Data have become a new economic resource for creating and capturing value. Learning will be always in the flow of work. Organizations should leverage new technologies that can not only contextualize information, but push it through an organization's systems to teams in ways that support problem-solving and help workers innovate and uncover new insights (See Volini et al. 2020). Therefore, knowledge discovery, which aims to turn data into digital intelligence and bring organizations strategic value, is key for them to succeed. For example, Honda invested efforts in 2019 to better understand driver behavior for improving the driver experience. By using an AI tool called Watson Discovery from IBM Watson, Honda was able to create new knowledge from analyzing complaint patterns from drivers, enabling engineers to respond to quality challenges in vehicles more efficiently. This improved not only their own work experience, but the experience of Honda's customers as well (refer to Anderson, 2019). Furthermore, the power of people and machines working together offers an opportunity for knowledge creation.

Technologies-Driven Knowledge Management Paradigm Shift

Traditional KM Technologies and Systems

According to Nonaka (1994), knowledge is dynamic, since it is created in social interactions among individuals and organizations. Nonaka and Takeuchi (1995) conducted multiple impactful research on dynamic knowledge creation for competition in the leading Japanese companies. Knowledge is also context-specific, as it depends on a particular time and space. Therefore, KM is generally defined as performing the activities involved in discovering, capturing, sharing, and applying knowledge so as to enhance the impact of knowledge on goal achievement in organizations (Becerra-Fernandez et al., 2003). Technology is undoubtedly a big part of the growing need for more effective KM. Advanced technologies, new ways of working, and shifts in workforce composition are rendering traditional views of KM obsolete.

KM systems utilize a variety of KM mechanisms and technologies to support the KM processes (Alavi and Leidner, 2001; Dong et al., 2016). Technologies that support KM include data mining and AI technologies, encompassing those used for knowledge acquisition and case-based reasoning systems, online forums, computer-based simulations, databases, decision support systems, enterprise resource planning systems, expert systems, management information systems, expertise locator systems, videoconferencing, and information repositories, encompassing best practices databases, and lessons learned systems.

According to the knowledge processes, KM systems can be classified into KM discovery systems, KM capture systems, KM sharing systems, and knowledge application systems (Becerra-Fernandez et al., 2003). Knowledge discovery systems support the process of developing new tacit or explicit knowledge from data and information or from the synthesis of prior knowledge. Knowledge capture systems support the process of retrieving either explicit or tacit knowledge that resides within people, artifacts, or organizational entities. Knowledge-sharing systems support the process through which explicit or implicit knowledge is communicated to other individuals. Discussion groups or chat groups facilitate knowledge-sharing by enabling individuals to explain their knowledge to the rest of the group. Knowledge application systems support the process through which some individuals utilize knowledge possessed by other individuals without actually acquiring that knowledge.

KM systems are also related to function-based information systems that focus on managing organizational knowledge resources and processes (Alavi and Leidner, 2001). Sources of organizational knowledge can be both external and internal. The external sources consist of inter-organizational processes, competitors, suppliers/partners, and customers and competitors, while the major internal knowledge is from employees. Accordingly, the KM systems are embedded in different information systems such as competitive intelligence system (CIS), supply chain management system (SCMS), and customer relationship management system (CRMS) and enterprise portal. These are related to four important organizational functions, including competitive intelligence, supply chain management, customer relationship management, and internal knowledge-sharing, which concentrate on different sources of knowledge. Knowledge management is embedded in organizational functions, rather than remaining isolated from them. These systems capture the generic KM processes, such as creation, storage, retrieval, and representation of knowledge, and thus can be used for managing organizational knowledge, despite the fact that each of them has its own functional specificity for certain operations.

CIS supports the management of knowledge from competitors, government, and other public knowledge, and consists of systematic processes for the acquisition, analysis, interpretation, and exploitation of competitive information. It supports innovation processes by systematically managing the competitive intelligence and tracking fast changes in markets (Lemos and Porto, 1998). Similarly, SCMS and CRMS support the management of knowledge embedded in inter-organizational processes and exchanges with the firm's partners. SCMS enable a close inter-organizational collaboration, facilitate knowledge creation and sharing among supply partners, and subsequently enhance innovativeness. CRMS contributes to products or services innovation by enabling a closer connection between the firm and its customers and facilitating their interaction with the firm. While CIS, SCMS, and CRMS serve as efficient channels for acquiring and managing external knowledge, enterprise portals focus on internal knowledge. Enterprise portal integrates knowledge from multiple functions or systems, provide access to the knowledge repertoire, and facilitate communication throughout the organization, thus enabling/supporting the important KM processes within the organization such as facilitating new ideas generation. The appropriate usage of these KM systems can enhance organizational innovativeness (Yu et al., 2013).

CPS Redefining KM Systems

The advancement of IT, such as cloud computing, big data, Internet of things (IoT), mobile Internet, and AI in recent years have refined the KM systems and applications. The cyber-physical system (CPS) helps to analyze how KM systems should be reconfigured for organizations in the era of digital economy (Dai et al., 2018). The CPS is an algorithm-enabled system, in which physical and virtual components are closely intertwined, able to operate on different spatial and temporal scales, and interact with each other depending on the changing contexts. The architecture of CPS entails five layers. Different layers are supported by differential technologies, thus enabling the value chain of transforming data toward knowledge and differential capabilities (see Figure 8.1).

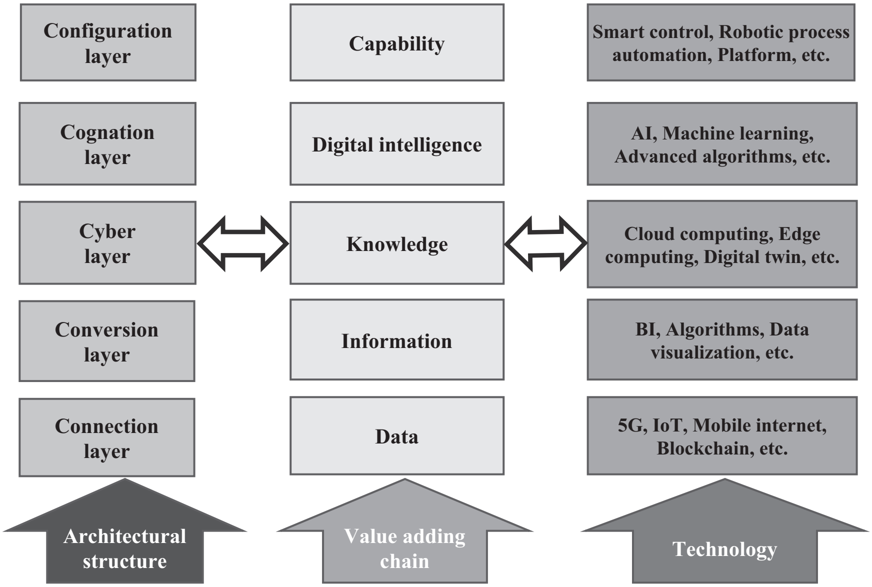

Figure 8.1 CPS Architecture-Technology along the Value-Adding Chain

(1) **The connection layer** digitizes the elements of the physical space (such as sensors, equipment, factory, process, and service), and drives the digitization of the elements and processes of the physical space, so that it has the ability of free flow and exchange in the interconnected cyberspace. The connection layer is closely related to the development of 5G, IoT, blockchains, etc. It is tightly related to data collection and storage, and further establishes the connections among the large scale of data.

(2) **The transformation layer** is to further realize the value addition of data on the basis of a large number of elements and processes in the connection layer. Data increment refers to the use of computing tools and algorithms to collect data from the connection layer. Integration, processing, analyzing, and mining help realize the transformation of data

to information. Therefore, the transformation layer is closely related to data mining and knowledge discovery.

(3) **The network layer** gathers and integrates massive data of various types and sources in cyberspace supported by cloud computing, mobile Internet, and other computing technologies. Heterogeneous digital resources interact with each other through standardized connection and heterogeneous computing methods to form a wide area data analysis basis. The aggregation of big data in the network layer breaks the information isolation between entity objects and becomes an important foundation of building digital platforms. In the network layer, knowledge, rather than data, is created and connected. Knowledge graph technologies are emerging and empower the development of a large scale of knowledge network.

(4) **The cognitive layer** uses AI and advanced algorithms to develop intelligent machines that can respond similarly as human intelligence, including natural language processing (NLP), image recognition, expert system, and deep learning. The cognitive layer can process the multi-sourced heterogeneous data (such as transaction data, user-generated data, and senor captured data) as well as knowledge (such as business rules, experience, and common knowledge). Advanced algorithms, such as machine learning and deep learning, aim to generate digital intelligence, thereby providing users with highly personalized services.

(5) **The configuration layer** entails the feedback of cyberspace information to the physical space and the guidance control of the system comprising the bidirectional interaction between the virtual world and physical world that points to the ultimate demoing market. By using preset rules and semantic norms and other control technologies, the corrective and preventive decisions made by the cognitive layer are applied to the supervised system to drive the knowledge resources to flexibly and dynamically allocate and control the underlying industrial equipment and machine components, so that the whole system has the ability of self-adaption and self-configuration. The configuration layer enables organizations to self-optimize for disturbance, self-adjust for variation, and self-configure for resilience. This is in line with the capability view of knowledge (Grant, 1996).

Box 8.1: Advanced Technologies Enabling the Digital Economy

Internet of things (IoT) refers to the growing array of Internet-connected devices, such as sensors, meters, radio frequency identification (RFID) chips, and other gadgets, that are embedded in various everyday objects enabling them to send and receive various kinds of data.

Fifth generation (5G) wireless technology is expected to be critical for IoT due to its greater ability to handle massive volumes of data. 5G networks can process around 1,000 times more data than today's systems (Afolabi et al., 2018). In particular, it offers the possibility of connecting many more devices (e.g., sensors and smart devices).

Blockchain technologies are a form of distributed ledger technologies that allow multiple parties to engage in secure, trusted transactions without any intermediary.

Cloud computing is enabled by higher Internet speeds, which have drastically reduced latency between users and far away data centers. Cloud service is transforming business models, as it reduces the need for in-house IT expertise, offers flexibility for scaling, and consistent applications rollout and maintenance (Yu et al., 2018).

Automation and robotics technologies are increasingly used in manufacturing, which could have significant impacts on employment. There are concerns that such technologies may constrain the scope for developing countries to adopt export-led manufacturing as a path to industrialization, and that the more developed economies may increasingly use robots to "reshore" manufacturing jobs.

Artificial intelligence (AI) and data analytics are enabled by the large amounts of digital data that can be analyzed to generate insights and predict behavior using algorithms, as well as by advanced computer processing power. AI is already in use in areas such as voice recognition and commercial products (such as IBM's Watson).

Digital twin consists of three distinct components, i.e., the physical product, the digital/virtual product, and connections between the two products. The connection between the physical product and the digital/virtual product is data that flow from the physical product to the digital/virtual product and information that is available from the digital/virtual product to the physical environment.

Challenges of Traditional Knowledge Management in the Digital Economy Era

Traditional KM emphasizes the process of knowledge leverage, i.e., from data to information and then to knowledge. The main activities are reflected in knowledge acquisition, processing, integration, analysis, application, and sharing. However, in the digital economy era, organizational strategy, focus, competitive approaches, value-added activities, and core knowledge appear with large changes. Traditional KM takes the organization or individual as the core, and focuses on solving the problems of knowledge acquisition, knowledge integration, knowledge application, knowledge-sharing, and knowledge creation. Among them, how to transform individual tacit knowledge into tacit and explicit knowledge at the team and organizational level, so as to improve the ability of organizational knowledge creation is the strategic goal. Traditional KM activities emphasize the influence of leaders, strategy, culture, and incentive mechanism on the effect of KM, and computer technology plays an auxiliary role. However, traditional KM encounters multiple challenges derived from the emergence of massive heterogeneous data and AI technologies in the era of digital economy. Digital data are core to all fast-emerging digital technologies, such as data analytics, AI, blockchain, IoT, cloud computing, and all Internet-based services. Data-centric business models are being adopted not only by digital platforms, but also, increasingly, by leading organizations across various sectors.

Demand for Data-driven Value Creation

Knowledge management practices are expected to result in improved productivity, improved customer and employee satisfaction, increased revenues, preparedness for AI, and effective remote work. Developing clear business value is critical for KM initiatives. In particular, the importance of proving the clear value KM offers is more important in the time of global pandemic and economic uncertainty than ever. The right KM efforts for an organization will help organizations be more agile and perform more effectively.

Business logic has changed from product dominant logic to service dominant logic (Vargo and Lusch, 2008; Vargo et al., 2010; Lusch and Nambisan, 2015; Vargo and Lusch, 2015). In the product dominant logic, enterprises impose value on commodities through a series of production activities, and then go to market to interact with consumers for product improvement. The corresponding KM practices focus on the production process and internal organization. In the service dominant logic, service is defined as "the application of specialized competences (knowledge and skills) through deeds, processes, and performances for the benefit of another entity and the entity itself" (Vargo and Lusch, 2004). Value creation is produced and completed via the proactive interaction between products/services vendors and consumers.

Interactive service shapes a process of value co-creation. Value co-creation indicates actor benefit realized from integration of resources through activities and interactions with other collaborators. Service providers offer value propositions acting as promises for stakeholders to engage in service. Value is uniquely and phenomenologically determined by service beneficiaries based on their experiences. Mining relevant knowledge from consumer data and taking it as the source of product/service innovation is crucial for value co-creation. Therefore, KM practices should expand to discover user's' potential needs in specific situations through the data-driven approach.

Demand for Heterogeneous Resource Integration

In the service dominant logic, resources are classified into operand resources and operant resources. The operand resources refer to the resources (such as land and minerals) that can be used by human beings, and their characteristics are tangible, static, and finite. Operand resources can be liquefied, unbundled, or re-bundled. Differently, operant resources refer to the resources that are capable of affecting other resources (Vargo and Lusch, 2004, 2008). Operant resources are intangible, dynamic, and infinite. The traditional economic model emphasizes the development of natural resources, such as land and material resources. In the era of digital economy, the ability to process multi-source heterogeneous data in the cyberspace has become the core competence for organizations. Barrett et al. (2015) emphasizes ITs as operant resources to enable service innovation. Advanced ITs can increase digitalization and unleash generativity to enable resource integration and create novel opportunities for value co-creation (Akaka and Vargo, 2014; Lusch and Nambisan, 2015).

Service innovation emerges when the existing resources are re-bundled or new resources are bundled to form new ways of value co-creation and develop new value (Lusch and Nambisan, 2015; Vargo and Lusch, 2015). Thus, resources integration is most important in the product/service innovation process. In a cyberspace, the integration of knowledge from different sources, structures, and characteristics will become the focus of KM. In the network layer of CPS, a large number of physical assets can be reflected and projected in cyberspace, as the so-called "digital twins". These resources are massive, diversified, volatile, heterogeneous, and so on. Leading organizations can make the large-scale and efficient integration and utilization of these resources in the cyberspace. The stronger the ability of resource integration, the greater the breadth, depth and speed of integrating resources, the higher the resource density, and the more opportunities for value co-creation among beneficiaries that can be generated. Knowledge management practices based on previous management information systems are not adequate nor competent. The advancement of AI and machine learning technologies are demanded to apply in KM practices.

Demand for Understanding the Knowledge Ecosystem and Multi-Modal Data Analytics

The increasing multi-source heterogenous data requests an improved understanding of the knowledge ecosystem, including all types of knowledge, information, and data. Organizations demand to be able to effectively capture, manage, and find everything together. Thus, KM efforts should help organizations consolidate, present, find, discover, and relate all of their different types of content (including files, data, knowledge, collaborative materials, and even people). This enables paths of discovery where an end-user can traverse content, data, and people in order to find all of the content that can help them complete their immediate mission and develop their knowledge over the longer term. The analysis and interpretation of digital assets help people understand, analyze, and make forward-looking and accurate decisions. When implementing KM practices, organizations pay more attention to how to leverage everything they have, making it easily and intuitively available to the people, connecting knowledge, and empowering people to act on the discovered knowledge.

With the integration and rapid growth of data, the capability of knowledge analysis and discovery are demanded to further improve. In the connection layer of CPS, the technology application realizes full connection, including the connection between people via social media, the connection between people and things via e-commerce platforms, the connection between things via IoT, Internet of vehicles, aeroengine data network, etc., and the connection between people and things and processes via logistics platforms. Sensors installed on physical objects can collect massive data in the product and its production process, projection of physical assets in the cyberspace to form digital twins, and present the real-time and accurate mirror images of physical objects, attributes, and states, including shape, position, state, and motion. The advancement of analytics on multi-source, multi-modal data in the cyberspace and creation of dynamic and real-time digital simulation model impose challenges to knowledge capture and discovery.

Trends of KM for Leveraging Digital Economy Development

In the era of digital economy, the importance and strategic significance of KM have been significantly recognized. Technology has a tremendous impact on KM, inspiring the development of robust platforms to leverage KM strategies. Knowledge management technologies and tools continue to evolve in response to new demands and challenges. We propose the following trends of KM development in the new era.

Change from Data Mining to Real-Time Decision-Making

Knowledge management efforts focus on initiating and realizing data-driven value creation and co-creation. Knowledge management is developed for offering decision supports to organizations. Advanced KM tools, such as dynamic digital dashboard, digital panel, and various visual tools, help employees judge, make decisions, and take countermeasures for problem-solving. Knowledge management needs to help organizations achieve their strategic objectives and better serve society. For examples, governments can effectively provide convenience services, crisis management, and social resource coordination through e-government system and smart city system; enterprises can accurately provide customized products and services to fulfill customer needs. To achieve these goals, organizations should develop data-driven decisions as organizational culture.

Change from Local Knowledge Management to Global Knowledge Management

From the architectural perspective, KM is changing from local KM to global KM at different levels of granularity. Knowledge management activities that previously developed in silos, including enterprise strategy, R&D, marketing, or production are requested to expand along the whole business processes and value chain. Also, knowledge embedded in people, equipment, processes, and activities that can be captured and analyzed at finer granularity. Therefore, organizations need to update the prior knowledge ontology and redefine the internal and external knowledge of the organizations. Knowledge ontology serves as blueprint to define the attributes and relationships of each agent in organizations.

Value Co-creation Enables Efficient Innovations in Organizations

Knowledge creation is a continuous, self-transcending process through which one transcends the boundary of the old self into a new self by acquiring a new context, a new view of the world, and new knowledge (Nonaka, 1994). The vertical and horizontal division of labor in traditional organizations has formed a large number of information silos. These silos impede knowledge dissemination and exchange, reduce knowledge-sharing efficiency, and thus result in a lower level of creativity and environmental adaptability for organizations. The digital connection in cyberspace provides unprecedented access to barrier-free knowledge flow and sharing, and creates a solid foundation for activating organizational creativity. Business insights derived from data mining and scene tracking can help organizations make quick trial and error, transform new ideas into business value, and thus continuously adapt to changing environments. In particular, large digital platform-based organizations, such as Alibaba, Tencent, and Tiktok, are able to tightly aggregate the creativity from data mining and knowledge discovery on large-scale user behaviors, as well as aggregate the demands from related stakeholders, such as product manufacturers, service providers, financial institutions, information providers, and so on. Value is co-created through the connections and interactions between consumers and relevant stakeholders, and the match between the supply side and the demand side.

Automate Unstructured Content Analysis to Drive Knowledge Discovery

Organizations are increasingly becoming insight-driven. On one hand, the development of IoT, mobile Internet, AI, and other technologies brings explosive growth of data; on the other hand, such development increases data complexity, weakens information reliability, and increases the difficulty of extracting valuable knowledge. The emerging knowledge fragmentation calls for more robust KM (Gray and Meister, 2003). Unlike structured data (tables, forms, log files), it is difficult to search for and analyze meaningful information from unstructured data. Knowledge management technologies are developed for acquiring, processing, and tagging massive unstructured content and making it available for search and analysis. The rapid development of AI technologies, such as machine learning, and NLP enables the automation processes of unstructured content analysis, including extracting entities (people, locations, companies, etc.), identifying sentiment, and categorizing topics. Therefore, the demand for AI-enabled search and analytics solutions will become more prevalent in organizations.

Build a Large-Scale Enterprise Knowledge Graph for Organization's' Intelligence

It is necessary to understand ontologies and knowledge graphs empower enterprise AI. The idea of a knowledge graph was first proposed in 2000 and developed by Google in 2012. A knowledge graph represents a collection of interlinked descriptions of entities, including objects, events, or concepts. Knowledge graphs put data in context via linking semantic metadata and, in this way, provide a framework for data integration, unification, analytics, and sharing. Foundational KM activities, such as taxonomy and tagging, content types and content cleanup, content governance, and tacit knowledge capture, are all critical to an organization's goals of connecting their knowledge, content, and data and automating ways of pushing it to the right users and assembling it for greater value and action. Enterprise knowledge graph is becoming the foundation of the navigation system to represent organizational knowledge assets in different segments, such as marketing, organizational structure, innovation, and human resources.

Traditional KM emphasizes the macro-level knowledge mapping and audit, such as developing an organizational knowledge map and competence map to reflect the knowledge asset. Knowledge objects are limited to documents and skills, and knowledge discovery is usually rule based. In the era of digital economy with massive data, organizations can use knowledge graph technology to build a large-scale, fine-grained, high-quality knowledge base. Knowledge graphs can reveal the structural relationships of people, equipment, products, and processes, and provide the support required for important decision-making, through the comprehensive use of algorithms, machine learning, graphics, information visualization technology, information retrieval, image recognition, speech recognition, and so on.

Knowledge graphs can serve as a kind of tacit knowledge elicitation and representation technology, and further establish dynamic relationships between different fields of knowledge. Knowledge graphs help to externalize the tacit knowledge of experts and transform them into organizational knowledge resources, thus helping organizations explore the value of their intellectual assets. Knowledge graphs can also enrich the knowledge-seeking experience for users. Google has pioneered question–answer capabilities in an effort to transform its "search engine" into a "knowledge engine" with the Google Knowledge Graph. The development of enterprise knowledge graphs, together with the rapid development of NLP technology, enable organizations to develop knowledge-driven intelligent businesses, such as answering highly complex questions faster and more accurately, providing innovative customer service, identifying employees for problem-solving, and predicting market trends.

Coordinate Interactions between Human and Machine Intelligence

Tacit KM has always been the difficulty and key of KM. Nonaka and other scholars (Nonaka,1994; Nonaka and Takeuchi, 1995; Nonaka et al., 2000) proposed a model of knowledge creation consisting of three elements: (i) the SECI process, including socialization, externalization, combination, internalization, for knowledge creation through conversion between tacit and explicit knowledge; (ii) ba, the shared context for knowledge creation; and (iii) knowledge assets: the input, output, and moderator of the knowledge-creating process. These three elements of knowledge creation have to interact with each other to form the knowledge spiral that creates knowledge. The SECI model emphasizes that knowledge creation can be promoted through the transformation spiral of tacit knowledge and explicit knowledge in social communication groups and situations. Tacit knowledge is shaped by the production experience, professional insight, and the practical wisdom of leader. Tacit knowledge is generated by mutual communication and collision among individual employees or groups. Tacit knowledge shapes an organization's' interpretation of the surrounding environmental changes.

In the era of digital economy, the source of tacit knowledge is further expanded into human-computer interaction. Digital twin is a real mapping of all components in the product life cycle using physical data, virtual data, and interaction data between them (Tao et al., 2019). Digital twins integrate IoT, AI, machine learning, and software analytics with spatial network graphs to create living digital simulation models that update and change as their physical counterparts change. A digital twin continuously learns and updates itself from multiple sources to represent its near real-time status, working condition, or position. This learning system learns from itself, using sensor data that conveys various aspects of its operating condition; from human experts, such as engineers with deep and relevant industry domain knowledge; from other similar machines; from other similar fleets of machines; and from the larger systems and environment of which it may be a part. A digital twin also integrates historical data from past machine usage to factor into its digital model. Therefore, digital twins foster rich human–machine interactions. As such, tacit knowledge is generated in a faster and more dynamic way, which requests robust KM to facilitate and coordinate the work between human and self-reinforcing machines.

In addition, the pandemic crisis has greatly accelerated the use of remote workers and a distributed workforce. Knowledge management should drive more effective collaboration across remote teams of workers, as well as the collaboration between workers and intelligent machines.

Concluding Remarks

In the era of digital economy, knowledge as the most important manipulative resource has become the core asset of an organization to create a competitive advantage. At the same time, we are only at the initial stage of understanding the challenges of KM with regard to concept, system, technology, and method in an era of digital economy. On the one hand, the difficulty of KM is increasing, and the requirements of users are increasing as well. The growth and dynamic changes of massive data put forward higher requirements for data acquisition and integration. Heterogeneous integration and data mining have become the key, while the accuracy, real-time, and accuracy of data to information and then to knowledge are higher. On the other hand, original KM needs to be constantly updated in technical means, and the role of human-computer interactions and AI needs to be actively explored. In order to deal with the challenges of KM in the digital economy era, more human and material resources should be invested; multi-disciplinary experts should be integrated for collaborative exploration; and KM systems and methods should be constructed to meet the requirements of the digital economy era.

Therefore, it is important for organizations to adopt agile KM that emphasizes iteration, collaboration, self-organization, and customer-centric designs. Organizations are requested to address the challenges of business and operational performance, as well as the development and implementation of a KM-based strategy in the new era.

Acknowledgment

The authors would like to acknowledge the support from the National Natural Science Foundation of China "Organizational Ambidexterity of Technology Firms: Impact of Strategic Leadership and Organizational Learning" (Grant No. 71371017) and the partial support from the National Natural Science Foundation of China (Grant No. 72172155, 91846204) and the Beijing Social Science Foundation (Grant No. 17GLC056). Dr. Yan Yu will serve as the corresponding author of this chapter.

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