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# Artificial intelligence and knowledge management: A partnership between human and AI

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**Abstract** Emerging artificial intelligence (AI) capabilities will likely pervade nearly all organizational contours and activities, including knowledge management (KM). This article aims to uncover opportunities associated with the implementation of emerging systems empowered by AI for KM. In doing so, we explicate the potential role of AI in supporting fundamental dimensions of KM: creation, storage and retrieval, sharing, and application of knowledge. We then propose practical ways to build the partnership between humans and AI in supporting organizational KM activities and provide several implications for the development and management of AI systems based on the components of people, infrastructures, and processes.


## 1. Introduction

Advancements in information technology (IT) are widely seen as catalysts for organizational change programs within the knowledge management (KM) literature (Tsui, 2005). Recent breakthroughs in deep learning have dramatically improved the capacity for algorithms to simulate human capabilities such as "seeing" (image recognition), "hearing" (voice recognition, natural language processing), and "deciding" (analytical processing; Duffy, 2019). Combined with an abundance of data and increased computational power, such artificial intelligence (AI) tools are increasingly finding their way into commercial uses (Canhoto & Clear, 2020; Kaplan & Haenlein, 2019).

These AI tools draw from various approaches to simulate human intelligence, including supervised machine learning (ML), neural networks, and deep

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learning. The most effective deep-learning algorithms often take a supervised approach, in which large amounts of labeled data are employed to train the connection strengths between nodes in a massive, layered computational network, such that patterns in the training data are used to make accurate predictions on future unseen data (Brynjolfsson & Mitchell, 2017). This approach departs from traditional KM systems, such as expert systems, which leveraged a symbolic logic in which rules were articulated and provided by humans to the system (Pushpa, 2019).

As both AI and KM are inexorably bound up with the natures of knowledge and of learning, recent advances in AI can provide new foundations for transforming KM in organizations (Sanzogni et al., 2017). There are two complementary techno-organizational orientations in this space: (1) KM, which is directly concerned with managing knowledge in organizations, and (2) AI, seen as a branch of computing, which is primarily focused on developing systems that can mimic human knowledge and learning activities.

Firms should examine the potential roles for new AI systems in supporting organizational KM activities because of the intuitive connection between the two. There are lessons to be learned from traditional rule-based KM; however, given the characteristics of contemporary deep learning as a rather different way of computing, we need fresh insight into the potential relationship between AI and KM. Thus, in this article, we envisage and identify such potentials. In doing so, we adopt a balanced perspective that does not put humans and AI in conflict but emphasizes their partnership. Hence, this perspective focuses on the partnership between humans and AI and on the unique capabilities of each for KM. In this context, deep-learning AI augments and improves people's lived experience, rather than claiming to replace or surpass human intellect.

We aim to articulate the role of AI in supporting KM; in doing so, we build on the typology of KM processes presented by Alavi and her colleagues (Alavi & Denford, 2011; Alavi & Tiwana, 2003). According to this framework, KM in organizations helps the delivery of products and services by creating, storing and retrieving, sharing, and applying knowledge. These processes are essential for an organization to learn, reflect, and develop core competencies to sustain its competitive edge in the knowledge-based economy (e.g., Davenport & Prusak, 1998).

## 2. Potential applications of AI in KM

In what follows, we discuss some potential implications of AI systems for KM (Table 1) and then broach possible ways through which a synergistic partnership between humans and artificial agents in organizational KM can be achieved.

### 2.1. Knowledge creation

The process of knowledge creation may occasionally involve developing ideas and solutions from scratch, but it more frequently amounts to a reconfiguration and recombination of already existing background knowledge. This enables organizations to adapt to new situations (Bhatt, 2001; Davenport & Prusak, 1998). Additionally, firms may acquire knowledge from external sources (Alavi & Denford, 2011). As a result, knowledge creation may take the form of knowledge acquisition through searching for or sourcing information.

The potential of deep-learning AI for knowledge creation lies in its predictive power in situations such as forecasting sales probabilities (Eitle & Buxmann, 2019). Agrawal et al. (2017, p. 23) described this facet as "the ability to take information you have and generate information you didn't previously have." As a result of this capacity to derive their own rules based on similar patterns in the data, deep-learning AI can discover patterns in the available data sets previously unknown to the organization. For instance, AI can help raise new questions and develop new sets of declarative knowledge in specific domains by connecting variables in new ways. This is only possible through self-learning analytical capacities and features for pattern recognition, which allow organizations to harness big data in unprecedented ways (Faraj et al., 2018).

As an example of the application of AI in this context, a deep-learning approach was recently employed to compute analogies between various terms in 3.3 million abstracts of materials science research articles published over 96 years (Tshitoyan et al., 2019). Not only could the algorithm independently capture complex materials science concepts (e.g., the structure of the periodic table), but it also identified unnoticed correlations of materials with promising functional applications (e.g., compounds with similar thermoelectric properties). Similar techniques can contribute to organizational KM as many organizations collect and store much more knowledge than they can use. One report estimates that 60%—70% of data collected by enterprises go unused (Gualtieri, 2016). AI capabilities can similarly help organizations find unknown and unexpected connections and insights from data sets containing interactions with customers (e.g., call

**Table 1. Potential AI applications in different KM processes**

| The KM process | Possibilities created using AI systems | Examples of use cases |
|---|---|---|
| Knowledge creation | • Fostering predictive analytics via self-learning analytical capacities<br>• Recognizing previously unknown patterns<br>• Sifting through organizational data and discovering relationships<br>• Developing new declarative knowledge | • Forecast sales probabilities<br>• Discover organization inefficiencies by analyzing CRM records |
| Knowledge storing and retrieving | • Harvesting, classifying, organizing, storing, and retrieving explicit knowledge<br>• Analyzing and filtering multiple channels of content and communication<br>• Facilitating knowledge reuse by teams and individuals | • Organize and summarize legal precedents relevant to a new case<br>• Retrieve dispersed nuggets of information related to a troubleshooting situation |
| Knowledge sharing | • Connecting people working on the same issues by fostering weak ties and know-who<br>• Facilitating collaborative intelligence and shared organizational memory<br>• Generating a comprehensive perspective on knowledge sources and bottlenecks<br>• Creating more coordinated, connected systems across organizational silos | • Facilitate feedback and peer review on communication systems (e.g., Slack)<br>• Facilitate real-time smart sharing between marketing channels and sales pipelines |
| Knowledge application | • Enhancing situated knowledge application by searching and preparing knowledge sources<br>• Offering more natural and intuitive system interfaces (e.g., voice-based assistants)<br>• Promoting equitable access to knowledge without fear of reprisal or social cost | • Find and apply question—answer pairs in online manuals to manage service knowledge<br>• Provide more human-centered and accessible applications of knowledge through chatbots |

transcripts), email exchanges, enterprise chat systems, discussions on social network sites, and records on customer relationship management (CRM) databases (Lavenda, 2019; O'Dell & Davenport, 2019).

## 2.2. Knowledge storage and retrieval

Another key function of KM is to create and maintain an organizational memory that tracks generated and acquired knowledge resources. Effective storage and retrieval strategies are one of the primary mechanisms for preserving organizational memory (Alavi & Leidner, 2001). This process is specifically focused on extracting knowledge, making it explicit, and recording it systematically for future uses, often through the implementation of knowledge repositories.

The utility of AI in KM is most evident in enhancing the storage and retrieval of explicit knowledge. Since deep-learning AI holds a constitutive relationship with big data (Brynjolfsson & McAfee, 2017), these data-driven, self-learning algorithms open new possibilities for harvesting, classifying, organizing, storing, and retrieving big data being generated in organizations, including data that were previously deemed unwieldy and difficult to parse (Paschen, Wilson, & Ferreira, 2020). For example, AI can search for, organize, and summarize previous legal precedents relevant to a new case (Bhattacharya et al., 2019). Furthermore, AI can analyze multiple channels of content and communication, generate summaries, ascertain relevant topics (to emerging problems), isolate proprietary and confidential knowledge, and present reusable insights that are immediately applicable to new situations (O'Dell & Davenport, 2019). For instance, Google's Gmail algorithms recognize implicit social groups and recommend potential email recipients when creating an email.

In this way, deep-learning AI learns from individuals' or teams' recurrent KM or communication practices (e.g., history of emails) and offers individualized solutions. For example, the system can learn over time which documents or messages to retain or to bring to the attention of the knowledge worker, as well as what customer purchase history and supply-chain issues need to be retrieved for specific troubleshooting team meetings. This output can increase productivity for many knowledge workers, who spend nearly 32 working days a year retrieving bits and pieces from various documents and spreadsheets or switching between folders in daily work practices (Lavenda, 2019).

## 2.3. Knowledge sharing

Distributing knowledge throughout the organization is a prerequisite to applying it effectively in problem-solving and decision-making. But knowledge sharing is often plagued by temporal, spatial, and, more evidently, functional barriers. As a result, in many organizations, knowledge sharing tends to be local and fragmentary. AI can contribute to breaking down these organizational silos in two ways: (1) by bringing together people who are working on the same issues but are separated by different boundaries or geographies, and (2) by creating more connected systems of coordination, which give managers a better sense of knowledge constraints.

One of the key challenges of knowledge sharing is overcoming silos to connect disparate people with the practices and knowledge that they need (Jarrahi, 2019). AI approaches can redress this by discovering and strengthening weak ties, thus facilitating community-based learning. For example, intelligent KM systems used by MITRE—a federally funded research organization in the U.S.—aggregates knowledge concerning where workers are present, when they are active, and what they are doing to proactively connect people working on similar projects or technical problems (O'Dell & Davenport, 2019). In this context, the most fundamental use of AI for knowledge sharing pertains to its contribution toward collaborative intelligence—something not attainable by traditional database systems. AI can help animate creative thinking, can create a shared memory among various team members, and can facilitate feedback and peer review. These smart features are increasingly embedded into enterprise or personal communication systems such as Slack or Yammer, providing more than just a communication channel for connecting workers.

AI systems can likewise generate dynamic social graphs that capture interconnections between people and teams to provide a comprehensive perspective about knowledge sources and bottlenecks in the organization (Jarrahi, 2019). For example, Campaign 360, offered by People.ai, enables businesses to gain real-time insight into selling opportunities created by various marketing campaigns, enabling more cohesive coordination and sharing between marketing channels and sales pipelines (Latinovic & Chatterjee, 2019). In addition, via enterprise social graphs, organizations may be able to more accurately and equitably reward sources of expertise and knowledge contribution.

## 2.4. Knowledge application

Knowledge application refers to putting knowledge into practice after it has been retrieved or shared. It often involves repackaging available knowledge resources (e.g., a set of best practices) into applicable solutions or delivering new products and services to a new context (Bhatt, 2001). Knowledge application in many cases hinges upon a reinvention process, which "is not merely about tweaking the ideas of others. [But] It requires the skillful selection, analysis, and assimilation of the right external knowledge...[matched] to the right local needs at the right time" (Cranefield & Prusak, 2016, p. 100). IT can facilitate the process of knowledge application by providing faster, more effective access to knowledge resources, as well as by codifying and automating routines that help workers apply and integrate specialized knowledge (Alavi & Leidner, 2001).

Emerging tools powered by AI, such as intelligent assistants, can enhance knowledge retrieval and representation needs for situated knowledge application (Maedche et al., 2019). This addresses one of the nontrivial challenges of knowledge repositories concerning knowledge application: "getting the right knowledge to front line workers in real-time" (Davenport, 2019). Traditional knowledge repositories are typically challenging to search through when a quick answer is needed. By contrast, intelligent assistants can make what is already known readily available for processing through AI-enabled storage/retrieval strategies, like automatic content cleaning, classification, and tagging. Repsol, a global energy and utility company, used AI to whittle 5 million crude oil production scenarios—100 million data points a day—down to a manageable group that its engineers could then evaluate. The accessibility of this timely, contextualized knowledge to its engineers helped Repsol achieve a 40%—50% reduction in nonproductive time across 30 drill sites (Ransbotham, Khodabandeh, Kiron, et al., 2020). Situated knowledge offered by AI can be particularly valuable in customer service, where a knowledge worker needs immediate access to previous cases and a summary of the issue at hand. As an example, Talla, an AI-based service knowledge automation platform, cleans up, searches through, and classifies manuals and online documentation, finding question—answer pairs to manage service knowledge (Davenport, 2019).

AI systems can also provide more interactive and intuitive interfaces that may converse with or debate the knowledge worker using everyday language. For example, natural language processing is a type of AI that enables machines like digital assistants or chatbots to understand and simulate human conversations (O'Dell & Davenport, 2019; Raghavan, 2019). These more natural and humanoid ways of interacting with the retrieval mechanisms can facilitate knowledge application. Specifically, chatbots can provide knowledge and aid in its application through a natural conversation with humans. This can reduce social barriers that impede equal access to organizational knowledge. A compelling example here comes from the use of chatbots in higher education to help students access organizational knowledge and feel more supported by the university (Agrawal, 2021). The chatbot allows students to ask questions in a casual tone, as if texting with a friend, and to receive relevant answers. Because students were interacting with a machine, rather than a human, they could ask sensitive questions about finances and mental health without fear of potential social costs.

## 3. Human—AI symbiosis in KM

As we outlined above, AI systems will likely percolate throughout the KM foundation of organizations, but it is important to bear in mind that knowledge production and management are inherently human-centered (Davenport & Prusak, 1998; Sanzogni et al., 2017). Therefore, the most effective roles assigned to AI in KM will mostly augment humans rather than replace them, thereby achieving *collaborative intelligence*, in which AI and humans enhance each other's complementary strengths (Paschen, Wilson, & Ferreira, 2020; Wilson & Daugherty, 2018). This relationship can be captured through the concept of human—AI symbiosis. In the rest of this article, we outline some potential scenarios and practical ways for building this partnership in KM (Figure 1). In Figure 1, the application of personal intelligent assistants in KM mostly concerns storing and retrieving knowledge; the discussion of specialized or general intelligence focuses on knowledge-creation processes; codification or collaboration of knowledge has to do with knowledge-sharing processes; and the discussion of know-how, know-what, and know-why is primarily about knowledge application.

### 3.1. Personal intelligent assistants and personal KM

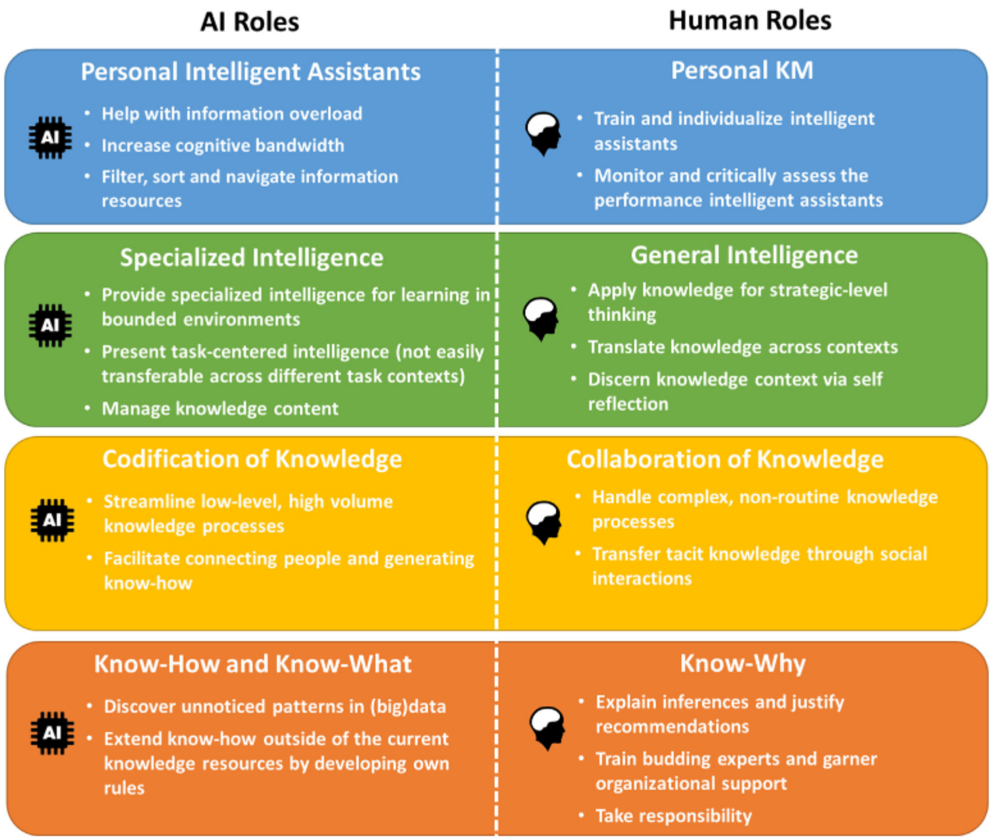
KM for organizations embodies an important dimension of personalization in which the focus is on individual workers and their "personal enquiry" (Pauleen & Gorman, 2016). For that reason, conceptualizations of knowledge often recognize the centrality of each worker in defining the concept of knowledge. For example, Davenport and Prusak (1998, p. 5) define knowledge as "a fluid mix of framed experience, values, contextual information, and expert insight that provides a framework for evaluating and incorporating new experiences and information."

An emerging genre of AI systems called personal intelligent assistants can occupy a unique position in personal KM. Information overload is one of the key challenges of the information environment for knowledge workers (Pauleen & Gorman, 2016). Personal intelligent assistants can help broaden the cognitive bandwidth of knowledge workers and change the way they digest relevant knowledge by providing more effective capabilities for processing, filtering, sorting, and navigating information resources (Maedche et al., 2019).

Personal intelligent assistants are self-learning, interactive systems that can learn and refine their interactions with the user over time. In doing so, they can learn each worker's dynamic knowledge needs, workflows, preferences, and feedback to provide individualized solutions. For example, at one financial institution, personal intelligent assistants are deployed alongside traders to assist in managing the information overload and to broaden workers' cognitive bandwidth (Ransbotham, Khodabandeh, Fehling, et al., 2020). After observing patterns in the traders' data-monitoring practices, decision-making, and results of their trades, these personal intelligent assistants learned to support traders by bringing relevant information to their attention in real time. This timely information enables better decisions on the part of the traders and represents a continually improving partnership, as the personal intelligent assistant receives additional feedback both each time a trader dismisses or acts on the information it provides and from the outcome of that trade.

Humans are still central in shaping the effectiveness of personal intelligent assistants, as these systems thrive on the worker's feedback and interaction with the information they provide. In other words, personal assistants must undergo continual training by humans to be able to display

Figure 1. A symbiotic relationship between humans and AI in managing knowledge




complex and subtle human traits (Wilson & Daugherty, 2018). After all, these tools are assistants that are designed and trained to augment individual workers, and augmentation involves a mutual learning process through which both humans and AI learn from each other and hence coevolve (Raisch & Krakowski, 2020). A heedless approach to the use of personal intelligent assistants can result in what researchers call cognitive complacency, whereby workers put too much trust in their artificial partners without mindfully analyzing the outcomes (Jarrahi, 2019).

## 3.2. Specialized intelligence versus general intelligence

AI presents specialized intelligence that enables sensing the environment, learning from experience, and creating possibilities for action in relation to specific task contexts. For example, it can store, retrieve, and analyze explicit forms of knowledge (e.g., images, text data) and sensibly respond to customer inquiries about the compatibility of their heating system with smart thermostats (e.g., Google Nest). But AI's role in KM and elsewhere is largely task-centered and cannot easily transfer across different contexts.

General intelligence remains a human-centered characteristic, as "we remain very far from artificial general intelligence. Machines cannot do the full range of tasks that humans can do" (Brynjolfsson & Mitchell, 2017 p. 1530). Specifically, the application of knowledge for strategic-level thinking and decision-making requires elements of general intelligence—which tend to be more holistic—and builds from the uniquely human prerogatives such as foresight, social and emotional intelligence, self-development, imagination, and curiosity. Strategic-level decisions can be data-driven but are rarely repetitive and mundane.

Furthermore, unlike data manipulation and information management, KM entails a crucial judgment component (Davenport & Prusak, 1998). Judgment is a profoundly human-centered capability; humans can judge a new situation, consider what is known, and decide the best course of action by holistically weighing the social and organizational ramifications of various options. Whereas AI systems provide a powerful lever for storing, retrieving, and managing knowledge content, humans are well-positioned to navigate and discern knowledge context—that is, the specific circumstances that surround the knowledge problem. Knowledge application activities require an understanding of the peculiarities of the new context in which knowledge is put into use, its relationship with the contexts of discovery, and what can be transferred between the two contexts. Such a contextualization process typically requires a human's general intelligence.

Finally, a central attribute of general intelligence is self-reflection. Self-reflection perpetuates the need for self-awareness about one's knowledge regarding areas of strength and weakness. This undergirds the capacities to learn and to reinvent, which are germane to knowledge-application processes (Jarrahi et al., 2019). Compared with humans, AI systems lack self-awareness and self-reflection. Human decision makers can sustain KM systems by emphasizing their unique capabilities in observing and reflecting on past experiences and in developing corrective strategies, as well as in formulating problems that are worthy of attention (von Krogh, 2018).

## 3.3. Codification versus collaboration

Previous work (e.g., Alavi & Tiwana, 2003; Hansen et al., 1999) highlights two dimensions of KM that can be supported by IT uses: (1) codification of knowledge and (2) human collaboration (personalization). While codification aims to deal with explicit aspects of KM, collaboration concerns tacit elements of functional KM. Here, we rethink the utility of new waves of AI in relation to these dimensions.

### 3.3.1. Codification

Codification strategy pertains to the storage and maintenance of explicit knowledge in databases or knowledge repositories where it can be reused for new problems (Hansen et al., 1999). AI systems afford a broad diversity of opportunities to streamline low-level, prosaic, high-volume, routine tasks of collecting, classifying, analyzing, and presenting content in ways that are not possible solely through human cognitive capabilities. Knowledge workers can then direct their attention to "high touch and higher value-added" analysis of explicit knowledge that is more directly related to strategic business issues (O'Dell & Davenport, 2019).

### 3.3.2. Collaboration

Tacit knowledge is couched in the situated practices of humans, although some of it can be transferred through social interactions (Hansen et al., 1999). Malone (2018) summed up the potential roles of AI in connecting people in new ways: "the most valuable contributions of computers will not just be their AI but also their ability to provide hyperconnectivity—connecting people to other people in rich new ways." AI technologies provide great capabilities for generating know-who (i.e., sources of expertise) within and across organizational boundaries and for extending and augmenting social networks that serve as conduits of knowledge. But transferring tacit knowledge remains a highly human-centered practice, gleaned through person-to-person social interactions and informal relationships such as apprenticeships, enabling workers to engage in practice-centered knowledge encounters. For this reason, attempts to turn inherently tacit knowledge into explicit knowledge and to facilitate its transfer through technological mechanisms have failed in the past (Orlikowski, 2002).

One example of an AI system that harnesses the unique contributions of both humans and machines is Swarm AI. Modeled after the kinds of swarm intelligence found in biological systems, this platform enables groups of humans to collectively converge on a decision in real time (Metcalf et al., 2019). The AI algorithm trains on human behaviors made through the platform to implicitly determine the confidence each individual has for a decision. The dynamic group preference is then visualized in real time, allowing participants to apply their tacit knowledge and to engage in reflection as they update their preferences. Forecasts made on this platform have been shown to outperform ML, prediction markets, and online crowds.

## 3.4. Know-how and know-what versus know-why

Emerging AI systems transcend the limitations of traditional KM systems. In traditional KM systems, the algorithms were precoded with rules created by humans, and then, through a rather well-defined process, they could transform standard inputs to standardized outputs. In contrast, AI systems can now exhibit self-learning capabilities to develop and improve know-how and know-what, offering more effective outputs as they process new data (Pushpa, 2019).

But previous generations of symbolic knowledge-based systems were primarily rule-based, and the system was therefore able to provide justifications for its recommendations based on the rules that were encoded in it. On the contrary, emerging AI systems empowered by deep learning come with high levels of complexity and low levels of interpretability, making it difficult, if not impossible, to explain the inferences generated by AI (Maedche et al., 2019). The reasons for an AI algorithm providing a particular recommendation exist in an unknowable black box. The potential for spurious relationships to hide within opaque AI outputs accentuates the need for testing the inferences to ensure their validity. But an AI algorithm cannot evaluate its own inferences because it cannot contextualize and ground them in meaning (Mitchell, 2019). The role of humans as explainers in their partnership with intelligent machines is even more salient in evidence-based industries—such as medical and legal, financial, or public administration contexts with more strict compliance requirements—wherein there are clear obligations for explaining how AI systems may weigh inputs they receive into certain recommendations (Wilson & Daugherty, 2018). As such, the role of humans is indispensable in formulating know-why for AI-based inferences; know-why is essential for alleviating the black box of AI, justifying decisions, training budding human experts, and garnering organizational support.

## 4. Practical implications

A recent survey indicates that a vast majority of AI investments bring about minimal or no impact (Ransbotham, Khodabandeh, Fehling, et al., 2020). Years of research indicate that for an IT deployment to be successful, there need to be accompanying organizational changes. These are referred to as organizational complements (Brynjolfsson et al., 2017). So the value of AI for KM lies not only in technology but in new infrastructures, trained people, and redesigned processes. We discuss the practical implications of AI and its role in KM based on the three complements of people, infrastructure, and process (Figure 2).

### 4.1. People

#### 4.1.1. Elevate humans in KM

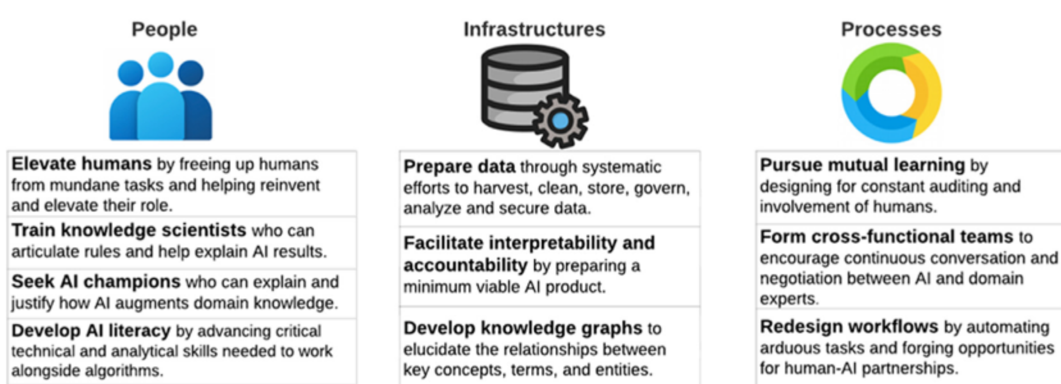
Metaphors such as "human-in-the-loop" AI or "the last mile problem" in AI-empowered automation fall short of capturing the key role workers can play. These formulations tend to present humans as an afterthought, as an appendage to the technological AI system, or as a roadblock to full automation. Instead, we argue for a symbiotic relationship, one that both recognizes the irreplaceable contributions of humans to knowledge work and that seeks ways to reinvent and elevate their role. No one is more central to AI success than the workers who work at the front line of organizations and who integrate AI into their work practices.

One way in which AI can elevate knowledge workers is through reskilling and upskilling. As human skills and activities become more visible to AI systems, organizations can harness this knowledge to provide targeted training and development. For example, EdCast uses AI to personalize training programs for individuals by comparing their current skills with future labor market needs (Caine & Firth-Butterfield, 2020). Realizing the promise of AI in organizations will likely force knowledge workers, including knowledge scientists and AI champions, to adopt new roles in the organization. We explain knowledge scientists and AI champions in the following sections.

#### 4.1.2. Train knowledge scientists

Recent developments in explainable AI (XAI) or neural-symbolic learning advocate for new roles, such as knowledge scientists and data scientists, who collect and prepare training data sets for ML

**Figure 2.** Organizational changes needed to accompany AI adoptions for KM



algorithms (Doran et al., 2017). *Knowledge scientists* can contribute to the process of combining the two distinct AI strategies—symbolic AI (using more traditional approaches) and statistical AI (based on neural networks)—by helping to build knowledge graphs that represent background knowledge and that complement training data. Knowledge graphs can be used to make decisions made by the AI agent more explainable and transparent by articulating rules and associated explanations. In this way, both knowledge scientists and ML algorithms work in tandem and as integral elements of this approach to explainable AI (Blumauer, 2019).

Given their understanding of the KM context and their close interaction with the AI system, knowledge scientists are also central in articulating know-why, at least in some degree. This articulation can serve as the first step in persuading diverse stakeholders whose buy-in is needed for the successful implementation of any decisions driven by the KM system. Rallying support within and outside an organization remains a profoundly human capability (von Krogh, 2018).

#### 4.1.3. Seek AI champions

*AI champions* can be instrumental in presenting an alternative narrative that emphasizes augmenting knowledge workers rather than replacing them—an alternative narrative that describes the expected improvement in the kinds of tasks knowledge workers perform. AI champions are boundary spanners who find correspondence between specific AI capabilities and specific KM needs and functions. These are people aware of and excited about AI, but more importantly, they possess deep domain knowledge and robust business and communication acumens by which they can clearly convey how knowledge processes and people's strengths can be augmented by AI.

While in some cases, new people need to be hired with the right cognitive skills and analytical backgrounds, current employees generally must be trained and retrained to occupy these new positions. As noted, the core capabilities of these individuals are captured not only in better data and technology skills but also in "business analysis skills and the ability to frame business problems to identify what technologies are appropriate to address them" (Davenport & Mahidhar, 2018, p. 22). Beyond the specific roles noted above, we expect that all knowledge workers will be required to develop AI literacies that define the success of knowledge-intensive work.

#### 4.1.4. Foster AI literacy

As AI automates repetitive and mundane tasks that were performed by humans, workers will need to learn how to interact with intelligent systems rather than with humans for many of these tasks. AI literacy is a key component needed for upskilling both managers and workers interacting with AI systems. This requires knowledge workers to develop a fuller appreciation of their artificial counterparts, algorithmic competencies (Jarrahi & Sutherland, 2019), and new analytical, data-centered skills that help workers interpret AI-based decisions. Know-why encompasses justifying these decisions, as does taking a critical perspective. Bersin and Zao-Sanders (2020) argued, as a critical component of data literacy, "modern professionals have a growing need to understand how to challenge the outputs of algorithms, and not just assume system decisions are always right." In this way, decision makers need to develop a curious mindset, to ask questions, to critically and actively engage with algorithmic results, and to provide feedback that can be used as a dynamic training ground for the AI system.

### 4.2. Infrastructure

Infrastructural readiness here encompasses both data and algorithmic systems that feed on data and that augment knowledge processes.

#### 4.2.1. Prepare data

The new generation of AI is powerful partly owing to the abundance of data generated in contemporary organizations (Paschen, Pitt, & Kietzmann, 2020). Deep-learning approaches, for example, require rather large sets of training data to produce reliable outcomes. Hence, quality and quantity of data are key success factors of deep-learning systems. Even though we noted that AI systems can help organizations overcome silos, the fact that data that are scattered across these silos is what makes AI solutions robust. Data with the right combination of quality and quantity cannot be integrated with AI systems for KM unless there are deliberate cross-functional efforts and collaboration among different parties within the organization. These dependable data come from a data value chain that involves systematic efforts to harvest, clean, store, govern, analyze, and secure data (Joshi & Wade, 2020). To more effectively train AI models, internal data sources must be combined with external data sources regarding the ongoing competitive landscape in order to generate a comprehensive milieu for AI-empowered analysis.

#### 4.2.2. Facilitate interpretability and accountability

AI technology itself also needs to be adapted for organizational rollout. Many of the AI capabilities developed in academic and corporate labs may not be ready to be deployed in knowledge practices owing to the issues of interpretability and accountability. The most prevalent machine-learning models in businesses today are still supervised learning models, in part because the labeling of their training data enhances the interpretability and accountability of the model. One significant cost that businesses must incur in producing these models is the labor-intensive cleansing and preparation required to implement a minimum viable AI product using proprietary data (Davenport & Seseri, 2020). The granular manner in which data must be tagged to be effective for supervised learning models takes a unified, cross-functional effort.

#### 4.2.3. Develop knowledge graphs

One of the key challenges of leveraging knowledge has to do with the fact that data are dynamically being generated in real time, and most such data are unstructured. This presents barriers to timely and meaningful AI-empowered analysis. Knowledge graphs are an emerging way in which organizations can harness this data. Knowledge graphs manage the key concepts, terms, and entities and their relationships in the business. In doing so, a knowledge graph produces an understanding of the relationships between data points, allowing for complex integration, discovery, and analysis. For example, a knowledge graph might be constructed to understand the complex relationships between regions, weather, cost, and manufacturing, allowing the business to learn how inclement weather will impact the cost of a part produced in Texas.

Many businesses already use knowledge graphs for AI-enabled KM. AstraZeneca uses knowledge graphs to inform drug discovery through exploring a network of known relationships between chemical compounds, molecules, diseases, and biological entities (Dhuri, 2020). AI systems build on knowledge graphs, but at the same time, their role in creating knowledge graphs is essential as they can dynamically assign meaning to the relationships between various data points. In other words, knowledge graphs can overcome the limitations of dynamic, unstructured, and varied sources of data typically present in organizations (Elnagar & Weistroffer, 2019). Knowledge graphs are particularly useful for KM because they can draw from its understanding of the relationships between objects to explain the reasons behind their recommendations.

### 4.3. Processes

A major complementary investment for successful AI deployment has to do with aligning ways of working with AI. A process-centered approach requires shifting from a mindset of using AI to automate processes to seeing it as an opportunity to augment or reinvent processes.

#### 4.3.1. Pursue mutual learning

Process redesign must both draw on and facilitate mutual learning between humans and AI. Designing for mutual learning recognizes the limits of the AI system in managing knowledge and precipitates the need for constant auditing and involvement of human supervisors. Datafication and digitalization, coupled with the use of AI, can give the wrong impression of authentic knowledge, but over-estimating or trusting too much in the learning capacities of AI may thwart the real value of these systems for KM. For example, AI systems can carry or even amplify implicit biases embedded in existing organizational systems. The knowledge that these systems generate, share, or propagate throughout the organization can provide the impression of objectivity or cogency even when the system is as biased as the human thinking it replaces. Hence, organizations need to undertake continual AI audits (Brown et al., 2021).

#### 4.3.2. Form cross-functional teams

In addition to redesigning processes to foster collaboration between AI and knowledge workers, AI capabilities themselves can also be used to re-engineer existing organizational processes (Daugherty & Wilson, 2018). As noted, algorithmic systems thrive on comprehensive data that span multiple units. Providing this data for AI systems requires organization-wide initiatives. Interdisciplinary and cross-functional teams could facilitate these initiatives and connect business domain proficiency with algorithmic capabilities. These teams provide a mix of skills and perspectives that are critical to the implementation of AI systems. The teams involve AI and analytics experts working closely with domain experts, frontline workers, and operational people.

The redesign of workflows (e.g., digitalization, datafication, and quantification) and the identification of ways in which algorithms' recommendations can augment various knowledge activities require a continual conversation and negotiation between technology and domain experts. Such a process cannot be performed top-down; AI will touch upon many processes and people (Paschen, Pitt, & Kietzmann, 2020). Knowledge workers have a unique perspective about their core activities and must therefore feel empowered to make decisions, to decide on how to integrate algorithms, and subsequently to develop trust in their applications.

#### 4.3.3. Redesign for automation and augmentation

Automation is not necessarily the opposite of human augmentation and can in fact foster augmentation (Raisch & Krakowski, 2020). Elevating humans necessitates that organizations look for opportunities to free knowledge workers from arduous and monotonous work by automating it. Some of this repetitive work can be delegated to intelligent assistants that learn and automate routines by observing knowledge workers and team collaborations (e.g., by scheduling meetings). These intelligent systems can extend their reach into exception handling. For example, AI can identify invoices that miss order numbers and figure out shortfalls or excesses, thereby helping financial staff focus on more strategic and meaningful tasks (Dan et al., 2017).

When redesigning processes, organizations also need to simultaneously consider opportunities for augmentation. For example, organizations might develop processes in which AI and humans make decisions in parallel and then compare the outcomes. Alternatively, the decision-making process can be sequential, in which one—typically the human—corroborates the decision made by the other party. These processes are opportunities for mutual learning; using explainable AI and interactive ML techniques, the two can come to understand the underlying logic.

## 5. Conclusion

The goal of KM is to connect knowledge workers with the right set of knowledge resources or people, at the right time, to make better decisions (O'Dell & Davenport, 2019). The rise of AI capabilities and promising features for achieving these goals may call for different forms of division of work between workers and intelligent machines than those we have witnessed in organizations in the past. Such new roles require a new set of skills and competencies for humans and new design mindsets for intelligent machines. Humans must nurture perceptions, skills, and work practices to be able to take advantage of their artificial partners for KM while avoiding such pitfalls of automation as cognitive complacency or algorithmic aversion. Such preparations by organizations help put into practice the unique capabilities of AI in KM, which are only utilized and realized through an effective symbiotic partnership between knowledge workers and intelligent systems.

## References


Agrawal, N. (2021, March 9). Artificial intelligence meets real friendship: College students are bonding with robots. *LA Times*. Available at https://www.latimes.com/california/story/2021-03-09/college-students-pour-out-emotions-amid-pandemic-to-bots

Agrawal, A., Gans, J., & Goldfarb, A. (2017). What to expect from artificial intelligence. *MIT Sloan Management Review, 58*(3), 23—27.

Alavi, M., & Denford, J. (2011). Knowledge management: Process, practice, and Web 2.0. In M. Easterby-Smith, & M. A. Lyles (Eds.), *Handbook of organizational learning and knowledge management* (pp. 105—124). Hoboken, NJ: Wiley.

Alavi, M., & Leidner, D. (2001). Knowledge management and knowledge management systems: Conceptual foundations and research issues. *MISQ, 25*(1), 107—136.

Alavi, M., & Tiwana, A. (2003). Knowledge management: The information technology dimension. In M. Easterby-Smith, & M. A. Lyles (Eds.), *The Blackwell handbook of organizational learning and knowledge management* (pp. 104—121). Hoboken, NJ: Blackwell Publishing.

Bersin, J., & Zao-Sanders, M. (2020, February 12). Boost your team's data literacy. *Harvard Business Review*. Available at https://hbr.org/2020/02/boost-your-teams-data-literacy

Bhatt, G. D. (2001). Knowledge management in organizations: Examining the interaction between technologies, techniques, and people. *Journal of KM, 5*(1), 68—75.

Bhattacharya, P., Hiware, K., Rajgaria, S., Pochhi, N., Ghosh, K., & Ghosh, S. (2019). A comparative study of summarization algorithms applied to legal case judgments. In *Advances in information retrieval* (pp. 413—428). Cologne, Germany: ECIR.

Blumauer, A. (2019, December 30). Explainable AI: The rising role of knowledge scientists. *Forbes*. Available at https://www.forbes.com/sites/forbestechcouncil/2019/12/30/explainable-ai-the-rising-role-of-knowledge-scientists/#428c9b8603f0

Brown, S., Davidovic, J., & Hasan, A. (2021). The algorithm audit: Scoring the algorithms that score us. *Big Data and Society, 8*(1). Available at https://doi.org/10.1177/2053951720983865

Brynjolfsson, E., & McAfee, A. (2017, July 18). The business of artificial intelligence. *Harvard Business Review*. Available at https://hbr.org/2017/07/the-business-of-artificial-intelligence

Brynjolfsson, E., & Mitchell, T. (2017). What can machine learning do? Workforce implications. *Science, 358*(6370), 1530—1534.

Brynjolfsson, E., Rock, D., & Syverson, C. (2017). *Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics* [Working Paper No. 24001]. Cambridge, MA: National Bureau of Economic Research.

Caine, M., & Firth-Butterfield, K. (2020, October 22). How AI can train workers for the jobs of the future. *World Economic*

*Forum*. Available at https://www.weforum.org/agenda/2020/10/ai-jobs/

Canhoto, A. I., & Clear, F. (2020). Artificial intelligence and machine learning as business tools: A framework for diagnosing value destruction potential. *Business Horizons, 63*(2), 183–193.

Cranefield, J., & Prusak, L. (2016). Managing your own knowledge: A personal perspective. In D. J. Pauleen, & G. E. Gorman (Eds.), *Personal knowledge management* (pp. 121–136). Abingdon, UK: Routledge.

Dan, W., Elliott, T., & Noga, M. (2017, May 31). Eight ways machine learning is improving companies' work processes. *Harvard Business Review*. Available at https://hbr.org/2017/05/8-ways-machine-learning-is-improving-companies-work-processes

Daugherty, P., & Wilson, J. (2018). Processes reimagined. *Accenture*. Available at https://www.accenture.com/_acnmedia/pdf-76/accenture-process-reimagined.pdf

Davenport, T. (2019, October 10). Managing support knowledge with AI: Talla helps Toast. *Forbes*. Available at https://www.forbes.com/sites/tomdavenport/2019/10/10/managing-support-knowledge-with-ai-talla-helps-toast/#4d88ade77267

Davenport, T., & Mahidhar, V. (2018). What's your cognitive strategy? *MIT Sloan Management Review, 59*(4), 19–23.

Davenport, T., & Prusak, L. (1998). *Working knowledge: How organizations manage what they know*. Boston, MA: Harvard Business Press.

Davenport, T., & Seseri, R. (2020, December 15). What is a minimum viable AI product? *MIT Sloan Management Review*. Available at https://sloanreview.mit.edu/article/what-is-a-minimum-viable-ai-product/

Dhuri, S. (2020, July 29). How AstraZeneca is using Netflix like knowledge graph to discover new drugs. *Medium*. Available at https://medium.com/@siddhesh.s.dhuri/how-astrazeneca-is-using-netflix-like-knowledge-graph-to-discover-new-drugs-a6cd187e5b10

Doran, D., Schulz, S., & Besold, T. R. (2017). *What does explainable AI really mean? A new conceptualization of perspectives*. Available at https://arxiv.org/pdf/1710.00794.pdf

Duffy, R. (2019, January 31). AI and robotics made 10 years of steady gains. *Morning Brew*. Available at https://www.morningbrew.com/emerging-tech/stories/2019/12/20/ai-robotics-make-10-years-steady-gains?fbclid=IwAR0HpX-IxXrxhZId8DcESvOOkEXcwUjmBdBxaHFtQi1WYjh98HL0TPnw1OY

Eitle, V., & Buxmann, P. (2019). Business analytics for sales pipeline management in the software industry: A machine learning perspective. In *Proceedings of the 52nd Hawaii international conference on system sciences*. Available at https://aisel.aisnet.org/hicss-52/

Elnagar, S., & Weistroffer, H. R. (2019). Introducing knowledge graphs to decision support systems design. In *Information systems: Research, development, applications* (pp. 3–11). Cham, Switzerland: Springer.

Faraj, S., Pachidi, S., & Sayegh, K. (2018). Working and organizing in the age of the learning algorithm. *Information and Organization, 28*(1), 62–70.

Gualtieri, M. (2016, January 21). Hadoop is data's darling for a reason. *Forrester*. Available at https://go.forrester.com/blogs/hadoop-is-datas-darling-for-a-reason/

Hansen, M. T., Nohria, N., & Tierney, T. (1999). What's your strategy for managing knowledge? *The Knowledge Management Yearbook 2000–2001, 77*(2), 106–116.

Jarrahi, M. H. (2019). In the age of the smart artificial intelligence: AI's dual capacities for automating and informating work. *Business Information Review, 36*(4), 178–187.

Jarrahi, M. H., Philips, G., Sutherland, W., Sawyer, S., & Erickson, I. (2019). Personalization of knowledge, personal knowledge ecology, and digital nomadism. *Journal of the Association for Information Science and Technology, 70*(4), 313–324.

Jarrahi, M. H., & Sutherland, W. (2019). *Algorithmic management and algorithmic competencies: Understanding and appropriating algorithms in gig work*. Available at https://www.researchgate.net/publication/329336053_Algorithmic_Management_and_Algorithmic_Competencies_Understanding_and_Appropriating_Algorithms_in_Gig_work

Joshi, A., & Wade, M. (2020, August 10). The building blocks of an AI strategy. *MIT Sloan Management Review*. Available at https://sloanreview.mit.edu/article/the-building-blocks-of-an-ai-strategy/

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons, 62*(1), 15–25.

Latinovic, Z., & Chatterjee, S. C. (2019, September 24). How AI is helping companies break silos. *MIT Sloan Management Review*. Available at https://sloanreview.mit.edu/article/how-ai-is-helping-companies-break-silos/

Lavenda, D. (2019, August 28). Machine learning should make tech work for us—Not the other way around. *TechTalks*. Available at https://bdtechtalks.com/2019/08/28/machine-learning-data-management/

Maedche, A., Legner, C., Benlian, A., Berger, B., Gimpel, H., Hess, T., Hinz, O., Morana, S., & Sollner, M. (2019). AI-based digital assistants: Opportunities, threats, and research perspectives. *Business and Information Systems Engineering, 61*(4), 535–544.

Malone, T. W. (2018). How human-computer 'superminds' are redefining the future of work. *MIT Sloan Management Review, 59*(4), 34–41.

Metcalf, L., Askay, D. A., & Rosenberg, L. B. (2019). Keeping humans in the loop: Pooling knowledge through artificial swarm intelligence to improve business decision making. *California Management Review, 61*(4), 84–109.

Mitchell, M. (2019). Artificial intelligence hits the barrier of meaning. *Information: An International Interdisciplinary Journal, 10*(2), 51.

O'Dell, C., & Davenport, T. (2019). Application of AI for knowledge management. *CIOReview*. Available at https://knowledgemanagement.cioreview.com/cxoinsight/application-of-ai-for-knowledge-management-nid-30328-cid-132.html

Orlikowski, W. J. (2002). Knowing in practice: Enacting a collective capability in distributed organizing. *Organization Science, 13*(3), 249–273.

Paschen, U., Pitt, C., & Kietzmann, J. (2020). Artificial intelligence: Building blocks and an innovation typology. *Business Horizons, 63*(2), 147–155.

Paschen, J., Wilson, M., & Ferreira, J. J. (2020). Collaborative intelligence: How human and AI create value along the B2B sales funnel. *Business Horizons, 63*(3), 403–414.

Pauleen, D. J., & Gorman, G. E. (2016). The nature and value of personal knowledge management. In *Personal knowledge management* (pp. 23–38). Abingdon, UK: Routledge.

Pushpa, R. (2019, June 16). *Artificial intelligence and knowledge management—Understanding how they are linked*. LinkedIn Blogs. Available at https://www.linkedin.com/pulse/artificial-intelligence-knowledge-management-how-linked-pushpa/

Raghavan, S. (2019). 2020 AI predictions from IBM Research. *IBM Research*. Available at https://www.ibm.com/blogs/research/2019/12/2020-ai-predictions/

Raisch, S., & Krakowski, S. (2020). Artificial intelligence and management: The automation-augmentation paradox. *Academy of Management Review, 46*(1), 192—210.

Ransbotham, S., Khodabandeh, S., Fehling, R., LaFountain, B., & Kiron, D. (2020, October 15). Winning with AI. *MIT Sloan Management Review*. Available at https://sloanreview.mit.edu/projects/winning-with-ai/

Ransbotham, S., Khodabandeh, S., Kiron, D., Candelon, F., Chu, M., & LaFountain, B. (2020, October 20). Expanding AI's impact with organizational learning. *MIT Sloan Management Review*. Available at https://sloanreview.mit.edu/projects/expanding-ais-impact-with-organizational-learning/

Sanzogni, L., Guzman, G., & Busch, P. (2017). Artificial intelligence and knowledge management: Questioning the tacit dimension. *Prometheus, 35*(1), 37—56.

Tshitoyan, V., Dagdelen, J., Weston, L., Dunn, A., Rong, Z., Kononova, O., Persson, K. A., Ceder, G., & Jain, A. (2019). Unsupervised word embeddings capture latent knowledge from materials science literature. *Nature, 571*(7763), 95—98.

Tsui, E. (2005). The role of IT in KM: Where are we now and where are we heading? *Journal of Knowledge Management, 9*(1), 3—6.

von Krogh, G. (2018). Artificial intelligence in organizations: New opportunities for phenomenon-based theorizing. *Academy of Management Discoveries, 4*(4), 404—409.

Wilson, H. J., & Daugherty, P. R. (2018). Collaborative intelligence: Humans and AI are joining forces. *Harvard Business Review, 96*(4), 114—123.