



# KNOWLEDGE MANAGEMENT IN THE ERA OF ARTIFICIAL INTELLIGENCE—DEVELOPING AN INTEGRATIVE FRAMEWORK

*Research in Progress*

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## Abstract

*Artificial intelligence (AI) and its rapid technological advancement will considerably affect the future of work and the way organizations manage their knowledge management (KM) processes. Typical KM initiatives include the development, transfer, storage, and evaluation of a firm's knowledge throughout the knowledge lifecycle, but often neglect ongoing advances in the AI area. Thus, organizations struggle to integrate AI into working environments to leverage outcome efficiency. Starting with a descriptive literature review, we draw on two KM strategies—personalization and codification—and introduce an adaptive, AI-specific approach for organizational KM implementation. Our approach supports KM strategy and research, as it outlines how AI affects current working processes. This enables to understand which role AI can take in the human-AI interaction. Knowledge managers are provided with a tool to align organizational KM with the business strategy and current technological progress in AI context. We also outline future research to validate the construct.*

*Keywords: Knowledge Management (KM), Artificial Intelligence (AI), Personalization Strategy, Codification Strategy, Adaptive Knowledge Management*

## 1 Introduction

For many decades, the discipline of knowledge management (KM) has been attracting great interest in academia and practice. Researchers and practitioners have devoted their attention to the question of how to successfully implement KM in organizational settings (Chua, 2011). An essential success factor in this context involves the underlying KM strategy and its implementation to achieve organizational benefits and competitive advantages (Dayan, Heisig and Matos, 2017; Jennex, 2019). KM will continue to play an important role in organizations in the future, given that our economy is relying on specialized knowledge and information exchange (Brynjolfsson and McAfee, 2017). Accordingly, digitization and the rise of new technological advances in different fields will swallow up many routine jobs, leaving behind merely sophisticated tasks for highly qualified, mostly white-collar, workers (Frey and Osborne, 2017; Kofler *et al.*, 2020). Simultaneously, new kinds of knowledge are produced through using these new technologies, resulting in new requirements for handling and managing knowledge. Literature suggests two main approaches to KM, introduced by Hansen, Nohria and Tierney (1999). The first one, known as *human-oriented KM*, considers individuals as the central source of knowledge and pursues a personalization strategy. The second one, known as *technology-oriented KM*, pursues a codification strategy aiming to obtain explicit knowledge stored in external databases. Over the past years, both strategies were adopted by numerous organizations. Although mixed forms of both approaches are often applied implicitly (e.g., Lam and Alton, 2005; Storey and Hull, 2010; Kotlarsky, Scarbrough and Oshri, 2014), research so far considers both approaches as detached from each other (Hansen, Nohria and Tierney, 1999). As a consequence, there is a need to develop an integrative approach that combines the creative and intellectual abilities of humans with the emerging capacities of data and information

processing technologies—i.e., artificial intelligence (AI)—to achieve real synergies. Some endeavors have been made towards such so-called integrative solutions (e.g., Maier and Remus, 2003; Chua, 2011), but they mostly represent situation- or case-specific attempts and a holistic solution is still missing (Lehner, 2021).

This need is further reinforced through ubiquitous digitization and the ability to effectively process large volumes and diverse data, information, and knowledge with AI and related technologies. AI applications are characterized by two properties, which affect our understanding of knowledge and its processing in organizations. First, AI applications can process data and detect pattern therein automatically, sometimes more effectively than humans do. These *learning algorithms* can therefore automatically acquire a new kind of knowledge from data (Faraj, Pachidi and Sayegh, 2018). For example, image processing techniques can make more accurate decisions in cancer detection than doctors, who have underwent extensive and expensive training (McKinney *et al.*, 2020). Second, AI represents a knowledge-based system that increasingly acts independently of humans (*agency*), makes own decisions, and interacts with humans (Ågerfalk, 2020). We see this in voice assistants like *Amazon's Alexa* and *Microsoft's Cortana* that conquered our homes and workplaces. These capabilities of AI lead to a noticeable transformation and evolution of the KM discipline that needs to rethink existing KM approaches and strategies. For instance, the ability of AI to learn and act independently requires KM strategies to consider successful collaboration between humans and AI actors. Also, the traditional view on knowledge property requires a redefinition, given that AI technologies can develop, possess, and use knowledge by applying advanced machine learning techniques (e.g., deep learning). Thus, a new form of hardly articulable knowledge emerges that is comparable to tacit knowledge held by humans (hidden and not completely articulable knowledge like personal experiences and thoughts), but managed and held by AI. As knowledge is currently considered as person-bounded (Nonaka, 1994), this novel knowledge type, produced by AI, deserves closer investigation and requires integration in KM strategies to evaluate how it can be stored, communicated, and handled using appropriate tools (similar to the case of person-bounded knowledge in a personalization approach). Yet, some areas may remain constant. For example, the topics of creativity and innovation, but also human-to-human communication, represent components that rely and depend on humans and will therefore be dedicated to human actors at the present time. AI, in particular, is subject to active discussion in KM research. However, although numerous studies have dealt with KM strategies, their implementation, and the property of knowledge, little attention was paid to how AI can be effectively considered a new actor and component of traditional KM strategies. Our ongoing research project therefore aims to pursue the following research question:

*How does the advent of AI alter prominent KM approaches, in particular the strategies of codification (technology-oriented KM) and personalization (human-oriented KM)?*

We first conducted a descriptive literature review (Paré *et al.*, 2015) in scientific journals to incorporate the state of research on both KM approaches in our analysis. Second, we evaluated the approaches with respect to the changes that AI brings in. Third, based on the criteria that earlier research used to define the KM approaches (e.g., Hansen, Nohria and Tierney, 1999; Maier and Remus, 2003), we formulate a prescriptive adaptive KM approach and plan to validate it in our future research. The remainder of this research in progress paper first resumes the theoretical background and places our research idea in context of existing literature. Section 3 describes our research method. In section 4, we present our interim results and formulate an AI-oriented KM approach. We close the paper with a discussion and an outlook to the future research.

## **2 Theoretical Background and Research Gap**

We draw on two KM approaches—the human-oriented (personalization strategy) and the technology-oriented KM (codification strategy)—and consider recent advances in AI (Coombs *et al.*, 2020). This section discusses these topics and outlines the research gap that we address. Given that the use of AI involves transferring and processing knowledge, KM approaches are a helpful framework for this study.

## 2.1 Human-oriented KM

The human-oriented approach focuses on the individual as a central source of knowledge and aims to assist individuals in using their own cognitive skills. Knowledge is thus anchored in people's minds and their memories and is hard to imitate and access (Gould, 2009). Considering that humans are given priority, a personalization strategy is pursued to handle the development and transfer of knowledge through personal communications channels (Hansen, Nohria and Tierney, 1999; Greiner, Bohmann and Krcmar, 2007). Involved actors are, for instance, experts who offer specialized knowledge and knowledge communities promoting a culture of openness and shared knowledge exchange. Interactive systems such as chat systems provide instruments that are supposed to assist both synchronous and asynchronous communication between firms and their individuals (Zack, 1999). As a consequence, life-long learning as well as training are essential capabilities and features. Evaluation criteria of this approach are, for instance, user satisfaction and the quality of the communication processes. Furthermore, the impact achieved by group interaction (e.g., learning outcomes) is a measurable quality criteria (Hansen, Nohria and Tierney, 1999; Maier and Remus, 2003). An example use case of the human-oriented approach is a task force used for the development of new products.

## 2.2 Technology-oriented KM

This approach focuses on the maximized use of technological solutions, detached from individuals' minds, to develop explicit knowledge. Knowledge is thus documented (codified) in external databases and storage systems (Basten, Schneider and Michalik, 2013) and easily interpretable and accessible. The underlying KM strategy is the codification strategy, which prioritizes investments in new and pioneering IT systems (Hansen, Nohria and Tierney, 1999; Greiner, Bohmann and Krcmar, 2007). Typical actors are knowledge brokers and systems administrators, who design the technical solutions leading to a technocratic-focused culture. Technologies execute a variety of knowledge-related functions, which mainly enables the computer-assisted processing of knowledge (e.g., knowledge structuring in knowledge bases or their localization using search functions), the technical implementation of knowledge, its storage, presentation and visualization. The systems category which best enables such functions is referred to as integrative systems such as databases or wikis (Zack, 1999). Evaluation criteria of this approach are, for example, system usage rates or the quality of information and provided knowledge (Hansen, Nohria and Tierney, 1999; Maier and Remus, 2003). An example of this approach is the development of a knowledge base in a help desk system.

## 2.3 Limitations of the Human- and Technology-oriented KM approaches

The two KM approaches found much attention in research, but KM strategies employed in practice are often combining both implicitly, without having a clear systematics and explicitly recommending how to combine both approaches holistically to achieve real synergies. Reasons for their combination are the technological progress (e.g., gamification features in a KM system motivate individuals to document their knowledge), the need to align working processes to employees' preferences, environmental changes, and the fact that both strategies are simultaneously present in organizations. Systems for codification, communication processes, and humans between which they take place are likewise relevant. The theory-practice gap is further reinforced by recent advances of information technology, where sensors and learning algorithms are combined in intelligent agents, which automate more and more parts of human labor and knowledge work (Coombs *et al.*, 2020).

## 2.4 Artificial Intelligence in Work Environments

There is no doubt that the arrival of AI in working environments will lead to fundamental changes in organizations. Given the current AI's ability to extract rules from data, which is referred to as *learning* (Faraj, Pachidi and Sayegh, 2018) and the ability to perform actions by applying rules to data independently of humans, which is referred to as *agency* (Ågerfalk, 2020), a new form of *partnership* between humans and AI will emerge. This affects AI application in working environments and

contributes to KM by tackling a new perspective on organizational KM. From the current debate around AI in organizations, we observed two AI properties that require attention in KM approaches.

First, while current AI can learn (through the execution of machine learning), patterns are automatically detected in data. AI can use these patterns to make predictions about future events. These patterns form a new kind of knowledge (Faraj, Pachidi and Sayegh, 2018), which is often not tangible, not easy to explain, and not accessible for humans without great effort, technical expertise and time. We conclude that *a new form of hardly articulable knowledge evolves, which is comparable to tacit knowledge, but held and managed by AI*. Tacit knowledge, which is considered to be a human property (Nonaka, 1994), can therefore also be created and possessed by machines. Second, current AI performance reaches or even exceeds human abilities in some applications. Task responsibilities can therefore be handed over to AI (Coombs *et al.*, 2020), even in the case of complex activities. To varying degrees, AI can even automate knowledge-intensive tasks or augment business activities depending on the type of the task (Grønsund and Aanestad, 2020). Thus, humans and AI can collaborate in a partnership: While highly innovative tasks require more human intervention and expertise, automatable, computationally intensive jobs allow AI to outperform humans. These observations corresponds to current debates and visions emerged in the literature on human-computer interaction (Wang *et al.*, 2019; Schneidermann, 2020).

These developments have several implications for KM strategy: 1) Existing knowledge processes (from knowledge development to its storage and monitoring) must be reconsidered because of the effective knowledge discovery through learning algorithms. For instance, knowledge sharing between humans and AI will differ from common processes of knowledge sharing between humans. Strategy must think about the accessibility of knowledge by all involved actors. Standardized knowledge access and retrieval can benefit from AI technology, but clear control and monitoring mechanisms must prevent data abuse or even the loss of control by humans (knowledge protection). 2) New interactions and learning modes between humans and AI may evolve and the question arises how humans can effectively communicate decisions and results to AI. Conversely, it becomes relevant how humans can interpret AI decisions and transfer AI's results in an understandable form to humans. 3) A new potential knowledge type, which is developed and used by AI, emerges and poses the question about its property and specific characteristics (e.g., how strategic knowledge can be made available for AI).

### **3 Research Method**

We start our research with a comprehensive literature review on the two established KM approaches and their underlying strategies. Based on the literature synthesis, we derive a novel adaptive KM approach considering AI. We will conduct further research to validate our results in the future.

#### **3.1 Literature Review**

As a starting point, we conducted a descriptive literature review (Paré *et al.*, 2015) in scientific journals to collect and summarize existing studies on both KM approaches that either present theoretical reviews or concrete application scenarios in organizations. We follow the guidelines of Webster and Watson (2002) and vom Brocke *et al.*, (2009). In the analysis of the articles found, we only went as deeply into each article as was necessary for our understanding of the two KM approaches. The analysis allowed us to develop an overview of the established KM approaches and their strategies, to understand the rationales behind their diffusion and application in different business domains.

We initiated our search by querying the following five electronic databases: *ACM*, *AISel*, *EBSCOHost*, *Scopus* and *Web of Science*. The database selection followed a selective level of coverage (Cooper, 1988) and ensured on the one hand that relevant journals and conferences in the area of information systems (e.g., *Senior Scholars' Basket of IS Journals*, *ECIS*, *ICIS*) were covered. On the other hand, the selection accounts for KM journals and conferences (e.g., *Journal of Knowledge Management*, *Journal of Information & Knowledge Management*), ensuring the specific KM orientation. Using the search string "*knowledge management AND (personalis(z)ation strategy OR codification strategy*)," we focused on English written academic articles. Since in literature, authors are often talking about the

underlying strategies of KM rather than of KM approaches, we focused our search procedure on the keywords “*personalization*” and “*codification*.” We excluded papers without an original scientific contribution (e.g., magazines, editorials, discussions) and elements not in English. The initial set of hits in all five databases resulted in 224 articles, from which 28 were duplicates. Subsequently, we went through the titles and abstracts of the remaining 196 articles and analyzed them. We used two further exclusion criteria to evaluate the content-related fit of the article: First, research lacking a specific focus on a KM strategy (e.g., papers dealing with personalization in terms of information retrieval domains and search engines development), second, papers in which no specific business context was recognizable were excluded too. For instance, we did not consider papers where KM approaches were applied in library or education domains. In cases where no explicit link to a KM strategy was visible in the abstract, we reviewed the corresponding full text. This led to a further reduction of the relevant hits by 33 articles, remaining 163 relevant articles as the final analysis base for the subsequent synthesis.

### **3.2 Analysis and Literature Synthesis**

Starting from the resulting 163 hits, we began with the descriptive data synthesis and extracted four aspects: First, we investigated which of the two KM strategies dominated in the studies. Second, we extracted information about the applications of the strategies in the organizational context. Therefore, we checked the relevance of KM strategies for different organizational settings. Third, we examined to what extent AI was thematized in our review corpus to ascertain whether any of the 163 studies in which the two KM strategies are discussed and applied have attempted to derive a KM strategy tailored to AI. Finally, if applicable, we identified the criteria that these studies use to define their KM approach. All four aspects are an essential prerequisite for the derivation of our adaptive AI-tailored KM approach.

### **3.3 Conceptual Framework Development**

The adaptive approach that we developed is intended to give recommendations to companies for the implementation of their AI-supported KM strategy. Thus, our approach will go beyond descriptive ones (e.g., Harb and Abu-Shanab, 2020) and help firms with their decision-making as a prescriptive one (Gregor, 2006; Varshney, Nickerson and Muntermann, 2015). In the past, similar procedures were applied to a number of neighboring application domains with comparable objectives. The adaptive approach was developed based on the preceding literature analysis and the deductive and theory-based derivation (Bailey, 1994; Nickerson, Varshney and Muntermann, 2013) of its components based on already existing knowledge on traditional KM approaches and strategies. Complementary, the authors' long-term expertise in the fields of KM and AI as well as the results of recent literature reviews in the AI field were incorporated. In the future, we plan to empirically validate the approach.

## **4 Preliminary Results**

Descriptive results of our literature analysis underline the need for the development of an adaptive KM approach, which incorporates the human- and the technology-oriented KM approach and accounts for the recent advances in AI technology. We identified criteria that differentiate the KM approaches in our review and used them to develop our current conceptualization of the proposed adaptive KM approach.

### **4.1 Results of Descriptive Literature Analysis**

The analysis shows a high interest in the KM strategies after their initial discussion in 1999 until today. The hits are distributed relatively evenly over periods of seven years each (2000-2006: 41, 2007-2013: 68, and 2014-2020: 54) with the highest research activity being observed in the second period. The analysis (see Table 1) revealed that not even a third of the studies use one of the strategies alone: The personalization strategy appeared in 17% and the codification strategy in 16% of the articles. 21% of the studies consider both strategies, but dependent on the situation and context (i.e., contingent). A combined application of both strategies is thematized with a percental mention frequency of 45%. These

studies propagated and recommended the use of both strategies either in the form of a theoretical review and discussion or based on real-life application scenarios. Yet none of them suggested an integrated strategy with corresponding systematic guidelines. Only one study (Salovaara and Tuunainen, 2015) suggested the use of a different strategy called mediated sharing. We thus observe a tendency towards mentioning or intuitively using a holistic approach during the implementation of KM, but researchers apparently stick to differentiating the two archetypical approaches instead of proposing a systematic and integrative one. An integrative approach should be therefore investigated and systematized in detail.

Table 1: Meta-Summary on dominant KM strategies according to search database

	Personalization	Codification	Contingent	Both	Other
ACM	0	1	2	5	0
AISel	11	10	10	40	0
EBSCOHost	0	2	2	1	0
Scopus	16	12	20	28	1
Web of Science	0	1	1	0	0
Summary	27 (17%)	26 (16%)	35 (21%)	74 (45%)	1 (1%)

With regard to AI coverage, none of the studies discussed the use of at least one strategy in the context of AI. Only two studies (Botha, 2018; Lokshina and Lanting, 2018) deal with Internet of Things as a technological trend and put this topic into the general context of KM and knowledge work. In light of current technological progress, this confirms the relevance of an adaptive KM approach, tailored to AI. Table 2 lists the organizational application domains that are the focus of the identified studies. The majority of several studies, however, indicated a general context (45%). In this context, studies have been applied without specifying a more concrete application sector. Topics like innovation, ideation or organizational learning also fall into this general category. The domains of IT and software engineering (15%) and manufacturing and service development (9%) follow on the second and third place. Project management comes in fourth place (5%), followed by the fields of healthcare and consulting (4% each).

Table 2: Application domains and their absolute frequencies

Domain	Freq.	Domain (cont'd)	Freq.
General organizational context	73	Human resource and recruiting	3
IT and software engineering	25	Marketing and customer relationship management	3
Manufacturing and (new) service development	14	Cross-sector domains	3
Project management	8	Finance	2
Healthcare	7	Food	2
Auditing and consulting	7	Automotive	2
Public administration and governance	4	Other domains	5
Oil	4		

## 4.2 Towards an Adaptive AI-oriented KM

The four criteria that we found in the literature to differentiate the two KM approaches helped us as well to formulate differences to these approaches through the advent of AI: 1) *Approach & Strategy* describes the underlying understanding of knowledge and central strategic goals pursued. 2) *Actors & Roles* indicates the organizational culture anchored in the firm. 3) *Instruments & Tools* describes elementary functions and supporting technologies. 4) *Evaluation* describes how the achievement of targets and the resulting benefit for the company is typically measured. We use these four criteria in the following to describe our novel adaptive approach and differentiate it from the traditional KM approaches. We provide an overview of the criteria and the approaches in Figure 1.

**Approach & Strategy:** Knowledge workers and executives must put the strategic focus on the task-oriented interaction between individuals and AI. Both actors (humans & technology) will act together to different degrees, depending on the context and complexity of a task and the underlying decision-making style (rational vs. intuitive) in the organization (Abubakar *et al.*, 2019). Both tacit knowledge of individuals (e.g., their expertise in data collection) and knowledge in databases (e.g., training data) are required for task execution. Simultaneously, AI components may develop a new form of tacit-like

knowledge (e.g., through the application of machine learning algorithms). For instance, deep neural networks are capable to perform data analysis through learning, which in turn leads to new knowledge that is part of machines' intelligence, but hardly understandable for humans (Dourish, 2016; Faraj, Pachidi and Sayegh, 2018). Knowledge storage is realized for example through external knowledge databases, expert systems, or humans' own memories and their cognition. Knowledge is also contained in the memory of the algorithms and the different data paths that AI accesses. Thus, efficient storage capacities and new forms of knowledge retention are required. With an adaptive strategy, both personal interaction and communication and knowledge access in external databases become essential components and a form of mutual learning between humans and evolving AI. Education and learning are no longer only relevant for employees but also for AI, given that humans must train AI correctly. In the resulting interaction, both actors involved can profit and learn from each other and innovative solutions as well as competitive advantages are enabled.

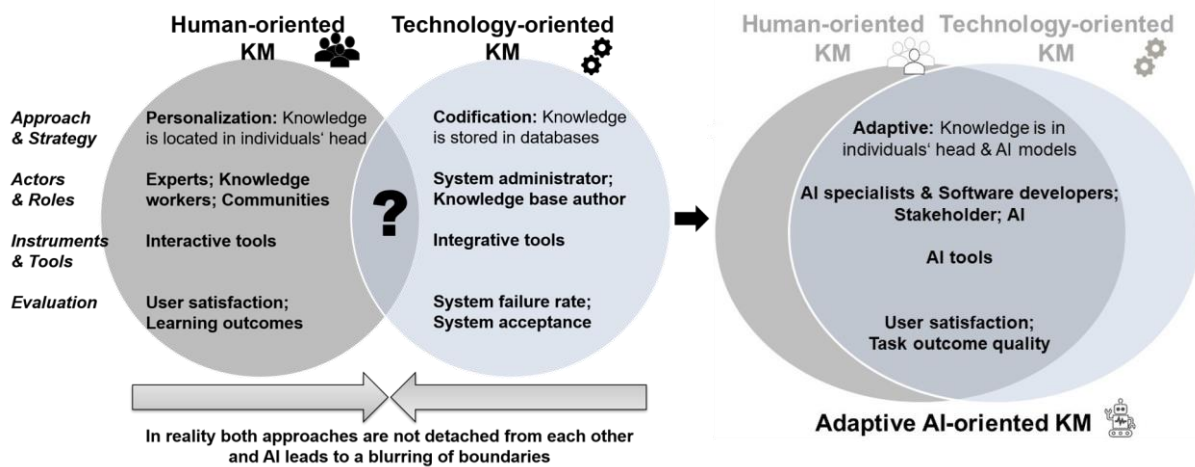


Figure 1: Moving from Traditional KM Approaches Towards an Adaptive AI-oriented KM

**Actors & Roles:** In addition to the human experts (e.g., AI specialists and software developers, customers whose data is processed by AI), an adaptive KM introduces AI technology as a new role. AI is thereby no longer only supportive in the fulfillment of tasks but also works independently and autonomously as an actor in this interaction. To pursue an adaptive AI-oriented approach, knowledge managers also must establish and promote a socio-technical culture. According to that, a structured entity of humans and technologies systematically works together according to specific rules to manage knowledge. This culture type therefore promotes an interaction between humans and AI.

**Instruments & Tools:** From a KM perspective, requirements towards AI technologies include the quality of knowledge distributed and shared (e.g., by means of the ability to support synchronous and asynchronous communication between all participants). In doing so, dynamic environmental changes (e.g., technological progress, governance regulations) need to be considered. Furthermore, AI will be capable to learn and prioritize knowledge according to situation and context. This leads to valuable contributions for humans. However, greater importance needs to be given to storing the required knowledge and filtering irrelevant or redundant knowledge to enable an effective resource management. Here, effective data analysis approaches can help. The main supporting tool in the adaptive approach is therefore the AI technology, which we state to meet the previously described functions.

**Evaluation:** Evaluating the application of an adaptive KM can be performed by measuring the success of the interaction outcomes between humans and AI e.g., by the use of (big) data and learning analytics methods. Criteria are, for example, stakeholder satisfaction, their motivation, and their trust into the working processes of AI, which can be decisive for the evaluation. User acceptance and customer satisfaction with the output are also relevant criteria as well as the collaboration and learning levels between all actors. Furthermore, the failure rate of AI will have a crucial influence on the further

involvement of AI technologies. The measures are not restricted to use cases where AI is involved. They represent crucial enablers (or barriers in case of non-fulfilment) for the success of any KM initiative (Lehner and Haas, 2010; Sedighi and Zand, 2012; Abubakar *et al.*, 2019; Jennex, 2019). Consequently, the prevalent black-box behavior of AI that results from its autonomous working mode requires a high degree of transparency and necessitates the knowledge workers' trust in the technology and its results. Finally, AI can also be utilized to measure and determine KM initiatives (Abubakar, Behraves, E. Rezapouraghdam and Yildiz, 2019).

## **5 Preliminary Contribution and Future Work**

The aim of our ongoing research project is to investigate how the advent of AI alter the traditional view on well-known KM approaches and their corresponding strategies. Having started with a descriptive literature analysis and synthesis regarding two well-known KM approaches, namely the human-oriented and the technology-oriented approach (or personalization and codification strategy, respectively), we incorporated the current debate on how AI may alter our world of work and propose a new AI-oriented KM approach. We thereby address the research gap in integrating both strategies and address the current developments in AI and related technologies. Ultimately, the integrative framework will enable to understand which role AI can take in the interaction between humans and AI in the future. This role involves several tasks, like the management of new knowledge bounded to AI and the effective implementation of learning mechanisms. The resulting approach underlines the specific changes in KM, caused by the advent of AI. For *researchers*, our conceptualization can be a theoretical grounding to further investigate the interaction between humans and the new technological actor AI. Based on our concept, we will outline a research agenda for KM researchers in next steps. For *practitioners*, the proposed approach aims to guide managers with the development of a specific KM strategy for their organization and to plan future KM initiatives that involve AI. It also helps policy makers to connect human and technical components wisely to achieve benefits from both worlds hence generate synergies.

We underline that the proposed framework should be a subject to further investigation. Our research will extend the literature analysis in two directions: First, we are reviewing success factors of KM implementation in the articles we have already identified. Second, we plan to review management-related publications (e.g., *MIT Sloan Management Review*, *MISQ Executive*, *Harvard Business Review*) as well as IT consultancy reports in order to incorporate practical issues in our framework. Both will allow to develop concrete recommendations for action addressed to practitioners. Moreover, we plan to evaluate our approach through a case study with a purposefully selected AI tool that is sufficiently popular and well-integrated into the work environment of knowledge workers. Based on these findings, we will further test the approach using surveys among knowledge workers and managers. We also want to investigate how the new form of knowledge, that is created and applied by AI, emerges and how it should be managed and integrated into existing working structures. Our results thus contribute to existing efforts that aim to harmonize the KM discipline (Heisig, 2009; Fteimi and Lehner, 2018).

In addition to our future research, there is also a need for research to expand the frontiers of AI in terms of knowledge management. We notice three current limitations in this area. First, the human interfaces to today's AI need improvement, given that current visualizations hardly help users to understand the results of AI computations. Second, the role of AI in the organizational context needs to be better understood, especially how people can train AI to support them in their work (Grønsund and Aanestad, 2020). Third, AI systems also have biases that result primarily from the data available. Research on data collection for machine learning and, where appropriate, the problem of stale data should have a greater place in research. A fourth research direction is to examine how AI requires a different view on the organizational forgetting processes. Until now, the problem was that people forget knowledge too quickly and firms started to establish mechanisms (e.g., gamification elements, chatbots, and microlearning units regarding KM) to act against. Yet human forgetting also has positive sides, since it allows humans to control and regulate their memories and eliminate obsolete knowledge (Kluge and Gronau, 2008). As AI becomes data-driven and can process much more information, it will also be necessary to strip out or expire data for AI so that models are not stuck in outdated patterns.



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