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EDITORIAL

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Special Issue Editorial: Artificial Intelligence in Organizations: Implications for Information Systems Research

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Abstract

Artificial intelligence (AI) technologies offer novel, distinctive opportunities and pose new significant challenges to organizations that set them apart from other forms of digital technologies. This article discusses the distinct effects of AI technologies in organizations, the tensions they raise and the opportunities they present for information systems (IS) research. We explore these opportunities in term of four business capabilities: automation, engagement, insight/decision making and innovation. We discuss the differentiated effects that AI brings about and the implications for future IS research.

Keywords: Artificial Intelligence, Research Agenda, Machine Learning, Algorithms, Robotic Automation, Conversational Agents, Robotics, AI Capabilities

1 Introduction

The artificial intelligence[1] (AI) pioneers of the 1950s envisioned building machines that could sense, reason, and think like people. While such a vision remains in the realms of science fiction, modern advances in computing and the ubiquitous availability of large datasets have allowed organizations to implement AI technologies that go beyond automating and informating. Recently developed AI agents are capable of "learning," solving problems, recognizing and displaying emotions, and creating outcomes in increasingly diverse domains, from developing new products to autonomously managing business processes and supply chains (Daugherty & Wilson, 2018). For example, machine learning algorithms detect suspicious financial transactions and recommend decisions to manage fraud (Davenport, 2018). Smart bots and vehicles are autonomously delivering food and medicine. Robots and machines serve as reliable companions, responding to human emotions, answering queries, and offering assistance in diverse settings (e.g., isolated elderly).

AI technologies offer both novel distinctive opportunities and pose new and significant challenges to organizations in ways that differ from other digital technologies. First, AI technologies differ in their capacity to constrain, complement, and/or substitute for humans at work once they are deployed in an organization (Murray et al., 2020). These differences shift the locus of action, choice, control, and power away from the exclusive domain of humans, requiring

[1] Artificial intelligence is typically defined as the ability of machines to perform human-like cognitive tasks. These can include automation of physical processes such as manipulating and moving objects, sensing, perceiving, problem solving, decision-making and innovation (Benbya, Davenport et al. 2020)

the development of an understanding of how humans and AI technologies interact in new ways to provide a stabilizing force, a coevolution of work, or the emergence of novel forms of work and organizing (Benbya & McKelvey, 2006).

Second, AI technologies fundamentally challenge our long-held beliefs dividing the realms of human ability and machine capabilities (Schuetz & Venkatesh 2020). Recent AI technologies are capable of performing various human feats, such as perception, sensing and recognizing emotions, conversation, and even creativity. Such new capabilities allow AI to enter domains that have thus far remained exclusive to humans (e.g., algorithmic management, new product development, and emotions recognition). Although how machines should behave or think is still disputed, recent advances in AI capability invoke several tensions that go beyond human-machine interactions or new human-machine configurations.

Third, AI technologies exhibit increasing levels of complexity that often lead to many unexpected dual outcomes (Benbya, Nan et al., 2020). While AI technologies offer many positive benefits to organizations, their introduction often creates significant unintended (or intended) consequences for individuals and organizations. Since the impact of AI implementation varies greatly among stakeholders, decisions to decouple stakeholders from the process of designing, implementing, and using AI systems often lead to the ultimate failure of systems (Wright & Schultz 2018). To account for such complexity given the wide spectrum of stakeholders involved warrants a multi-stakeholder perspective (Clarke & Davison 2020).

The distinct effects of AI technologies in organizations present opportunities for information systems (IS) research. We explore these opportunities in terms of four business capabilities: automation, engagement, insight/decision-making, and innovation. We discuss the implications for IS of the differentiated effects engendered by AI. Before doing so, we briefly discuss the evolution of AI technologies.

2 Developments in Artificial Intelligence

The AI field emerged in the 1970s based on research on developing machines able to perform humanlike cognitive tasks (e.g., thinking, learning, and conversing), spanning contributions from diverse fields such as biology, linguistics, psychology, cognitive sciences, neuroscience, mathematics, philosophy, engineering, and computer science.

Table 1. AI Technologies and Domains of Application

Technology	Brief description	Example application
Machine learning Reinforcement learning Supervised learning Unsupervised learning	Learns from experience Learns from a set of training data Detects patterns in data that are not labeled and for which the result is not known	Highly granular marketing analyses on big data
Deep learning	A class of machine learning that learns without human supervision, drawing from data that is both unstructured and unlabeled.	Image and voice recognition, self-driving cars
Neural networks	Algorithms that endeavor to recognize the underlying relationships in a set of data through a process that mimics the way the human brain operates.	credit and loan application evaluation, weather prediction
Natural language processing	The ability of a computer program to understand human language as it is written or spoken	speech recognition, text analysis, translation, generation
Rule-based expert systems	A set of logical rules derives from human experts	Insurance underwriting, credit approval
Robotic process automation	Automates structured digital tasks and interfaces with systems	Credit card replacement, validating online credentials
Robots	Automates a physical activity, manipulates and picks up objects	Factory and warehouse tasks

Early efforts in artificial intelligence aimed at building machines capable of simulating human intelligence. Despite such attempts and promises of the practical usefulness of AI, efforts largely failed to deliver and faced several obstacles, particularly during the 1960s and 1970s, the biggest of which was the lack of computational power to do anything substantial. During the 1980s and 1990s, expert systems emerged as practical applications based on earlier research in AI. And, in the early 2000s, machine learning and neural networks began to flourish as firms integrated statistics and probability into diverse business applications. Over the next decade, digital systems, sensors, and the internet proliferated, providing all kinds of data for machine learning experts to use to train adaptive systems. Although the growth of AI and machine learning has been intermittent, the current unprecedented computing capacity and growing volumes of data have led to the emergence of contemporary AI technologies.

Information systems scholars have a long history of conducting research on artificial intelligence. IS as a discipline emerged when computers enabled the automation of business processes and the digital capture of business transactions. IS research on AI has been conducted since the 1970s, with early developments in decision support systems (Alter, 1978), expert systems and knowledge-based systems (Meyer & Curley, 1991), and, later, recommendation agents (Xiao & Benbasat, 2007). Such systems, however, were not capable of automatically learning and improving their methods and were reliant on human programmers to adjust them. In contrast, more contemporary AI technologies are designed not only to help managers with repetitive decisions and complex unstructured problems but are also capable of learning, adjusting their behaviors, and making autonomous complex decisions. Such technologies include machine learning (and its deep learning and reinforcement learning subclasses), natural language processing, robots, various automation technologies (including robotic process automation), and rule-based expert systems (still in broad use although not considered a state-of-the-art technology). Table 1 provides brief definitions, domain of applications, and classifications of different AI technologies in organizations are given in the Appendix.

3 Research Opportunities in AI-Enables Organizations and Business Capabilities

AI technologies are increasingly overlapping and becoming embedded within different organizational applications (Davenport, 2018). Rather than narrowing our focus on a single distinct technology (e.g., machine learning), we examine research opportunities according to the following different business capabilities:

- Automation of structured (or semistructured) work processes, often via robotics, robotic process automation, machine learning, and rule-based systems.
- Engagement with customers and employees, using natural language processing chatbots, intelligent agents, machine learning, and computer vision.
- Decision-making through extensive analysis of structured data, most often using machine learning algorithms and neural networks.
- Creation of novel outcomes by combining machine learning, neural networks, and computer vision.

Such AI-enabled capabilities are on-going, dynamic, overlapping processes between different sociotechnical and data-related entities and the tensions that emerge from their manifold interactions (Benbya, Nan, et al. 2020). Although these and other capabilities such as innovation are often combined or presented simultaneously, for the sake of simplicity, we will discuss each of the capabilities and their associated tensions individually and then present related research questions.

3.1 AI-Enabled Automation

AI-enabled automation revolves around the use of technologies to support structured and semistructured tasks. These tasks are often repetitive, labor intensive, and include physical as well as cognitive tasks. Performing physical tasks is the traditional domain of robots in settings such as factory automation. AI-enabled robots are equipped with the ability to sense their environment, comprehend, act, and learn. This helps robots perform many tasks by successfully navigating their surroundings, identifying objects around them, and assisting humans with various tasks such as autonomous deliveries and robot-assisted surgeries (Benbya, Davenport et al. 2020). Cognitive automation consists in using technologies such as robotic automation or machine learning technologies. Robotic process automation (RPA) typically automates routine administrative tasks (e.g., data entry work) (Lacity & Willcocks, 2016), whereas machine learning is used to analyze and identify anomalies in large datasets and increase the speed, granularity, and productivity of modeling. Developing such technologies in organizations to enable automation capabilities invokes several tensions about how work is performed. Below, we discuss some of them.

3.1.1 Substitution of Occupations vs. Tasks

A widely discussed tension related to AI-enabled automation is that between the substitution of occupations vs. tasks. Although anxiety about technological unemployment is not new and dates back to the industrial revolution, recent AI-related automation not only concerns manual work but extends to cognitive and nonroutine jobs as well, especially those once considered beyond the reach of mechanization (Brynjolfsson & McFee, 2014). Studies on AI-enabled automation warn about AI automation potentially eliminating countless occupations, involving routine, semiroutine, manual, and even cognitive work (e.g, Frey & Osborne, 2017; McKinsey, 2017). Predictions suggest, for example, that the share of tasks that are performed by robots will rise from a global average of around 10% across all manufacturing industries to around 25% by 2025 (Sirkin et al., 2015).

Despite such claims, there is little evidence supporting the potential demise of numerous professions. Critics maintain that it is typically tasks rather than entire jobs that are automated, arguing that these tasks exist within a broader role alongside other tasks not prone to automation. For example, Brynjolfsson et al. (2018) report that while most occupations in most industries have at least some tasks that could be replaced by AI, there is, at present, no occupation in which all the tasks could be replaced. Rather than simply substituting humans with machines, preliminary studies in IS organizations indicate that such technologies will reshape work and workplace relations in complex and unexpected ways (Mayer et al., 2020).

The implementation of AI technology in organizations may reconfigure power structures vertically but may also cause status and power struggles horizontally (Anthony, 2018). The implementation of AI tools might deskill and displace specific occupational groups, while at the same time making other occupational groups more indispensable and powerful. For example, although the implementation of algorithmic technology in sales has resulted in the displacement of account managers, data scientists have become tasked with locating sales opportunities instead (Pachidi et al., 2020). Similarly, research on predictive policing shows that a new occupational group responsible for "translating" AI insights has gained increasing power by providing guidelines to officers on how to perform in the field (Waardenburg et al., 2020).

3.1.1.1 Research Opportunities

As different AI technologies are introduced to substitute for various tasks, opportunities to address how such technologies become integrated within the organization are continuously arising. IS researchers focusing on adoption could focus on the characteristics or features of AI technologies that increase acceptance and use. For example, the visibility of the work carried out by physical robots may trigger employees and managers to more easily recognize the value of automating such physical tasks. Pachidi et al (2020) found that when a robotic process automation tool runs in the background, it may become more difficult for employees to let go of cognitive tasks in which they have invested knowledge and expertise.

Task automation implies increasing interaction of humans with machines. This type of interaction may differ if one focuses on physical robots versus robotic process automation tools. Physical robots are seen and felt by workers and their physical activity causes visible changes in the physical environment of the workplace. IS researchers focusing on human-machine interaction could study in detail how workers interact with physical robots, and how they alter their routines in order to accommodate robots' movements in the workspace. In contrast, robotic process automation tools may not be visible to workers and their algorithms are likely to be black-boxed to them. Researchers could investigate the challenges that workers face as they interact with automation tools that automate various tasks or the outputs created by those tools. Potentially, workers may come to develop various workarounds in order to overcome difficulties.

As AI-enabled automation technologies become further implemented, we are likely to see changes in organizational communication. For example, the use of robotic process automation tools will likely alter information flows in the organization, leading to the integration of new roles focused on configuring automation tools and communicating effectively with other stakeholders. AI-enabled automation technologies can also trigger significant changes in how coordination is achieved among human experts. For example, Sergeeva et al. (2020) illustrate the redistribution of tasks resultant from the introduction of robots in medical operations. The coordinative adaptations they examined eventually led to the reconfiguration of roles, expansion of occupational knowledge, and shifts in occupational boundaries and status arrangements. However, more still needs to be learned about this. For example, how do other less tangible forms of automation technologies such as algorithms affect coordination among human experts? How will coordination change as human experts start collaborating with automation tools? What are the characteristics of automation tools that may shape coordinative adaptations?

The tension surrounding substitution of jobs vs. tasks also has implications for how technology impacts the nature of work (Frey & Osborne, 2017) and new occupations (Brynjolfsson & McAfee, 2014; Susskind & Susskind, 2015). IS research has much opportunity to contribute in this regard. As AI technologies become increasingly implemented to provide knowledge insights and support experts in their work, questions will continue to arise regarding how these technologies impact workers, how they alter the content of work, and how they alter the ways in which knowledge is created, transformed, and shared (Pachidi et al., 2018). Several AI technologies are already being implemented in various domains to tackle narrowly scoped functions and routine tasks. These technologies are increasingly beginning to integrate different activities in order to improve personal efficiency, work productivity, and overall business performance (Tarafdar et al., 2019; Tschang & Mezquita, 2020). Some of these technologies have been developed by incorporating the codified knowledge of domain experts, while others are capable of self-learning from training data using machine learning and deep learning techniques. Thus, it will be important to investigate what types of complex knowledge work do not have automation solutions capable of outsmarting human experts whose tacit knowledge cannot be codified and programmed (Pettersen, 2019).

It remains unexplored how and when AI technologies will render organizations' operations "mindless" because AI will become increasingly capable of outperforming humans in terms of quickly responding to changing and complex situations (Salovaara et al., 2019). We fully agree with other scholars that the discussion on tacit knowing is in need of fresh thinking (Hadjimichael & Tsoukas, 2019).

Furthermore, physical robots will unavoidably have a substantial impact on work practices because employees may need to physically adapt their ways of working in order to accommodate operations performed by robots. For example, employees may need to adjust to the pace of robots' operation rather than being able to set their own pace,[2] and robots may also impact collaboration among humans (Barrett et al., 2012).

The substitution-of-tasks tension may also be associated with specific changes in an organization's structure. Given that AI-based algorithms are increasingly automating middle-management tasks such as task allocation, control of workers' daily performance, pricing, etc., it is important to understand what the various pathways for flattening the organization's structure are (Möhlmann et al., in press). For instance, how will organizations incorporate AI agents as members of the board (Libert et al., 2017)? How will these organization structure changes impact management practices, employees, and labor relations?

Finally, as more tasks are automated in organizations, security concerns will become increasingly relevant. Robotic process automation can now be applied to a wide range of tasks, including tasks that impact large populations of people and businesses. Potential security breaches of robotic process automation systems may have tremendous impacts and, in some situations, could potentially threaten lives. For example, recently, a computer hacker reportedly gained access to the water system of a city in Florida and tried to poison the water supply (Tidy, 2021). While this might be an extreme case, future research needs to identify how organizations can manage and prevent potential security breaches that could potentially cause a broad range of consequences, ranging from inefficiencies and privacy invasion to physically harmful events.

3.1.2 Automation vs. Augmentation

The increasing use of automation technologies in organizations introduces an emerging tension between the automation and augmentation of human work. The automation capability assumes that tasks are performed by a machine without any human involvement. The augmentation capability assumes that there is continuous close interaction between humans and machines, with machines learning from humans via training datasets and humans learning from the insights gained through machines (Amershi, et al., 2014; Rahwan et al. 2019). It is unclear why organizations opt for automation versus augmentation.

For example, are such choices based on the nature of the task (e.g., a well-structured task such as reviewing a contract could be easily automated using clear rules whereas a more complex task that requires humans to adjust to the situation and could benefit from the additional insight provided by machines)? Or, are they based on issues of accountability and what is at stake if an incorrect choice is made? Some scholars argue that automation and augmentation require different implementation approaches that are mutually exclusive (Lindebaum et al 2020). However, rather than viewing automation and augmentation as mutually exclusive, we ascribe to Raisch and Krakowski's (in press) position: Automation cannot be easily separated from augmentation, yet there seem to be detrimental consequences for a firm's performance when either of the two is overemphasized.

Issues of control are foregrounded in the tensions between automation and augmentation. Silver (1990) advanced the notions of restrictiveness versus guidance with model-based decision support systems, noting how such technologies both expanded and restricted the decision processes in order to align with

[2] https://www.ft.com/content/087fce16-3924-4348-8390-235b435c53b2?sharetype=blocked

organizational objectives. The prevailing agency theory perspective of control assumes that the purpose of control is to ensure that relevant stakeholders act in alignment with organizational goals (Kirsch, 1996). Some research even defines AI technologies in terms of alignment with goals (Kaplan & Haenlein, 2019), which could be investigated through an IS alignment lens (Benbya et al., 2019). Cram and Wiener (2020) discuss how the agency theory-driven research on control in IS has almost exclusively focused on the direct interaction between human controllers and controlees and, thus, largely neglected the role of technology in control processes. They introduce the notion of technology-mediated control as "managers using ubiquitous technologies to influence workers to behave in a way that concurs with organizational expectations" (p. 6) and apply this notion to cases involving UPS and Uber among others. They define technologies as operating either in automation or support roles but still within the controller-controllee relationship. Similarly, Mohlmann et al. (in press) discuss algorithmic control in the context of Uber drivers and identify tensions that arise and responses that either follow market or organizational forms.

3.1.2.1 Research Opportunities

The automation vs. augmentation tension offers opportunities for future research on IS implementation, control, and the future of work, including topics related to employee well-being—in particular, when it is most appropriate to choose automation versus augmentation approaches. Further research is also needed to define what types of tasks are more appropriate for automation than augmentation. As mentioned above, organizations will most likely succeed by implementing a synergy of the two approaches, and researchers will need to investigate the best practices for managers to adopt to achieve such synergy.

The topic of AI-enabled automation vs. augmentation offers opportunities to rethink the concept of control and how it interacts with trust when the target itself is beyond controllability and explainability or when high levels of vulnerability exist. Stewardship theories based on trust notions may offer an opening (Wiener et al., 2019) in that they advocate for more integrative and commitment-based views with shared interests, accounting not only for instrumental goals but also for moral values. In advancing the sociotechnical axis of cohesion for the IS discipline, Sarker et al. (2019) emphasize not only fit between humans and technologies but also harmony with humanistic goals. They also encourage diversity in the conceptualization of the interplay between technology and social actors in terms of entanglement, imbrication, and inscription, Similarly, the second paper of the special issue (Asatiani et al.) relies on a sociotechnical perspective to illuminate how an organization can simultaneously pursue instrumental outcomes (better performance), while accounting for humanistic outcomes (making sure the AI models does not diminish human agency or harm people) this in the context of explainability. However, it remains unclear how technology could be guided to commit to values and then self-monitor its adherence to them and the role of humans in the process. Other theories on control, such as those on organizational socialization, tradition, and identity, could also be extended or elaborated as leadership and team member functions become increasingly embedded in AI technologies (Höddinghaus et al., 2021; Seeber et al., 2020).

Research is needed to clarify how AI-enabled automation coordinates work in organizations. Increasing digitalization allows for feeding task-related data into AI tools that can automate various coordination mechanisms (von Krogh, 2018). For example, machine learning algorithms offer the ability to locate the optimal combination of experts who can form a high-functioning team or can reroute tasks if performance bottlenecks are flagged (Faraj et al. 2018); Valentine et al., 2017). The increasing modularization of work is particularly applicable where work can be rationalized, i.e., when it follows a clear set of rules, making it measurable and standardizable (Pettersen, 2019; Shestakofsky, 2017). Future research should examine how automated coordination tools might apply to more complex nonroutine tasks lacking generic rules.

Finally, more research is needed to investigate how intelligent automation might affect workers, work cultures, and their well-being, as some tasks may be merely enhanced or complemented by AI while other tasks will become fully automated by AI technologies. Research could also address what happens when AI tools outperform human experts, and how this may transform knowledge collaboration, occupational jurisdictions, human resource management, and workers' careers and well-being. Some scholarship specifically suggests examining the kind of skills and relationships that humans will need to develop in order to adjust to changing work environments in the context of increasing AI automation of work tasks (Tschang & Mezquita, 2020).

Another important consideration concerns the development of expertise. In a number of fields, AI technologies can now automate routine tasks previously performed by junior members of the profession, e.g., in the legal industry (Kronblad, 2020). As routine tasks are automated, junior members of those professions will need to seek alternative ways of developing their expertise (Beane, 2019). Thus, research on how AI impacts the nature of work will need to consider the reconfigurations of knowledge and expertise that take place as organizations automate tasks and processes. Much opportunity for research also exists regarding the influence of AI technologies on work cultures and work climate and the short- and long-term health implications associated with the implementation of AI technologies.

3.2 AI-Enabled Engagement

AI-enabled engagement refers to the general capability of computers to understand, respond, engage, and converse with humans using natural human language. Although such engagement includes both voice- and text-based technologies, the technologies used differ largely based on their capability, domain, and level of embodiment. Simple AI engagement technologies are mainly used to handle repetitive client queries whereas smarter technologies, enabled by machine learning and natural language processing, have the potential to undertake more complex tasks that involve greater interaction, conversation, reasoning, prediction, accuracy, and emotional display. Such technologies have been used in many different fields, including finance, commerce, marketing, retail, and healthcare. Although the technologies behind AI-enabled engagement are continuously under development, they currently do not have full human-level language abilities, sometimes resulting in misunderstanding and user dissatisfaction.

3.2.1 Humanlike vs. Machinelike Conversations

As more organizations rely on AI agents such as chatbots to engage with employees and customers via voice or/and text-based conversational technologies, organizations face new tensions related to managing human-AI interactions. Foremost among these is the tension between machinelike and humanlike conversations. Increasingly, organizations are designing conversational technologies with social interaction and anthropomorphism or humanlike attributes (e.g., personality and form) to ensure that the customer's experience is both effective and enjoyable. Although anthropomorphism in IS research has been studied in different technologies (e.g., virtual worlds, e-commerce systems, and decision-making systems), (Riedl et al., 2014; Lankton et al., 2015), conversational agents differ from previous technologies in that they enable real-time individualized interactions and can therefore mimic real-life human interactions (Pfeuffer et al., 2019; Diederich et al., 2020). Studies have found that incorporating anthropomorphism in chatbots (e.g., via social presence, communicative delay, and humor) has positive effects such as increasing conversion rates (Schanke et al., in press). However, research also suggests that more humanlike conversation should not always be the goal, as it can lead to unintended negative consequences such as undesirable perceptions of anthropomorphism (Hill et al., 2015). For example, Zheng and Jarvenpaa (in press) examine how and why egocentric biases occur in technology anthropomorphism. Such biases occur when users attribute their own or other people's egocentric beliefs, expectations, and feelings to the technology (Epley et al., 2004). Further, as users interact with an AI agent, they alternate between unthinkingly treating it as human and actively probing to find its limits (Brahnam, 2009). This pivoting between the two effects, referred to as the oscillation effect, often has negative consequences, especially when the bot is presented as more human than machine. In some cases, organizations want users to perceive and interact with a chatbot just as they would with any other computer system (Schuetzler et al., 2020). This is frequently the case for procedural tasks for which keyword matching bots are most appropriate. In other cases, users need to feel a social connection with the bot, just as they would with a human agent. Organizations should therefore carefully manage the tension between machinelike and humanlike conversations considering both the context, the type of humanlike attributes manifested by the AI agent, and the oscillation effect.

3.2.1.1 Research Opportunities

IS researchers focusing on human-machine interaction could further investigate the features of physical robots most likely to evoke "humanness." Research focused more on conversational AI could also further specify the technology features or combination of features that would suffice to evoke "humanness" in different contexts without introducing the uncanny valley (Mori, 2012) and its negative consequences (e.g., withdrawal). Research on adoption could also identify the settings under which anthropomorphism is needed to evoke people's trust and acceptance versus when it is seen as a redundant feature.

The tension around humanlike vs. machinelike conversations also touches on ethical aspects. Assuming that people trust conversational AI agents because of their anthropomorphic features, could this make them more vulnerable when following the tool's suggestions? And, in such circumstances, how would accountability be managed? Further, most studies on chatbot design, for example, are intended to primarily influence human behavior to drive profits and customer satisfaction (Adam et al., 2019). Future research in this area could investigate settings in which the sole beneficiary is the user and examine how such technologies can assist and improve the decision-making process and benefit individuals, groups, and communities.

Another relevant direction for AI engagement technologies related to IS research would be to expand the engagement models to account for the various configurations of direct and indirect use. As the first paper (Strich et al.) of this special issue finds, AI not only enables engagement but can also lead to disengagement.

Engagement has been studied extensively in IS research through various models of direct and indirect use (Jasperson et al., 2005) and there are often complex interdependencies in use among individuals, giving rise to emergence and collective use models (Negoita et al., 2018). However, there have been few studies investigating how interdependencies in indirect use impact organizational outcomes. Given that the extant IS literature on AI notes the presence of many different layers of stakeholders, theorizing on use models is needed to examine different configurations of indirect use and nonuse. In fully automated AI systems, even information use (or indirect use) is eliminated as systems transfer information to systems that are able to program themselves. The human condition becomes merely an artifact that technology manipulates (Demetis & Lee, 2018). Jarvenpaa and Valikangas (2020, p. 580) paint a bleak picture of a world where technology has taken over mother earth and the "ultrarich are preparing their escape vehicles for space voyage."

3.2.2 Human vs. Emotion Artificial Intelligence

Increasingly, AI technologies are not only used to understand what individuals and groups say (i.e., language) but also how they feel (i.e., emotions). Emotion AI[3] refers to the capacity of machines to see, read, listen, classify, learn, and respond to human emotions (Purdy et al., 2019). This is often achieved through reading words and images, as well as seeing and sensing facial expressions, gaze direction, gestures, and voice, and by integrating bodily behaviors such as heart rate and body temperature. Machines can sense and recognize expressions of human emotion as diverse as interest, anger, distress, and pleasure and respond appropriately by adjusting to human behavior. The ability of AI systems to sense human emotions and perform actions introduces several tensions. On the one hand, this ability enhances human-machine interactions as it makes technology more adaptive and responsive to human behavior. On the other hand, machines should be trained to respond to emotions when appropriate and ignore others (Picard, 2004). For example, customers' dissatisfaction with service often leads to an escalation of anger feelings, which should not be ignored by an AI agent like a chatbot.

The use of sentiment, facial, voice, biofeedback, and neurotechnologies also raise ethical quandaries regarding the emotional and mental privacy of individuals and groups and question whether machines should even display emotions that they don't actually have (Porra et al., 2019). Beyond data privacy concerns (e.g., dignity, consent, choice, and abuse of personal control), Emotion AI connects with concerns about the negative use of nudge theory, framing, and behavioral economics primarily because understanding emotions increases scope and influences decision-making (McStay, 2016). Finally, the subjective nature of emotions makes them especially prone to bias (Purdy et al., 2019).

3.2.2.1 Research Opportunities

Although emotions are clearly important to almost every facet of human and organizational life, they are highly contextual and cultural. It might be premature to assume concepts such as artificial emotional intelligence in the prevailing AI technologies. The concept of human emotional intelligence has received intense criticism and has largely failed to live up to its potential in explaining behavior and outcomes (Ybarra et al., 2014). Furthermore, AI and neuroscience researchers agree that while current forms of AI cannot have emotions, they can mimic emotions such as empathy. IS research studies on the role of human emotions in systems such as e-commerce, information acquisition, decision-making, and social networking suggest integrating three emotion systems: physiology, language, and behavior (Gregor et al., 2014). Future research could thus rely on these three emotion systems to investigate the socioemotional aspects of AI in order to identify any unintended consequences on human behavior and reveal whether AI technology adaptation to human emotions can increase the acceptance of and satisfaction with AI. Machines' understanding of human emotions raises several issues regarding ethics, privacy, and control. For example, responding to human emotions in certain contexts could be linked to the notion of controlling negative emotions and may influence human behavior. However, for some contexts, understanding emotions can remove ambiguity, reduce anger, and increase satisfaction. Future research should therefore investigate the level of emotional display by machines that is most appropriate for different contexts.

3.3 AI-Enabled Insights and Decisions

AI-enabled insights revolve around the use of machine learning (ML) algorithms—a set of unambiguous instructions that a mechanical computer can execute. Some ML algorithms can be trained on structured data and are specific to narrow task domains, such as speech recognition and image classification. Other algorithms, particularly deep learning neural networks, can learn

[3] The term Emotion AI is used interchangeably in the literature with affective computing and artificial emotional intelligence to refer to machines' ability to recognize and respond to human emotions.

from large volumes of labeled data, enhance themselves by learning, and accomplish a variety of tasks such as classification, prediction, and recognition. For example, neural networks can analyze parameters of bank clients such as age, solvency, and credit history to decide whether to approve a loan request. Such networks can also employ face recognition to allow only authorized people into a building or predict outcomes such as the rise or fall of a stock based on past patterns and current data.

3.3.1 Decision Accountability Humans vs. Machines

The implementation of automated decision-making with machine learning is triggering important tensions related to accountability—specifically, who is responsible for the implications of the actions that are either automated or based on insights that come from AI. Machines themselves do not have any sense of self or purpose (Braga & Logan, 2017). Responsibility requires intentionality and machines are incapable of manifesting intentionality (Floridi, 2008). Thus, one common view is that humans need to define how machines will be implemented and used and take responsibility for related tasks and outcomes. However, humans often find themselves unable to take responsibility when automated decisions are made with a level of speed and a number of inputs that exceed the limits of human comprehensibility and reaction (Vesa & Tienari 2020). Furthermore, if humans rely too greatly on AI-enabled insights and decisions, they may become complacent and feel less responsible for AI-automated procedures (Parasuraman & Manzey, 2010; Skitka et al., 2000). Managing accountability appears to be even more complex in light of the frequent lack of transparency in automated decision-making. For agents (whether human or machines) to be accountable for decisions, they must be able to provide reasons underlying actions when asked for an explanation (Lindebaum et al., 2020). However, if organizations can no longer understand why certain actions are performed, they are unlikely to be able to maintain control over their outcomes.

Research indicates that the domain of application and, specifically, the characteristics of problems supported by AI matter significantly in terms of trust in decisions. Compared to tasks requiring social or emotional intelligence, individuals appear to be more trusting of AI tools for technical tasks that require complex processing such as data analysis (Salem et al., 2015; Dietvorst et al., 2016; Dzindolet et al., 2003). The transparency of the inner workings of AI algorithms and the explainability of AI-based outputs also are seen as important factors affecting individuals' trust in the predictions made by machine learning; however, research on this topic remains limited (Glikson & Woolley, 2020).

3.3.1.1 Research Opportunities

IS researchers have the potential to inform the understanding of how AI technologies will affect individual and organizational decision-making. Since machine learning algorithms can self-improve by adapting to the data they are given, humans are faced with the challenge of ensuring that they maintain and use their own intuition while also leveraging the efficiency and effectiveness of decision-making procedures assigned to AI tools.

Research on IS adoption and use could investigate the extent to which AI tools are integrated into and change individual decision-making practices. Individuals' propensity to make use of AI-generated output in their decision-making depends on their perceptions of the tool. The scale at which the tool learns from training datasets and improves directly affects whether users find the tool valuable and useful for supporting their decision-making processes (Gregory et al., 2020).

The increasing reliance on insights generated by AI tools may also lead to power tensions in institutional fields. For example, Orlikowski and Scott (2014) report that the established authority of the TripAdvisor algorithm has now displaced the AAA institution for evaluating and setting the standards of quality in the hospitality sector. IS research on AI could focus on the process through which such power struggles unfold and decipher the role of the materiality of AI regarding the reshaping of authority arrangements. Furthermore, increasing digitization has moved much of the work of external agents outside a firm's traditional organizational boundaries. Artificial intelligence has emerged as a tool for self-organizing the definition and resolution of problems via information processing (Steinberger, 2019), introducing questions concerning the way that AI redefines a firm's organizational design approaches and information processing capabilities (Phan et al., 2017). If more decisions are performed using AI-based insights, vertical and horizontal information structures and the flow of data will be disrupted, although we still do not have sufficient insight into the nature of such changes (von Krogh 2018). Perhaps this is also a moment for organizational scholars to rethink the role of technology for organizational design and for shaping firms' search strategies.

3.3.2 Human vs. Machine Bias

Often, managers assume that automating decisions with AI will remove humans from the loop, thus reducing or eliminating human bias. For example, using automation for credit approval presumably removes bias regarding gender, ethnicity, postal code, etc. (Daugherty & Wilson, 2018, p. 167). However, examples of AI applications have already shown us that new types of biases are caused by training datasets, noisy data, statistical errors, and so forth, potentially leading to even more systematic discrimination (Elsbach & Stigliani, 2019; Raisch & Krakowski, in press). Examples of such discrimination include machine learning systems used in courts to predict defendants' propensity to commit criminal acts that may be racist (Daugherty & Wilson, 2018, p. 179), as well as AI hiring tools that may discriminate against female applicants for STEM jobs (Dastin, 2018).

3.3.2.1 Research Opportunities

The tension surrounding human vs. machine bias triggers important epistemological and ethical concerns that need to be addressed by researchers focusing on IS development. It is crucial to further investigate the data practices that developers should employ in order to avoid bias, including not only quality checks of training datasets but also regular data audits to identify any accumulated biases or path dependencies. It is also essential that researchers investigate how developers can incorporate explainability and transparency in order to help track potential machine biases triggered by machine learning algorithms.

It is important to note that AI algorithms are now able to automatically capture and analyze trace data from business operations and work tasks, producing insights that can help monitor and assess work performance (Østerlund et al., 2020). Therefore, future research could focus on how AI brings about new types of visibility and new forms of control in organizations. The analysis of trace data brings about an unprecedented degree of visibility in work performance, thus enabling managers to closely surveil their employees to ensure adherence to rules, meet quality standards, or even to gain an advantage in the continuous cynical race toward beating the algorithmic evaluation scores (Faraj et al. 2018). For example, employees often can now be automatically nudged if they appear to be underperforming. Employers can use AI to evaluate employees' performance in terms of the frequency and length of work tasks, the quality of work output, communication patterns with colleagues or customers, and can even gain insight into employee sentiments (Kellogg et al. 2020).

The predictive capability of machine learning algorithms also enables managers to evaluate individuals based on predictions about future performance. For example, research has shown that human resource management now includes the incorporation of AI tools that can track productivity rates and generate warnings to employees regarding productivity lags (Tschang & Almirall, 2020). A major question that needs to be addressed is how such AI-enabled monitoring and evaluation affects employees' attitudes, behaviors, and performance. Further, it would be worth investigating whether employees engage in any counteractions in the attempt to distort the data entered into AI algorithms. Research could also investigate the impact of transparency and explainability for potentially alleviating such counteractions on the part of employees.

Finally, research on human-machine interaction could further investigate how potential cases of machine bias affect people's trust in the tool. Specifically, researchers might investigate what mechanisms and practices are useful to developers and/or organizations to restore eroded trust in the objectivity and efficacy of machine learning algorithms.

3.3.3 Machine Rationality vs. Human Judgment

Given their reliance on logical and mathematical procedures, combined with the ability to quickly process vast amounts of data and efficiently self-learn and adjust to new data, machine learning algorithms can help individuals and organizations overcome their bounded rationality and make better-informed decisions (Lindebaum et al., 2020). Thus, it is assumed that machine learning algorithms augment humans in their decision-making practices and enhance organizations' decision-making capabilities (Cohen, 2007). However, scholars caution against organizations relying too heavily on machine learning algorithms for making decisions (Pachidi & Huysman, 2016). If individuals increasingly base their decisions primarily on the recommendations of an algorithm, they may eventually become distanced from the decision-making process (Bader & Kaiser, 2019), lose their ability to judge intuitively (Eisenhardt, 1989), become emotionally detached and feel less responsible (Friedland, 2019), passively accept algorithmic outputs without exercising judgment (Newell & Marabelli, 2015), and may even become accustomed to feeling "helpless" (Moore, 2019).

3.3.3.1 Research Opportunities

The tension surrounding machine rationality vs. human judgment also has consequences for research investigating the impact of technology on the nature of work. Even though studies have predicted that the collaboration of humans and machines will outperform humans or machines alone (Brynjolfsson & McAfee, 2014), it is still unclear how humans interact and collaborate with AI tools to solve problems. Even though it is assumed that the AI insight capability will augment human capabilities, it may often instead lead to frustrating individuals, especially when the recommendations are not intelligible to them (Kellogg et al., 2020). For example, it has been observed that AI may decrease rather than increase work performance because AI insights may lead clinicians to doubt their diagnostic decisions, causing them to spend time to decrypt the process through which the recommendation emerged (Lebovitz et al., 2019). In the case of predictive policing, the application of AI has necessitated the emergence of new experts who exercise human judgment to interpret and present AI predictions to police officers (Waardenburg et al. 2020). Thus, research will need to focus not only on how the interaction between humans and machines impacts people's work practices, knowledge, and judgment (Fails & Olsen, 2003), but must also investigate how domain experts collaborate with other essential roles such as data scientists and translators to transfer their tacit knowledge, ensure continuous improvement of the AI tools, and eventually develop augmented work practices (Holzinger, 2016).

The tension surrounding decision accountability triggers important ethical considerations. In this respect, researchers could investigate what practices organizations follow for assigning accountability when the insights produced by machine learning algorithms affect a crucial part of a task/decision-making procedure. Furthermore, researchers could explore potential unintended consequences that arise as AI is increasingly integrated in decision-making practices. Several examples exist in which algorithmic decision-making (either intentionally or unintentionally) (O'Neill, 2016; Redden & Brand, 2018) caused data harm because the data fed into the algorithm were incorrect or were incorrectly preprocessed in that irrelevant data were not excluded or the structure of the algorithm and decision rules followed were not correctly validated (Lindebaum et al., 2020). If algorithms are not transparent, i.e., the inner workings of the algorithms (type of data used, decision criteria, etc.) are black-boxed from the users, or the AI-based output cannot be explained (sometimes not even by the developers of the algorithm), AI-based automated decision-making is even more likely to cause potential data harm.

More research needs to be performed on the potential unintended consequences of AI-automated decision-making, how actors conceive "harm" caused by the machines, how cases of data harm are managed, as well as what governance mechanisms institutions and organizations need to develop to avoid harmful impacts caused by automated decision-making. Finally, researchers studying IS development could also explore whether developers should enable reverse engineering of the insights produced by machine learning algorithms, which would be useful for investigating what went wrong in a specific instance and could potentially help better assign accountability in the future.

3.3.4 Learning vs. Myopia

Given its insight capability, it is assumed that AI will help organizations decrease search costs and become more rational by making better sense of the environment (customers' response, competitors, macroeconomic forces, etc). In other words, machine learning algorithms can decrease the dysfunctions in an organization's learning process (Pachidi & Huysman, 2016). However, if organizations rely too heavily on algorithms and the datasets that they process with limited human intervention in, for example, auditing and revising the datasets, they risk becoming path dependent and face new types of learning myopia (Levinthal & March, 1993). Balasubramanian et al. (in press) discuss temporal myopia or short-sightedness in terms of the past and future regarding machine learning algorithms that can negatively impact organizational learning without substantive human involvement. But there are negative impacts beyond temporality. Machine learning reduces within-organization diversity in routines and social and background knowledge. The former is critical for variation and the latter for adaptation. To overcome reduced variability, Balasubramanian et al. (in press) recommend "cloud ML," which taps into "variants that perform well across many organizations."

3.3.4.1 Research Opportunities

We know little about the long-term impact of automated decision-making on human cognitive capabilities. Automation often results in rendering human experts redundant or in deskilling them (Endsley & Kiris, 1995; Lindebaum et al., 2020). The loss of expert human cognitive skills could potentially limit the creativity and flexibility instinctively manifested by humans in their cognitive processes since automation is delimited to specific tasks following concrete rules in clearly defined domains (Raisch & Krakowski, in press). Especially when the design of AI algorithms is black-boxed to management, organizations may eventually lose touch with the thinking process behind the automated decision-making procedures (Pachidi & Huysman, 2016). Future research could thus focus more on how automated decision-making processes impact an organization's cognitive capabilities and on how organizations can maintain the creativity and spontaneity associated with human cognition while leveraging the efficiency and high search performance offered by the AI automation.

Researchers focusing on IS development have the skills to further investigate how AI could be put into use to ensure learning and avoid myopia. One potential area of inquiry would be exploring the data practices that developers follow in order to avoid path dependencies in the data—a situation that may lead to myopia. Another emergent area of inquiry refers to the analytical practices that data scientists resort to when faced with unprecedented situations that cannot be understood by using historical data. The insights gained from machine learning algorithms are (at most) as good as the data they are fed with. In other words, machine learning algorithms can provide predictions by analyzing historical data. The Covid-19 pandemic has shown that there are moments in time when historical data cannot be used to make any accurate predictions (Brown, 2021). In such situations, data scientists need to adjust their data sources and the types of algorithms that they use in order to impose some certainty on insights about the present and the near future.

3.4 AI-Enabled Innovation

Beyond the three business capabilities—AI-enabled automation, AI-enabled engagement, and AI-enabled insight—there are other business capabilities such as innovation. Machine learning and deep learning neural networks can automate or enhance innovation processes and outcomes. AI data-driven insights, models, and visualizations can facilitate the creative interpretation of data and support decision-making within the innovation process (Wu et al., 2020). Finally, deep learning has the potential to shorten the time required to bring new products to markets. As a result, several pharmaceutical companies and biotech start-ups have invested in AI to identify and validate potential drug candidates to accelerate the overall drug discovery process (Fleming, 2018). Although AI technologies may not yet be able to independently develop entire solutions, they can point human managers toward the most promising avenues for innovation. Nevertheless, the use of AI for innovation triggers several tensions.

3.4.1 Exploration vs. Exploitation

The large amount of training data required for machine learning to generate, discover, and recognize new creative ideas and opportunities invokes a tension between exploration vs. exploitation capabilities for organizational innovation. Exploitation is associated with building on the organization's existing knowledge base and involves the use and development of things already known (Levinthal & March, 1993). Exploration, in turn, entails a shift away from an organization's current knowledge base and skills. This suggests that AI-enabled innovation will mostly benefit domains where abundant data are available, whereas domains and contexts that require novelty or those for which limited data are available are not well-suited for AI. In such contexts, inferences based on limited data are still heavily dependent on tacit knowledge that is inherently costly to collect and transfer and therefore difficult to digitize for AI consumption (Nonaka & von Krogh, 2009). In addition, for certain discoveries, it is more important to use creativity or deeper insights derived from small but rich data, situations for which AI is not particularly well-suited (Wu et al., 2020). Furthermore, the constant data resourcing requirements that the development of new algorithms require are also underappreciated. Selander and Jarvenpaa (2020) discuss the use of crowds for data generation and show that crowds require more and more organizational resources to produce declining streams of data.

3.4.2 Credit Allocation in AI-Enabled Innovation

Since computer algorithms and learning machines are increasingly being used as a new source of creativity and innovation, they have the potential to expand the role of technology in innovation from an enabler to an autonomous "innovator." Computer algorithms with (and sometimes without) human assistance are increasingly able to create diverse innovative outcomes (e.g., to generate software, produce novel design, or identify new or novel compounds). Thus, it will become increasingly difficult to determine precisely what creators have created. Some argue that the use of AI in innovation may have an even larger impact by serving as a new general-purpose "method of invention" that can reshape the nature of the innovation process and the organization of R&D (Cockburn et al., 2018). Firms, for example, are using machine learning to try to invent new materials and new compounds. This raises issues concerning credit assignment and accountability in AI-generated outcomes. However, AI algorithms (as understood today) cannot be credited with authorship or copyright, and they still depend heavily on the creator of the algorithm, along with the team involved in training the machine and modifying the parameters to produce the work. Instead of redefining "authorship" to include nonhumans, it has been suggested that AI programmers and owners should be granted authorship of AI creations. As such, it is important to examine not only the role that AI technology plays in enabling innovation processes and outcomes but also the allocation of incentives.

In sum, the tensions that arise in tandem with the implementation of AI-enabled capabilities in organizations create several areas of inquiry. There are ample research opportunities to examine how AI technologies affect creativity as well as exploration and exploitation. Additionally, exciting opportunities exist to explore incentives and credit allocation in AI-enabled innovation. IS researchers from both qualitative as well as quantitative traditions have a unique set of skills to approach and offer valuable insights into the phenomena associated with AI in organizations. At the same time, the phenomenon of AI in organizations offers new possibilities to advance IS theorizing on various areas. Table 2 summarizes the major research opportunities identified here.

Table 2. Toward a Research Agenda for IS Research on AI in Organizations

AI-enabled capability	**Tension**	**Possible research areas**	**Research questions that arise**
Automation technologies (e.g., Physical Robots, Robotic Process automation, machine learning)	Substitution of jobs vs. tasks	Adoption	• What characteristics of AI automation technologies lead to acceptance for automating tasks? • How do users perceive the effectiveness of physical robots in automating tasks versus tools that enable robotic automation of cognitive tasks?
		Usage/ Human-machine interaction	• How do humans collaborate with physical robots in the work setting? How do humans adjust their routines in order to accommodate the changes that arise in their environment because of the robots' physical activity? • What difficulties do workers face when using a robotic process automation tool to automate a task? What workarounds do they develop to overcome those difficulties?
		Communication	• How does robotic process automation alter the information flows in the organization? • How do team dynamics evolve around the presence of physical robots?
		Coordination	• How will coordination change as human experts start collaborating with automation tools? • What are the characteristics of automation tools that may shape the coordinative adaptations? • How do physical robots affect team dynamics? • How may other less tangible forms of automation tools affect coordination among human experts?
		Nature of work	• How do automation tools alter the content of workers' jobs? • How do automation technologies transform the ways through which knowledge is created, transformed, and shared? • How do physical robots impact workers' health? • How does the presence of physical robots alter work and collaboration practices as they create or constrain visibilities in the workspace?
		Organizing	• How does the automation of tasks with AI alter organizational structure? • What management practices does task automation require in order to manage the altered organizational structure?
		Security	• What are the principles by which organizations can manage and avoid security breaches in robotic process automation tools?
	Automation vs. Augmentation tension	Implementation	• What technological architectures allow for the full automation of tasks and what technological architectures are most appropriate for augmentation? • What criteria should organizations use to decide which tasks will be automated and which tasks will be augmented? • What managerial practices are necessary to ensure effective implementation of both automation and augmentation?
		Control	• How does the use of AI-enabled tools impact organizational control and trust? • How can automation tools be guided to commit to values and then self-monitor their adherence to them and the role of humans in the process?
		Coordination	• How can AI-automated coordination tools apply to more complex non-routine tasks where there are no clear generic rules that apply?
		Nature of work	• How are workers affected when some of their tasks are automated while others are augmented? • What happens when AI tools outperform human experts? • What kind of skills become essential as tools are introduced to augment work? • How does automation affect knowledge management?

Engagement (conversational agents, chatbots,)	Humanlike vs. machinelike conversations	Human-machine interaction	• What are the features of physical robots that may evoke "humanness"? • What material features of conversational AI tools may increase perceived humanness?
		Adoption/Trust	• What is the impact of anthropomorphic features of AI tools on the perceived credibility of AI conversational tools? • In which settings does anthropomorphism appear to be an essential aspect to ensure people's trust in the AI tool?
		Ethics	• How does the employment of anthropomorphism alter humans' sense of accountability? How is accountability managed in cases of machine error? • What implications does anthropomorphism have for human actions?
	Human vs. artificial emotion intelligence	Emotions	• To what extent can AI tools emulate emotional intelligence that is typically a human trait?
		Use	• How does the perceived artificial emotional intelligence affect usage? • Under what conditions could it instead turn the users away? • How does artificial emotional intelligence affect other stakeholders in the organization who may not directly interact with the AI conversational tool?
Insight/decisions (neural networks, machine learning, deep learning, rule-based expert systems)	Machine rationality vs. human judgment	Decision-making	• How do individuals/groups/organizations integrate the insights produced with machine learning algorithms in their decision-making procedures? • How do humans manage the tension between rationality and intuition as they increasingly rely on AI-produced insights?
		Adoption	• In what kinds of domains/tasks are people more likely to trust the AI-produced insights? • How do transparency of machine learning algorithms and explainability of their outcomes affect user acceptance?
		Nature of work	• How do humans collaborate with AI tools to resolve problems? • How does the AI-enabled insight capability affect humans' judgment process? • What is the role of data scientists and translators to ensure effective use of the AI-enabled insights?
		Organizing	• What are the necessary characteristics of organizational culture to ensure reliance on AI-enabled insights? • How do the AI-enabled insights affect who has access to information in the organization? How does that further alter the power structures and authority arrangements? • How does the implementation of AI-enabled decision-making tools affect occupational boundaries in the organization? • How do the insights gained via AI tools change valuation schemes? • How does the reliance on machine learning algorithms for insights eventually affect an organization's structure?
	Human vs. machine bias	Development	• How do AI developers manage bias? • What are the essential data practices to limit potential biases in the training data fed to the machine learning algorithms? • What are the development principles to control potential machine bias?
		Ethics	• What ethical considerations arise when biased algorithms are used for organizational control? • How does potential bias in machine learning algorithms affect workers' behavior and performance?
		Human-machine interaction	• How do occurrences of machine bias affect users' trust in the tool? • What are effective practices that developers and/or organizations could use to restore people's eroded trust in the objectivity and efficacy of the machine learning algorithms?
	Decision accountability humans vs. machines	Ethics	• What are effective ways for assigning accountability when the insights produced by the AI tools are crucial for an activity? • What unintended consequences may arise as AI gets increasingly integrated in decision-making practices in the organization?

		Development	• What are the necessary principles in order to reverse-engineer the insights produced by machine learning algorithms in order to find why/how an unintended action took place?
	Learning vs. myopia	Cognition	• How does the increasing reliance on machine learning tools for decision-making affect individuals' cognitive capabilities? • What are the implications of automated decision-making for an organization's cognitive capability?
		Development	• What data practices are necessary to control for path dependencies? • Which machine learning algorithms are useful to help organizations learn from the environment when data about the past does not reflect the disruption faced in the present?

3.5 Implications for Research

There are a number of challenges associated with advancing new insights on AI in organizations. The first challenge relates to research methods: namely, small vs. large sample studies and qualitative vs. quantitative research. Both papers in the special issue are based on qualitative single case study approaches. Both involved extensive, in-depth data collection occurring over a period of one to two years. Case studies are often used for exploratory purposes when digital phenomena are still developing along a new frontier. Because many AI phenomena are present only in limited or unique contexts, large sample studies may not yet be viable.

To gain deeper insights, studies may be able to leverage mixed methods that combine qualitative and quantitative approaches along with both large and small samples. Such mixed methods might involve multiple case studies supplemented with simulation models and computational experiments. Mixed methods have been described as ideal for "understanding and explaining complex organizational and social phenomena" (Venkatesh et al., 2013, p. 22). Similarly, multilevel research adapts well to the study of complex IS phenomena that are difficult to address from a single-level perspective because it allows theory building from multiple perspectives (Zhang & Gable, 2017).

However, carrying out mixed-methods and multilevel research is notoriously slow, both in execution and in terms of publication. Data gathering can take years, and even when the data analysis is intermingled with data collection, the interpretation of data can take significant additional time. For the most part, journals are not well endowed with editors and reviewers equipped to shepherd such papers with great efficacy, which can make such research on AI technologies risky.

Another challenge relates to defining, classifying, and categorizing the AI technologies being studied so that the studies have impact and are positioned appropriately for a cumulative tradition. This paper defines AI as the ability of machines to perform humanlike cognitive tasks, including the automation of physical processes, such as manipulating and moving objects, sensing, perceiving, problem solving, decision-making, and innovation (Benbya, Davenport, et al., 2020). It also provides three typologies of AI systems: the first distinguishes AI applications based on the type of technology embedded into the AI system (e.g., ML, NLP, Neural networks), the second is based on the functions performed by the AI (algorithmic, conversational, robotic, biometric), and the third differentiates AI systems based on the kind of intelligence they display. We recognize, however, that both technologies and categories are increasingly overlapping.

Another challenge is related to the issues of context. Do AI technologies in organizations change the way we consider context in our studies and develop context-specific theories (Hong et al., 2014)? The papers in this special issue on AI technologies in organizations highlight how AI technologies introduce impacts well beyond those affecting the formal organization in question. Indeed, AI technologies in organizations provide continuity rather than disruption to the IS field's fundamental questions.

4 Papers of the Special Issue and Closing Thoughts

This special issue began as a conversation between the guest senior editors and the editors-in-chief of two journals: *Journal of the Association of Information Systems* (*JAIS*) and *MISQ Executive* (*MISQE*) on the need to create concerted efforts to contribute to both IS theory and practice. This special issue is the outcome of such dialogue. It uses an innovative format in that is a joint effort between *JAIS* and *MISQE* and represents the first joint special issue in IS. The pre-ICIS Special Issue Workshop held in Munich received over 50 extended abstracts; 30 submissions were selected for discussion and received early feedback from the special issue editorial board and the participating senior editors from both journals.

The call for papers issued for this special issue resulted in the submission of far more papers than we could publish. Following a rigorous and selective process, two articles were accepted for publication in the *JAIS* special issue, and these papers also have counterparts published in the *MISQE* special issue (*MISQE* 19.4, 2020). Other papers required more time, and we hope that this special issue will lead to the publication of exciting theoretical contributions about AI in organizations across the field in the coming years. Each of the accepted papers tackles important theoretical questions about AI in organizations and beyond and provides thought-provoking insights. We briefly present the papers included in the *JAIS* special issue.

The first paper in the special issue entitled "What Do I Do in a World of Artificial Intelligence? Investigating the Impact of Decision-Substitutive AI Systems on Employees' Professional Role Identity" examines the tension of automation versus augmentation from the viewpoint of professional role identity. The paper makes an astute point that much of extant literature on identity and technologies in information systems has examined how identities are shaped while interacting with technology. The authors examine a system pseudonymously called CleverLoan in a German bank that is viewed as a successful case of a decision-substitutive AI system. The system is able to learn based on historical customer behavior and data and optimizes lending criteria. This nontransparent system substitutes for key decisions and eliminates the ability for employees to interact with and influence the system. The system challenges professionals' role identities and different employees respond and adapt their role identity differently in response to the AI system. The study is particularly interesting because it takes place in a setting in which employees' ability to alter or reject the AI decision is eliminated.

The system introduced much uncertainty regarding these decision outcomes that employees were tasked with communicating to the bank's customers. The paper finds that the system equalizes two formerly distinct professional roles in terms of what the employees do. Yet, this equalization of the tasks imposed differing impacts on the two role identities. The positive impacts in terms of what the employees do and their role identity have been largely perceived by less skilled employees, whereas the negative impacts in terms of what the employees do and their role identify have been primarily perceived by more highly skilled employees.

The second paper in the special issue is entitled "Sociotechnical Envelopment of Artificial Intelligence: An Approach to Organizational Deployment of Inscrutable Artificial Intelligence Systems." The paper focuses on the challenging issue of explainability of machine learning algorithms, in particular deep learning algorithms, which cannot be easily explained because of the vast amount of feature layers involved in their production. The authors use envelopment as an approach to address the explainability issue and rely on a sociotechnical perspective to illuminate how an organization can simultaneously pursue instrumental outcomes (better performance), while accounting for humanistic outcomes by making sure that the use of such models does not diminish human agency or harm people affected by the use of the models. The authors analyze how envelopment is practiced by the Danish Business Authority, a government entity operating under the Denmark Ministry of Industry, Business, and Financial Affairs, and show how this approach enabled the organization to utilize inscrutable systems in the context of safety, even in settings necessitating explainability. The authors find that envelopment is a sociotechnical process and illustrate the social factors that pervade all aspects of envelopment, the role of human agents in the process, and the ways in which responsibilities can be defined and managed. Artificial intelligence is emerging as a fundamental, pervasive economic and organizational phenomenon that offers many theoretical and practical opportunities and challenges for information systems scholars. We hope that this article helps frame the necessity of investigating the many research opportunities related to AI-enabled organizations, the business capabilities they support, and the tensions they introduce to organizations, and that its theoretical and practical implications will contribute to finding a common and stronger way forward to advance artificial intelligence research in IS.

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Appendix

AI Types and Technologies

There are many types of AI systems. One typology differentiates AI systems based on the type of intelligence they display. A second typology distinguishes AI applications based on the type of technology embedded into the AI system, whereas a third is based on the function performed by the AI (Benbya, Nan et al. 2020).

Based on intelligence: Philosophical debates on AI are centered on the notion of intelligent machines, that is machines that can learn, adapt, and think like people (Lake et al.). AI types based on such a notion fall, in general, into three categories: artificial narrow intelligence, artificial general intelligence, and artificial superintelligence.

While narrow (or weak) AI is usually able to solve only one specific problem and is unable to transfer skills from domain to domain, general AI aims for a human-level skill set. Once general AI is achieved, it is believed that it might lead to superintelligence that exceeds the cognitive performance of humans in virtually all domains of interest (Bostrum et al.). This type of superintelligence can emerge following evolutionary and complex adaptive systems principles (Benbya, Nan, et al.).[4] It considers that if we humans could create AI intelligence at a roughly human level, then this creation could, in turn, create yet higher intelligence and eventually evolve further. AI enthusiasts are providing estimates and outline scenarios for when technological growth will reach the point of singularity, where machine intelligence will surpass human intelligence. This raises philosophical arguments about the mind and the ethics of creating artificial beings endowed with humanlike intelligence. Although the futuristic literature assumes that AI systems will be able to perform all tasks just as well as, or even better than, humans, this type of artificial general intelligence does not yet exist. There are, however, some AI programs, such as the GPT-3 language prediction application, that are beginning to exhibit some aspects of more general intelligence.

Based on technology: A second typology differentiates between the technologies embedded into AI systems and include machine learning, (as well as its subclasses, deep learning, and reinforcement learning), natural language processing, robots, various automation technologies (including robotic process automation), and rule-based expert systems (still in broad use although not considered a state-of-the-art technology). One recent survey suggests that all contemporary AI technologies (machine learning, deep learning, natural language processing) are either currently being used or will be used within a year by 95% or more of large adopters of AI. Table A1 below provides brief definitions and the domain of applications of AI technologies.

Based on function: This distinction differentiates between four types of AI: conversational, biometric, algorithmic, and robotic. These categories overlap somewhat; for example, conversational and biometric AI already make extensive use of algorithmic AI models, and robotic AI is increasingly doing so as well.

Conversational AI refers to the general capability of computers to understand and respond with natural human language as it is written or spoken.

Biometric AI: Biometrics relies on techniques to measure a person's physiological (fingerprints, hand geometry, retinas, iris, facial image) or behavioral traits (signature, voice, keystroke rhythms). AI-powered biometrics uses applications such as facial recognition, speech recognition and computer vision for identification, authentication, and security objectives in computer devices, workplace, and home security, among others.

Algorithmic AI revolves around the use of machine learning (ML) algorithms— a set of unambiguous instructions that a mechanical computer can execute. Some ML algorithms can be trained on structured data and are specific to narrow task domains, such as speech recognition and image classification. Other algorithms, especially deep learning neural networks, are able to learn from large volumes of labeled data, enhance themselves by learning, and accomplish a variety of tasks such as classification, prediction, and recognition.

Robotic AI: Physical robots have been used for many years to perform dedicated tasks in factory automation. Recently, AI including ML and NLP, has become increasingly present in robotic solutions enabling robots to move past automation and tackle more complex and high-level tasks. AI-enabled robots are equipped with the ability to sense their environment, comprehend, act, and learn. This helps robots do a lot of tasks from successfully navigating their surroundings, to identifying objects around the robot or assisting humans with various tasks such robotic-assisted surgeries.

[4] For a recent article on evolutionary principles that elaborates on such principles in IT management see Benbya & McKelvey (2006).

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