# Special Issue Editorial:

# Artificial Intelligence in Organizations: Implications for Information Systems Research


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## 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 data sets allowed organizations to implement AI technologies that go beyond automating and informating. Recent AI agents can "learn", solve problems, recognize and display emotions, and create outcomes in increasingly diverse domains, from developing new products to autonomously managing business processes and supply chains (Daugherty and Wilson, 2018). For example, machine learning algorithms are detecting suspicious financial transactions and recommending decisions to manage fraud (Davenport, 2020). Smart bots and vehicles are autonomously delivering food and medicine. Robots and machines are serving as reliable companions, responding to human emotions, answering their queries and helping them in diverse settings (e.g., isolated elderly).

As a result, AI technologies offer both novel distinctive opportunities and pose new significant challenges to organizations that set them apart from other forms of digital technologies. First, AI technologies differ from other technologies in their capacity to constrain, complement,

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and/or substitute for humans at work once they are deployed in an organization (Murray, Rhymer and Simon 2020). This shifts the locus of action, choice, control, and power away from the exclusive domain of humans; thus, affecting our understanding of how humans and AI technologies interact in new ways to provide either a stabilizing force, a co-evolution of work, or lead to the emergence of novel forms of work and organizing (Benbya and McKelvey, 2006).

Second, AI technologies fundamentally challenge our long-held beliefs about what falls into the realm of human ability and what is machine capability (Schuetz and Venkatesh 2020). Recent AI technologies are capable of various human feats such as perception, sensing and recognizing emotions, conversation as well as creativity. Such new capabilities allow AI to enter domains that have 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 raise several tensions that go beyond human-machine interactions or new humans-machines configurations.

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

The distinct effects of AI technologies in organizations present opportunities for information systems (IS) research. We explore these opportunities in term four business capabilities: automation, engagement, and insight/decision making and innovation. We discuss the differentiated effects that AI brings about the implications for IS. But before doing so, we briefly discuss the evolution of AI technologies.

## 2.Developments in Artificial Intelligence

Artificial intelligence's origins lie in 70 years research into developing machines able to perform human-like cognitive tasks (e.g., thinking, learning and conversing), and spans contributions from fields as diverse as biology, linguistics, psychology, cognitive sciences, neuroscience, mathematics, philosophy, engineering and computer science.

Early efforts in artificial intelligence aimed at building machines that can simulate human intelligence. Despite such attempts and the promises of the practical usefulness of AI, it largely failed to deliver and faced several obstacles 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 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 when training adaptive systems. Although the growth of AI and machine learning has been intermittent over the decades, unprecedented computing capacity and growing volumes of data led to the emergence of more 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. Research in AI has been undertaken since 1970s with early developments in decision support systems (Alter, 1978), expert systems and knowledge-based systems (Meyer and Curley, 1991) and later recommendation agents (Xiao and Benbasat 2007). Such systems, however, could not automatically learn and improve their methods and results and were reliant on human programmers to adjust. 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 behaviours and making autonomous complex decisions.

Such technologies include machine learning, (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). Table 1 in Appendix provides brief definitions, domain of applications and classifications of different AI technologies in organizations.

## 3. Research Opportunities in AI-enabled organizations and business capabilities

AI technologies are increasingly overlapping and embedded into different organizational applications (Davenport, 2019). Rather than narrowing our focus on a single distinct technology (e.g., machine learning), we examine research opportunities by different business capabilities.

- Automation of structured (or semi-structured) 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.

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

### 3.1 AI-enabled Automation

AI-enabled automation revolves around the use of technologies to support structured and semi-structured tasks. These tasks are often repetitive, labour-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 autonomous deliveries, and robot assisted surgeries (Benbya et al. 2020). Cognitive automation consists in using technologies such as robotic automation or machine learning technologies. Robotic Process Automation (RPA) usually automates routine administrative tasks (e.g., data entry work) (Lacity and Willcocks, 2016b) whereas machine learning is used to analyse and identify anomalies in large datasets, and increase the speed, granularity, and productivity of modelling. Developing such technologies in organizations to enable the automation capability raises several 4tensions 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 between substitution of occupations and tasks. Although anxiety about technological unemployment is not new and dates back to the 1930s, recent AI-related automation is not only about manual work but extends to cognitive and non-routine jobs, especially those once considered beyond the reach of mechanization (Brynjolfsson & McFee, 2014). Studies on AI-enabled automation warns about the possible demise of innumerable occupations ranging from routine, semi-routine, manual and cognitive jobs due to AI automation (e.g, Frey and 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, Zonser and Rose, 2015).

Despite such claims there is little evidence about the potential demise of several occupations due to AI automation. Critics maintain that it is tasks that are automated, not usually whole jobs, and these tasks exist within a broader role alongside other tasks that will not be automated. For example, Brynjolfsson and colleagues (2018) reported from their analysis that most occupations in most industries have at least some tasks that could be replaced by AI, but 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 reshape work and workplace relations in complex and unexpected ways (Mayer, Strich and Fiedler, 2020). The implementation of AI technology in organizations can reconfigure power structures vertically and may also cause status and power struggles horizontally (Anthony 2018). The implementation of AI tools can deskill and displace specific occupational groups, while at the same time it may render other occupational groups as more indispensable and powerful. For example, the implementation of algorithmic technology in sales resulted in displacing the account managers and giving authority over the task of finding sales opportunities to data scientists (Pachidi et al. 2020). Similarly, research on predictive policing shows that a new occupational group who have taken the role of translators of the AI insights have been gaining increasing authority, by providing guidelines to officers on how to act in the field (Waardenburg et al. 2020).

#### 3.1.1.1 Research opportunities

As different AI technologies are introduced to substitute various tasks, there are opportunities to address how such technologies get integrated in the organization. Researchers focusing on the IS 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 see value in automating such physical tasks. Pachidi et al (2020) already found that when a robotic process automation tool runs in the background, it could be more difficult for employees to let go of the cognitive task in which thus far they had been investing their 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, while 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 their physical robots, and how they alter their routines in order to accommodate the robots' movements in the space. In contrast, robotic process automation tools may not be visible and the algorithms running in their background are likely to be blackboxed to workers. Researchers could investigate the challenges that workers face as they interact with automation tools to automate various tasks, or with the outputs created by those tools. Potentially, workers may come to develop various workarounds in order to overcome their difficulties.

As AI-enabled automation technologies get implemented, we are likely to see changes in organizational communication. For example, the use of robotic process automation tools will most likely alter the information flows in the organization. This will likely lead to the integration of new roles who will configure the automation tools and who will need to communicate effectively with other roles. AI-enabled automation technologies can also trigger significant changes in how coordination is achieved amongst human experts as well. Such changes in redistribution of tasks have already been demonstrated by Sergeeva et al. (2020) who studied the introduction of robots in medical operations. The coordinative adaptations eventually led to reconfiguration of roles, expansion of occupational knowledge, and shifts in the occupational boundaries and status arrangements. Yet, more needs to be learnt. How do other less tangible forms of automation technologies such as algorithms affect coordination amongst human experts? 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?

The “substitution of jobs vs tasks” tension has also implications on the impact of technology on the nature of work (Frey & Osborne 2017) and new occupations (Brynjolfsson & Mcafee 2014; Susskind & Susskind 2015). IS research has much opportunity for impact. As AI technologies are implemented to provide knowledge insights and support experts in their work, questions arise on how they impact workers, how they alter the content of their work, and the ways through which knowledge is created, transformed and shared (Bailey et al. 2018; Pachidi et al. 2018). Several AI technologies are already being implemented in various domains to tackle narrowly scoped functions and routine tasks, and increasingly start to integrate different activities so as to improve personal efficiency, work productivity and overall business performance (Shollo et al. 2020; Tarafdar, Beath, & Ross 2019; Tschang & Mezquita 2020). Some of those technologies are developed by incorporating codified knowledge of domain experts, while others are capable to self-learn from training data using machine learning and deep learning techniques. In what types of complex knowledge work, can automation solutions not outsmart human experts, whose tacit knowledge cannot be codified and programmed (Pettersen 2018)? How and when do AI technologies render organizations’ operations “mindless” because AI will outperform humans in the speed with which it can respond to changing and complex situations (Salovaara et al. 2019)? We fully agree with other scholars that the discussion on tacit knowing invites fresh thinking (Hadjimichael and Tsoukas 2019).

In addition, physical robots will unavoidably have a substantial impact on workers’ work practices, who may need to physically adapt their ways of working in order to accommodate the operations performed by robots such as adjusting to the pace of the robots’ operation rather than being able to set their own pace[2]. How will robots impact collaboration amongst humans (Barrett, Oborn, Orlikowski & Yates 2012)?

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

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., what are the various pathways for flattening the organization's structure (Möhlmann et al. 2020)? How will organizations incorporate AI agents as members of the board (Libert, Beck, & Bonchek, 2017)? How do these organizational structure changes impact management practices, employees and labor relation?

Finally, as increasingly more tasks become automated in organizations, security concerns become more relevant than ever. 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 such robotic process automation systems could have tremendous impact that may even cost lives. For example, recently it was reported that a computer hacker 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 from inefficiencies, and invasiveness of privacy, to physically harmful events.

#### *3.1.2 Automation vs. Augmentation*

An emerging tension raised by the increasing use of automation technologies in organizations is between the automation vs. 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, where machines learn from humans via training data sets and humans learn from the insights gained through machines (Amershi, Cakmak, Knox, & Kulesza, 2014; Rahwan et al. 2019). It is unclear what determines whether organizations opt for automation versus augmentation; whether that has to do with the nature of task (e.g., a well-structured task such as reviewing a contract could be easily automated using clear rules versus a more complex task that requires humans to adjust to the situation and where machines could provide additional insights); or with issues of accountability and what is at stake if a wrong choice is made. However, some scholars argue that automation and augmentation require different implementation approaches that are mutually exclusive (Lindebaum et al 2020). Rather than viewing automation and augmentation as exclusive we ascribe to the position of Raisch and Krakowski (2020): 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.

The issues of control are foregrounded in the tensions of automation versus augmentation. Silver (1990) advanced the notions of restrictiveness versus guidance with model-based decision support systems and noted how such technologies both expanded and restricted the decision processes in order to align with the 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 even define AI technologies in terms of alignment with goals (Kaplan and Haenlein, 2019) which could be investigated with an IS alignment lens (Benbya, Leidner and Preston, 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 introduced the notion of technology-mediated control as "managers' using ubiquitous technologies to influence workers to behave in a way that concurs with organizational expectations and apply such notion to cases of UPS and Uber among others." In their definition, technologies are operating either in automate or support roles but still within the controller-controlee relationships. Similarly, Mohlmann et al (2020) discuss algorithmic control within Uber drivers and 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 future of work including employee wellbeing. Questions arise regarding when it is most appropriate to choose an automation versus when managers should opt for an augmentation approach. The nature of the tasks that are most appropriate for automation versus that of tasks most appropriate for augmentation will also need to be investigated. As we mentioned earlier, organizations ideally will most likely succeed by accomplishing a synergy between the two approaches. Researchers will need to investigate the best practices that managers can adopt in order to achieve synergy between the two competing logics.

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 and high levels of vulnerability exists. Stewardship theories based on trust notions may offer an opening (Wiener et al., 2019). Stewardship advocates for more integrative and commitment-based views with shared interests that would account for not just instrumental goals but also moral values. In advancing the socio-technical axis of cohesion for the IS discipline, Sarker et al (2019) emphasize not just fit between humans and technologies but also harmony with humanistic goals and encourage diversity in the way interplay between technology and social actors are conceptualized such as entanglement, imbrication, and inscription among others as the second paper of the special issue outline in the context of explainability. But how could technology be guided to commit to values and then self-monitor its adherence to them and the role of humans in the process remain open questions? Other theories on control such as those on organizational socialization, tradition, identity may be extended or elaborated as leadership and team member functions become increasingly embedded in AI technologies (Höddinghaus et al., in press; Seeber et al., 2020).

Research is needed on how AI-enabled automation coordinates work in organizations. The 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 find the optimal combination of experts who can form a high-functioning team or to reroute tasks if any performance bottlenecks are flagged (Faraj, Sayegh, & Rouleau, 2018; Valentine et al., 2017). The increasing modularization of work is particularly applicable where work can be rationalized, i.e. it follows a clear set of rules so it can be clearly measured and standardized (Pettersen 2018; Shestakofsky 2017). Research is needed on how automated coordination tools could apply to more complex non-routine tasks where there are no clear generic rules that apply.

Finally, more research needs to investigate how intelligent automation may affect workers, work cultures, and their wellbeing, as some of the tasks that they perform may be merely enhanced or complemented by AI, while other tasks get to be automated by AI technologies. Research could also address what happens when AI tools outperform human experts, such as how this may transform knowledge collaboration, occupational jurisdictions, human resource management, as well as workers' careers and wellbeing (Bailey et al. 2018). Other scholars specifically suggest examining the kind of skills and relationships that humans will need to develop in order to adjust with the changing work environment as AI increasingly automates work tasks (Tschang & Mezquita 2020). Finally, another important consideration has to do with the development of expertise. In several fields AI technologies can now automate the routine tasks thus far performed by junior members of a profession, e.g. in the legal industry (Kronblad 2020). As routine tasks are automated the junior members of an occupation need to seek alternative ways of developing their expertise (Beane 2019). Thus, research on the impact of AI on the nature of work will need to consider the reconfigurations of knowledge and expertise that take place as organizations automate many of their tasks and processes. Much opportunity for research also exists in terms of the influence of AI technologies on work cultures and work climate and the short and long-run health implications.

## 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. Such engagement includes both voice and text-based technologies whereby 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, has the potential to undertake more complex tasks that involve greater interaction, conversation, reasoning, prediction, accuracy and emotion 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 Human like vs. machine like 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. First is the tension between machinelike and humanlike conversations. Increasingly, organizations design conversational technologies with social interaction and anthropomorphism or human-like attributes (e.g., personality and form) to ensure that customers' experience is both effective and enjoyable. Although anthropomorphism in IS research has been studied in different technologies (e.g., virtual worlds, ecommerce systems, and decision-making systems), (Suh et al., 2011; Riedl et al., 2014; Lankton et al., 2015; Burgoon et al., 2002); conversational agents differ from previous technologies in that they enable real-time individualized interactions and therefore can mimic real-life human interactions (Go and Sundar 2019; Shevat 2017; Pfeuffer et al., 2019; Diederich et al., 2020). Studies find that incorporating anthropomorphism in chatbots (e.g., via social presence, communicative delay, and humour) has positive effects such as increasing conversion rates (Schanke, Burtch and Ray, 2020). 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, Ford, and Farreras, 2015, Du 2003). For example, Zheng and Jarvenpaa (2021) 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 oscillation effect often has negative consequences for the chatbot, 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, Grimes, Giboney, 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 human-like 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 that will most likely 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 falling into the uncanny valley (Mori 2012) with its negative consequences (e.g., withdrawal). Research on adoption could also identify the settings under which anthropomorphism is needed in order to evoke people's trust and acceptance, and when it is seen as a redundant feature.

The human vs machine like conversations tension also touches upon ethical aspects. Assuming that people trust a conversational AI agent due to its anthropomorphic features, could this make them more vulnerable in following the tool's suggestions? And, in such circumstances, how is accountability 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 can 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 IS research in relation to AI engagement technologies is to expand the engagement models to take into account the various configurations of direct and indirect use. As the first article of this special issue finds, AI does not just enable engagement but can also disengage.

Engagement has been studied extensively in IS research through various models of direct and indirect use (Jasperson, Carter, & Zmud, 2005; and Alavi, 200) and there are often complex interdependencies-in use among various people and use, giving rise to emergence and collective use models (Negoita et al., 2018). However, there has been less studies of how interdependencies-in indirect use impacts organizational outcomes. Given that the extant literature on AI in IS has noted the presence of many different layers of stakeholders, theorizing is needed on use models that examines 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 and are able to self-program themselves. The human condition becomes just an artifact that technology manipulates (Demetis & Lee, 2018). Jarvenpaa and Valikangas (2020: 580) paint a bleak picture of a world where technology has taken over the mother earth and "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[3] AI refers to the capacity of machines to see, read, listen, classify, learn, and respond to human emotions (Purdy, Zealley and Maseli, 2019). This is often achieved through reading words and images, seeing and sensing facial expressions, gaze direction, gestures and voice and 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 behaviour. AI systems ability to sense human emotions and perform actions introduces several tensions. On the one hand, such 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 only if appropriate while ignoring 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. Besides, the use of sentiment, facial, voice, biofeedback and neuro-technologies also raise ethical questions about the emotional and mental privacy of individuals and groups; and about whether machines should even display emotions they don't have (Porra, Lacity and Parks, 2019). Beyond data privacy concerns (e.g., dignity, consent, choice and abuse of personal control), emotion AI connects with concerns about negative use of nudge theory, framing and behavioural economics. This is primarily because understanding emotions increases scope to influence decision-making (MacStay 2016). Finally, because of the subjective nature of emotions, it is especially prone to bias (Purdy, Zealley and Maseli, 2019).

#### 3.2.2.1 Research Opportunities

Emotions are clearly important in nearly any facet of human and organization life. Yet, they are highly contextual and cultural. Hence, one might question the value of concepts such as artificial

[3] The terms emotion AI is used interchangeable in the literature along with affective computing and artificial emotional intelligence to refer to to xxxx

emotional intelligence in the current prevailing AI technologies. The very concept of emotional intelligence, popularized by Coleman (1995), has received intense criticism and has failed to live up to its potential in explaining behavior and outcomes (Ybarra, Kross, & Sanchez-Burks). In addition, AI and neuroscience researchers agree that current forms of AI cannot have their emotions, but they can mimic emotion, such as empathy. IS research studies on human emotions' role in systems such as e-commerce, information acquisition, decision-making and social networking suggests integrating three emotion systems: physiology, language, and behavior (Gregor et al. 2014). Future research can, therefore, rely on the three emotion systems to investigate the socio-emotional aspects of AI to uncover whether AI technology adaptation to human emotions can increase acceptance and satisfaction or if it leads to unintended consequences on human behavior. Machines' understanding of human emotions raises several issues about ethics, privacy and control. For example, responding to human emotions in certain contexts can be linked to the notion of control negative emotions and influence human behavior. While for some contexts, understanding emotions can remove ambiguity, reduce anger and increase satisfaction. Future research should therefore investigate the level of emotion display by machines that is most appropriate for different contexts.

### 3.3 AI-enabled insights and decisions

AI-enabled insight 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, can learn 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, and decide whether to approve loan requests. Such networks can also use face recognition to let 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, and 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 cannot manifest any intentionality (Floridi 2008). Thus, one common view is that humans need to define how the machines will be implemented and used and take responsibility for the related tasks and outcomes. However, humans often find themselves unable to take responsibility, when automated decisions occur faster and with a larger number of inputs that a human can comprehend and react to (Vesa & Tienari 2020). Furthermore, if humans rely too much on AI-enabled insights and decisions, they could potentially become complacent and feel less responsible for the AI-automated procedures (Parasuraman & Manzey, 2010; Skitka, Mosier, & Burdick, 2000). Managing accountability appears even more complex if we take into consideration the frequent lack of transparency in automated decision making. For agents (whether human or machines) to be accounted as responsible for a decision, they must be able to provide reasons for actions when asked for explanation (Lindebaum et al. 2020). However, if organizations can no longer understand why certain actions are made, they are unlikely to maintain control over their outcomes.

Research shows that the domain of application and specifically the characteristics of the problem that is supported by AI matter significantly in terms of trust in decisions. In technical tasks that e.g. require complex processing such as data analysis, individuals appear to easily trust an AI tool as compared to cases where the task requires social or emotional intelligence (Salem, Lakatos, Amirabdollahian, & Dautenhahn 2015; Dietvorst, Simmons, & Massey 2016; Dzindolet, Peterson, Pomranky, Pierce, & Beck 2003). Transparency into the inner workings of AI algorithms and explainability of the AI-based outputs also are seen as important factors to affect individuals' trust in the predictions made by machine learning, however thus far research is limited (Glikson & Woolley 2020).

#### *3.3.1.1 Research Opportunities*

IS researchers have the potential to inform our understanding of how AI technologies are going to affect individual and organizational decision making. As machine learning algorithms can self-improve by adapting to the data that they are fed with, humans are faced with challenges to ensure that they maintain and use their intuition while at the same time leveraging the efficiency and effectiveness in decision making procedures assigned to AI tools.

Research on IS adoption and use can investigate to what extent AI tools get integrated into individual and decision-making practices and how those eventually change. Individuals' propensity to make use of AI-generated output in their decisions depends on their perceptions of the tool. The scale through which the tool learns from training data sets and improves accordingly directly affects whether users will find the tool valuable and useful to support their decision-making processes (Gregory et al. 2020).

The increasing reliance on insights generated by AI tools may even lead to power tensions in institutional fields. For example, the established authority of the TripAdvisor algorithm has now displaced the AA institution for evaluating and setting the standards of quality in the hospitality sector (Orlikowksi and Scott 2014). Research on AI could focus on the process through which those power struggles unfold and decipher the role of the materiality of AI in how authority arrangements are reshaped. Furthermore, the increasing digitization has also moved a lot of work taking place by external agents outside a firm's traditional organizational boundaries. Artificial Intelligence emerges as tool for self-organizing the definition of problems and the attribution of agents to resolve those problems via the processing of information (Steinberger 2019). Questions arise as to how AI redefines a firm's organizational design approaches and information processing capabilities (Phan, Wright, & Lee 2017). If more decisions are performed with AI-based insights, both vertical and horizontal information structures as well as the flow of data will be disrupted, although we still do not have enough insight on how they are likely to alter (Von Krogh 2018). Perhaps this is also a moment for organizational scholars to rethink the role of technology in organizational design and in shaping a firm's search strategy.

### *3.3.2. Human vs. machine Bias*

Often, managers assume that automating decisions with AI removes humans from the loop and thus reduces human bias. For example, using automation for credit approval is supposed to remove any biases about gender, ethnicity, postal code etc. (Daugherty & Wilson 2018:167). However, examples of AI applications already show us that there are new types of biases caused by the training datasets, noisy data, statistical errors etc. that may even lead to a more systematic discrimination (Elsbach and Stigliani 2019; Raisch and Krakowski 2020). Examples of such discriminations include machine learning systems used in courts to predict defendants' propensity to commit a criminal act that have appeared to be racist (Daugherty & Wilson 2018 :179), or AI hiring tool appearing to discriminate against female applicants for STEM jobs (Dastin 2018).

#### 3.3.2.1 Research opportunities

The Human vs machine bias tension triggers important epistemological and ethical concerns that need to be addressed by researchers focusing on IS development. It is crucial to investigate further the data practices that developers need to employ in order to avoid bias in their data. That not only includes quality checks of the training datasets, but even regular data audits that track for accumulated biases or path dependencies. It is also highly important to investigate how developers can incorporate explainability and transparency in order to help track potential machine biases triggered by the 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, Crowston, & Jackson 2020). Thus, research can 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 enable managers to closely surveille their employees and ensure adherence to rules, meeting quality standards or even a continuous cynical race towards 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 are able to evaluate employees' performance in terms of the frequency and length of work tasks, the quality of output of their work, their communication patterns with colleagues or customers, or even their sentiments (Kellogg et al. 2020). The predictive capability of machine learning algorithms also enables managers to even evaluate people based upon predictions about their future performance. For example, research has shown that human resource management now includes the incorporation of AI tools that track the rates of people's productivity and generate warnings regarding their propensity to drop their productivity (Tschang and Almirall 2020). A major question to be addressed is how this AI-enabled monitoring and evaluation affects employees' attitudes, behaviors and performance (Bailey et al. 2018). Further, it would be worth to investigate what potential counter performances employees may engage in, potentially to distort the data fed into the AI algorithms. Research could also investigate the impact of transparency and explainability in potentially alleviating employees' counter performances.

Finally, research on human-machine interaction could investigate further how potential cases of machine bias affect people's trust in the tool. Specifically, researchers could investigate what practices developers and/or organizations are useful to restore people's eroded trust in the objectivity and efficacy of the 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 to quickly self-learn and adjust to new data, machine learning algorithms can help individuals and organizations to overcome their bounded rationality and to make better informed decisions (Lindebaum et al. 2020). They are thus assumed to augment humans in their choice making practices, and to enhance an organization's decision-making capability (Cohen 2007). However, scholars caution against organizations relying too much on machine-learning algorithms for making decisions (Pachidi & Huysman 2016). This is because if individuals base their decisions increasingly upon 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 1998), become emotionally detached and feel less responsible (Friedland 2019), passively accept the algorithmic output without exercising judgment (Newell & Marabelli 2015), and eventually get used to feeling "helpless" (Moore 2019).

*2.3.3.1 Research opportunities*

The machine rationality versus human judgment tension also has consequences for research on the impact of technology on the nature of work. Even though research suggests 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 (Jain et al. 2018). Even though the AI insight capability is assumed to augment humans, it may often instead lead to frustrating them, especially when the recommendations are not intelligible to them (Kellogg et al. 2020). For example, AI has been observed to decrease rather than increase work performance because the AI insights trigger clinicians to doubt their diagnostic decisions and spend time to decrypt the process through which the recommendation came to be (Lebovitz, Lifshitz-Assaf, & Levina, 2019). In the case of predictive policing, the application of AI has made indispensable the emergence of new experts who exercise human judgment to interpret and present the 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 also, on 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 result in augmented work practices (Holzinger 2019).

The tension on decision accountability triggers important ethical considerations. 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 gets increasingly integrated in decision making practices. Several examples exist in which algorithmic decision making resulted (either intentionally or unintentionally) in causing harm (O'Neill, 2016, and Redden & Brand, 2018). This can happen because the data fed into the algorithm were incorrect, or were not pre-processed correctly e.g., so as to leave irrelevant data out, or because the structure of the algorithm and decision rules followed were not correctly validated (Lindebaum et al. 2020). When algorithms are not transparent, i.e., the inner workings of the algorithms (type of data fed into it, 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 prone to causing 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 practices institutions and organizations develop to ensure avoiding harmful impact caused by automated decision making.

Finally, researchers studying IS development could also explore how developers ensure reverse engineering of the insights produced by machine learning algorithms. This could be useful to investigate what went wrong in a specific instance and could potentially help better assign accountability in the future.

*3.3.4 Learning vs. myopia*

Given the insights capability, AI is assumed to help organizations to decrease search cost and become more rational by making better sense of the environment (customers' response, competitors, macroeconomic forces, etc.). Organizations are thus thought to be able to make better sense of what happens in their environment, plan their actions, and eventually also understand how the environment responds to their actions. In other words, machine learning algorithms can decrease the dysfunctions in an organization's learning process (Pachidi & Huysman 2016). On the other hand, if organizations rely too much on algorithms and the datasets that they process with limited human intervention such as in auditing and revising the datasets, they risk becoming path dependent and face new types of learning myopia (Levinthal & March, 1993). Balasubramanian, Ye, and Xu (2020) discuss temporal myopia or short-sightedness in regard to the past and future with machine learning algorithms that can negatively impact organizational learning without substantive involvement of humans. 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. Much expertise can be tacit and hence not easily codified. To overcome reduced variability, Balasubramanian, Ye, and Xu (2020) recommend "cloud ML," which taps to "variants that perform well across many organizations."

*3.3.4.1. Research Opportunities*

Questions arise regarding the long-term impact of automated decision making on the cognitive capabilities. Automation often results in rendering human experts redundant or in deskilling them (Endsley & Kiris 1995; Lindebaum et al. 2020). The loss of those human cognitive skills could potentially limit the creativity and flexibility that humans instinctively manifest in their cognitive processes, while automation is delimited to specific tasks following concrete rules in clearly defined domains (Raisch and Krakowski 2020). Especially when the design of AI algorithms is blackboxed to management, organizations could eventually lose touch with the thinking process behind the automated decision-making procedures (Pachidi & Huysman 2016). Future research could thus focus more on the impact of automated decision making processes on an organization's cognitive capabilities, as well as how organizations strive to 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 to 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 would 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 are able to provide predictions by analysing historical data. The Covid-19 pandemic has proved to data scientists that there are moments in time when their historical data cannot be of use to make any accurate predictions (Brown 2021). In such situations, data scientists need to adjust the data sources and the types of algorithms that they use in order to have some certainty on the insights about the present and the near future.

### 3.4 AI-enabled innovation

Besides the three business capabilities - AI-enabled automation, AI-enabled engagement, and AI-enabled insight – there are other 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 are used to facilitate the creative interpretation of data and to support decision making within the innovation process (Wu, Lou and Hitt, 2020). Finally, deep learning has the potential to shorten the time required to bring new product 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 (Ekins et al. 2019, Fleming 2018). Although AI technologies may not be able yet to independently develop entire solutions, they can point human managers towards the most promising avenues for innovation. Yet the use of AI for innovation triggers several tensions.

*Exploration vs. exploitation*

Given the large amount of training data required for machine learning to generate, discover, and recognize new creative ideas and opportunities, it raises 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 and March 1993). In turn, exploration 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 is available whereas domains and contexts that require novelty and where limited data is available are not well-suited for AI and machine learning. In such contexts, inferences based on limited data still need to heavily depend on tacit knowledge that is inherently costly to collect and transfer, and therefore be difficult to digitize for AI consumption (Nonaka and 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). What is also under appreciated is the constant data resourcing requirements that the development of new algorithms require. Selander and Jarvenpaa (2020) discuss the use of crowds for data generation and how such crowds require more and more organizational resources to produce declining streams of data.

*Credit allocation in AI-enabled innovation*

As 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 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, Henderson and Stern 2018). Firms, for example, are using machine learning to try to invent new materials and new compounds. This raises issues around 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. Some arguments suggest that instead of redefining “authorship”, to include nonhumans, it is necessary to give authorship to AI programmers and owners. As such it is not just the role technology plays in enabling innovation processes and outcomes that changes with AI but also the allocation of incentives.

In sum, the tensions that arise along 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. There are also exciting opportunities to understand 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 the phenomena associated with AI in organizations and offer valuable insights. At the same time, the phenomenon of AI in organizations offers new possibilities to advance IS theorizing on various areas. Table 2 summarizes some of the research opportunities.

**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?<br>• 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 they adjust their routines in order to accommodate the changes that arise in their environment due to the robots' physical activity? |

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| | | | • 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?<br>• How do team dynamics evolve around the presence of physical robots? |
| | | Coordination | • How will coordination change as human experts start collaborating with automation tools?<br>• What are the characteristics of automation tools that may shape the coordinative adaptations?<br>• How do physical robots affect team dynamics?<br>• How may other less tangible forms of automation tools affect coordination amongst human experts? |
| | | Nature of work | • How do automation tools alter the content of worker's jobs?<br>• How do automation technologies transform the ways through which knowledge is created, transformed and shared?<br>• How do physical robots impact workers' health?<br>• 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?<br>• 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?<br>• What criteria should organizations use to decide which tasks will be automated and which tasks will be augmented?<br>• 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?<br>• 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?<br>• What happens when AI tools outperform human experts?<br>• What kind of skills become essential as tools are introduced to augment work? |

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| | | | • How does automation affect knowledge management? |
| **Engagement**<br><br>**(conversational agents, chatbots,)** | *Human like vs machine like conversations* | Human-machine interaction | • What are the features of physical robots that may evoke "humanness"?<br>• 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?<br>• 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?<br>• 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?<br>• Under what conditions could it instead turn the users away?<br>• How does artificial emotional intelligence affect other stakeholders in the organization who may not directly interact with the AI conversational tool? |
| **Insight**<br><br>**(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?<br>• 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?<br>• 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?<br>• How does the AI-enabled insight capability affect humans' judgment process?<br>• 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?<br>• 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? |

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| | | | • How does the implementation of AI-enabled decision making tools affect occupational boundaries in the organization?<br>• How do the insights gained via AI tools change valuation schemes?<br>• 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?<br>• What are the essential data practices to limit potential biases in the training data fed to the machine learning algorithms?<br>• What are the development principles to control potential machine bias? |
| | | Ethics | • What ethical considerations arise when biased algorithms are used for organizational control?<br>• How does potential bias in machine learning algorithms affects worker's behavior and performance? |
| | | Human-machine interaction | • How do occurrences of machine bias affect users' trust in the tool?<br>• 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?<br>• 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?<br>• 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?<br>• 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? |

## 4.2 Implications for Research Approaches

To advance new insights on AI in organizations, there are some challenges. The first challenge relates to research methods: small versus large sample studies and qualitative versus 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 the 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 are depicted as ideal for "understanding and explaining complex organizational and social phenomena" (Venkatesh et al., 2013, p. 22). Similarly, multi-level research adapts well to the study of complex IS phenomena that are difficult to address from a single-level perspective; it allows theory building from multiple different perspectives (Zhang and Gable, 2017).

Yet, carrying out mixed methods and multi-level research are notoriously slow, both in execution and in being published. 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, the journals are not well endowed with editors and reviewers equipped to shepherd such papers with great efficacy. This lack of efficacy can render research on AI technologies a risky research endeavor.

Another challenge relates to how to define, classify, and categorize 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 the ability of machines to perform human-like cognitive tasks, including the automation of physical processes such as manipulating and moving objects, sensing, perceiving, problem solving, decision making and innovation (Benbya et al. 2020). It also provides three typologies of AI systems, the first one 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). While the third differentiates AI systems based on the kind of intelligence they display. We recognize, however, that both technologies and categories are increasingly overlapping.

The third challenge might be 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)? This special issue was on AI technologies in organizations. The special issue articles highlight how the AI technologies had impact well beyond the formal organization in question. AI technologies in organizations provide continuity rather than disruption to the IS field's fundamental questions.

## 5. Papers of the special issue & Closing thoughts

This special issue started as a conversation between the guest senior editors and the editors in chief of two journals: the *MISQ Executive* (MISQE) and the *Journal of the Association of Information Systems* (JAIS) 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 as it is a joint effort between the MISQE and the JAIS and 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. From a rigorous and selective process two articles were accepted for publication in the JAIS special issue, the accepted papers have counterparts in the MISQE special issue. Other papers required more time, and we hope the 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 of this special issue.

The first paper in the special issue entitled "What do I do in a world of AI? 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 the literature on identity and technologies so far in information systems has examined how identities are shaped while interacting with technology. The authors examine a system 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 optimize the lending criteria. This non-transparent 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 where employees' possibility to alter or reject the AI decision is eliminated; yet the system introduced much uncertainty to these decision outcomes that employees had to communicate 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 has differing impacts on the role identities. The positive impacts in terms of what the employees do and their role identity are perceived by less skilled employees and the negative impacts in terms of what the employees do and their role identify are perceived by higher 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 which cannot be easily explained due to 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 would not diminish human agency or harm people affected by the models' use. The authors analyse how envelopment is practiced by the The Danish Business Authority (DBA), a government entity operating under the Ministry of Industry, Business, and Financial Affairs of Denmark and show how such approach enabled the organization to utilize inscrutable systems in safety even in settings that necessitate explainability. The authors find that envelopment is a socio-technical process and they illustrate how social factors pervade all aspects of envelopment, the role of human agents in the process and the ways in which responsibilities can be defined and managed.

As Artificial Intelligence is emerging as a fundamental, pervasive economic and organizational phenomenon it holds many theoretical and practical opportunities and challenges for information systems scholars. We hope that this editorial helps frame the necessity to investigate the many research opportunities related to AI-enabled organizations, the business capabilities they support, the tensions they bring about in organizations and contribute both theoretical and practical implications in order to find a common and stronger way forward for advancing artificial intelligence research IS.

Working on this joint Special Issue has been an immense privilege for us. We received many more submissions than we could publish, and we hope all these papers go on to be published in the future. The special issue process unfolded over a year during the COVID crisis. The support of Dorothy Leidner editor in chief of JAIS and Gabe Piccoli editor in chief of MISQE were key for the successful unfolding of the joint special issue. We would like also to acknowledge the support of Suprateek Sarker who accepted the JAIS special issue during his term as editor in Chief of JAIS. The contribution of all members of the SI editorial board and extended review team was essential to completing the special issue in a such short timeframe and we are very grateful for this collective effort.

## Appendix A

### 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 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[4]. AI types based on such a notion fall in general into three categories: artificial narrow intelligence, artificial general intelligence and artificial super intelligence.

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.[5] This type of superintelligence can emerge following evolutionary and complex adaptive systems principles[6]. 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[7]. 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 human-like 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 exist yet. 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.[8]

***Based on technology***: A second typology differentiates between the technologies embedded into the AI systems which include machine learning, (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[9] suggests that all the 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 1 below provides brief definitions and domain of applications of AI technologies.

| Technology | Brief Description | Example Application |
|---|---|---|
| **Machine learning**<br>• Reinforcement learning<br>• Supervised learning<br>• Unsupervised learning | - Learns from experience<br>Learns from a set of training data | Highly granular marketing analyses on big data |

[4] ***Lake***, B., ***Ullman***, T., ***Tenenbaum***, J. and ***Gershman***, J. "Building machines that learn and think like people, " *Behavioral and Brain Sciences*, 2017

[5] *Bostrom*, N. (*2014*). *Superintelligence Paths, Dangers, Strategies*. Oxford, Oxford University Press.

[6] See Benbya, H. Nan, N., Tanriverdi, H. and Yoo, Y. (2020), "Complexity and information systems research in the emerging digital world," *MIS Quarterly* (44: 1), pp. 1-18, for a recent article on evolutionary principles, and Benbya, H. and McKelvey, B. "Using coevolutionary and complexity theories to improve IS alignment: a multi-level Approach," *Journal of Information Technology* (21:4), 2006, pp. 284-298 for an elaboration of such principles in IT management.

[7] Hawking, S., Russell, S., Tegmark, M., & Wilczek, F. (2014). Transcendence looks at the implications of artificial intelligence - but are we taking AI seriously enough? *The Independent*, 01.05.2014.

[8] Thierry, 2020. New AI can write like a human but don't mistake that for thinking, The Conversation, Sept. 17., 2020, https://theconversation.com/gpt-3-new-ai-can-write-like-a-human-but-dont-mistake-that-for-thinking-neuroscientist-146082

[9] Deloitte (2020) "Thriving in the era of pervasive AI: Deloitte's state of AI in the enterprise, 3rd edition," Deloitte Insights, https://www2.deloitte.com/us/en/insights/focus/cognitive-technologies/state-of-ai-and-intelligent-automation-in-business-survey.html

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|---|---|---|
| | - Detects patterns in data that aren't labeled and for which the result isn't known | |
| **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 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 pick up objects | Factory and warehouse tasks |

**Table 1: AI technologies and domains of application**

***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.

*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, 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.

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