Chapter 14
What Does Artificial Intelligence Mean for Organizations? A Systematic Review of Organization Studies Research and a Way Forward

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Abstract Artificial intelligence (AI) is a swiftly evolving phenomenon that bears both economic and organizational significance. As organizations are increasingly benefiting from AI for both routine and highly complex tasks and decision-making, AI has developed as a key concern when contemplating the future of organizations and organizing. The ability of the AI to act autonomously distinguishes it from technologies historically used in organizations. This also entails new forms of organizing with a non-human actor and challenges existing conceptualizations of technology in organization studies. As AI is contributing to the automation of many aspects of management and impacting organizational dynamics, it has emerged as a very significant organizational phenomenon that entails both theoretical challenges and opportunities for management and organization studies scholars. Although the implications of AI for organizing has been at the centre of practitioner-oriented journals, the scholarly work has remained more nascent with regard to theory-driven research that could explicate the mechanisms between empirical cases and theoretical perspectives. This chapter aims to reveal the state of scientific knowledge on the relevance of AI in organization studies and delves into the potential implications of AI for management scholarship. The chapter first presents the historical trajectory of AI in organization studies by discussing both important antecedents for and consequences of adopting AI-based systems in organizations. It then systematically examines the extant research on the impact of AI on organizations published in the top management journals of the last two decades. The articles are delineated between theory-building and theory testing and further classified with respect to aspects of AI (such as AI as task input, task process or task output) and themes raised in them. The systematic review of these articles contributes to both identifying knowledge gaps and growing research agenda by introducing possible research questions with regard to future research directions for AI in organization studies. This review chapter ends with a brief discussion on the implications for organizational theorizing and the future of organization studies in light of AI.

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14.1 Introduction

Artificial intelligence (AI), which can be described as "a system's capability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaption" (Haenlein and Kaplan 2019, p. 17), has received substantial interest in terms of its potential impact on the work force. AI has become a core concern when considering the future of organizing, organizations, and society at large (Haenlein and Kaplan 2019). The advent of information technology along with the progress in artificial intelligence, machine learning and virtual reality has yielded new prospects in rethinking work, displacing the old ways of organizing and doing jobs (Özkazanç-Pan 2019). Organizations are increasingly using AI for highly complex activities, such as recruiting candidates for job positions (von Krogh 2018) and distributing expenses via blockchain-enabled contracts to partners in a complex supply chain system (Murray et al. 2020). As AI is increasingly contributing to the automation of many aspects of management and is impacting organizational dynamics, it is significant to better understand its relevance for organization studies.

AI is a very significant organizational phenomenon that bears both theoretical challenges and opportunities for management scholars (Bamberger 2018). In today's world, organizations are making use of AI across a wide range of tasks, such as recruiting employees for organizational positions, performing financial transactions, and forecasting technological developments. In a nutshell, AI is a compilation of computer-assisted systems for task performance that encompasses machine learning, automated reasoning, knowledge repositories, and natural language processing. These systems highlight the three main components of AI as "task input (data), task processes (algorithms), and task outputs (decisions, solutions)" (von Krogh 2018, p. 405).

Despite some exploratory empirical studies, theoretically grounded research that aims to understand AI and its organizational implications are relatively limited. The field is instead dominated by articles originating from practitioner-oriented journals that advise executives on the necessary guidelines for benefiting from AI without referring to the application of theory to the research. While firms have started to embrace AI, organization studies scholars have been largely silent about the recent developments, with few exceptions. This chapter aims to provide a comprehensive answer to the following research question: What role does AI play in management and organization studies? In discussing how organization studies scholars can advance the study of AI, we also seek an answer to the question of what the potential implications of AI are for management scholars in research.

The contributions of this review chapter are twofold. First, it aims to reveal the current state of the scientific knowledge on the relevance of AI in the field of organization studies. To do so, we examine the organization studies literature with regard to contributions on AI, and then we propose potential research avenues for studying the interplay of AI and organization theory. By comprehensively examining the articles published to date, we aim to reveal the emerging trends and topics that have been elaborated in the intersection of AI and organization studies. The remainder of the chapter is organized as follows: First, we map the historical trajectory of AI in the field of organization studies, and then we discuss both important antecedents for and consequences of adopting AI-based systems in organizations. We present our methodology and then the findings, and we end with a brief discussion on the potential research avenues and future of organization theory in light of AI.

14.2 AI in its Historical Trajectory: From Herbert Simon to the Current Day

This subsection aims to historically present the scientific knowledge on the role and relevance of AI in the organization studies field by addressing the repositioning of AI at the crux of management debates. Research in the 1950s revealed that AI would become important to management (Newell and Simon 1956). However, debates on AI in management were abandoned in the 1960s in favour of a contingency view in which argued that routine operational tasks carried out by machines were detached from more complex and managerial tasks. The field of AI then underwent a phase of progress and hype, subsequently followed by "AI winters". The initial winter of AI appeared in the 1970s due to the over-inflated promises made by developers, unrealistically high expectations of users, and overly extensive promotion in the media (Newquist 1994). The failure of AI in this period went hand in hand with pessimism in the AI community and cutbacks in funding, followed by the end of research in the field. During this period, research programmes had to hide the goals of their work under different names in order to receive funding. The field was then rejuvenated from the 2000s onwards, whereas its reflection upon organization studies scholarship had to wait almost two decades.

AI was first incorporated into the Dartmouth Summer Research Project on Artificial Intelligence at Dartmouth College, New Hampshire in 1956. The purpose of the project was to unite researchers across different fields to form a new research area aimed at building machines to simulate human intelligence. The subsequent decade witnessed two success stories, the first of which was a natural language processing tool named ELIZA, simulating conversation with a human, while the latter was the "General Problem Solver" program elaborated by Herbert Simon, J.C. Shaw and Allen Newell, aimed at solving certain kinds of simple problems. These systems aimed to collect rules that would presume that human intelligence could be formalized and rebuilt in a top-down method via a sequence of "if-then" statements.

However, this rising trajectory was reversed from the 1960s onwards with the liquidation of the discussion of AI in management and in the 1970s with the strong criticism of spending on AI research by the US Congress and the British government's ending support for AI research at a majority of universities (Edinburgh, Sussex, and Essex were exceptions).

With the rise and prominence of structural contingency theory in the 1960s, technology became increasingly viewed as a contingency factor for organizational structure and decision-making. Structural contingency theory suggested that different contingency factors such as environmental uncertainty, technology, and organizational size require different organizational structures, in which the fit between structure and contingencies is the key to better performance and organizational survival. From this perspective, technology had a narrower scope, such as production processes (Woodward 1965), information technology (Thompson 1967), and amount of variability (Perrow 1972). Early work focusing predominantly on manufacturing technology paved the way for research that sought to add a variety of other technologies (Perrow 1967). AI was decoupled from organization studies, where complex managerial tasks became detached from routine operational tasks that machines could handle.

The 1960s were also important with regard to Cyert and March's (1963) seminal work entitled *A Behavioral Theory of the Firm*, challenging neoclassical assumptions about firms by introducing concepts of uncertainty, conflict, satisficing behaviour and bounded rationality into explanations of firm processes, decision-making, and behaviour (Simon 1978). However, AI agents seemed to surmount these weaknesses in the economic models of firms, challenging many premises of the behavioural theory of the firm (Baum and Haveman 2020). To illustrate, in comparison to human agents, AI agents can be rational and persistently designed to maximize and not satisfy, as algorithms do as told while ignoring other considerations (Lindebaum et al. 2020). AI agents also have the capability to automate decision-making and processes within organizations by challenging bounded rationality with their abilities to process large amounts of knowledge. With AI agents becoming more advanced, there are the possibility of achieving fully automated organizations where human agents are managed by artificial agents (Curchod et al. 2020).

In this historical trajectory, AI-based solutions have been used by organizations to automate routine operations. More recently, developments in computing technology and new machine learning techniques have begun to enable organizations to benefit from AI-based solutions for managerial tasks (Raisch and Krakowski 2020). The literature on organization studies has mainly witnessed the paradigmatic change from viewing AI-based systems as replacing managers to promoting AI-enabled automation to augment tasks. The strategic value of AI-based systems depends not only on the algorithmic capability but also on the effective orchestration of organizational capabilities and managerial willingness to use them (Keding 2020).

The automation of cognitive tasks that makes substitutes of both humans and machines is referred to as the period of the "Second Machine Age" (Brynjolfsson and McAfee 2014). This age is characterized by the quick advancement of digital, computational and robotic technology or machine learning. Schwab (2017) also adopted the phrase "Fourth Industrial Revolution" to highlight the different ways in which technology is being introduced into society, while the first three revolutions were, respectively, represented by steam engines, electrification, and microprocessors. Birkinshaw (2020) conceptualized these perspectives as the exponential growth in the processing and transformation of information in the late 1960s leading to a shift in product types, internal functioning of firms, and accompanying changes in the basis of firm competitiveness.

AI has two broad applications in organizations. First, "automation" denotes that machines take over a human task, and second, "augmentation" implies that humans collaborate with machines in performing the task. In questioning the relationship between automation and augmentation, Raisch and Krakowski (2020) argued that augmentation goes hand in hand with automation in the management field. As the human–machine relationship is no longer dichotomous, both sides are perceived as having complementary strength and capabilities. That is to say, business managers need to be aware that AI bears the capacity to augment rather than replace humans in managerial tasks (Davenport and Kirby 2016). In their review of three books, Raisch and Krakowski (2020) revealed that organizations focusing on augmentation strategies would end up with superior performances and sustainable competitive advantages. However, they argued that the relationship between automation and augmentation was depicted as a trade-off in the studied books, whereas the paradox perspective replaces the traditional trade-off perspective and highlights both contradictory and interdependent elements between automation and augmentation. Throughout the entire process, they argued, these interdependencies allow management interventions in one task to have ripple effects. They suggested that raising a managerial task could allow its subsequent automation, with that automation in turn leading to augmentation managerial tasks closely related to it. As machines can only bring a certain range of options for relaxing real-life constraints, "managers need to use their intuition in matching the machine output with reality in order to arrive at a final decision" (Brynjolfsson and McAfee 2014, p. 92). Moreover, as machines are confined to a specific task, they fail to learn from their experience in one field to conduct tasks in other fields. Therefore, "managers need to ensure contextualization beyond an automated task" (Raisch and Krakowski 2020, p. 16).

14.3 Antecedents of Organizational Adoption of AI-Based Systems

In this subsection, we mainly discuss the role of decision-making and task variety as antecedents of organizational adoption of AI-based systems. The availability of relatively low-cost computing power, big data and the improvement of optimization algorithms paved the way for the new success of AI (von Krogh 2018). As argued by van Krogh (2018), the rapid adoption of AI by organizations can be attributed to four main reasons. First, the past two decades have witnessed advancements in the science and technology underlying AI methods, wherein many global companies have made these technologies available under open-source licences. Second, information technology has evolved to be very efficient in storing task-related data across organizations. Third, the decreasing cost of computer hardware has made computational power increasingly affordable. Finally, the growth of cloud-based services has also rendered AI available to organizations of different scales, from start-ups to mature firms.

The relationship of work and technology has long been studied, from the robotization of factory lines to the integration of computing technology into knowledge work. With the introduction of AI into existing practices, current organizing not only becomes computational but also algorithmic (Brynjolfsson and McAfee 2014). For many reasons, what algorithms actually do is of importance to organization studies. Algorithms influence decision-making in organizations because authority is increasingly conveyed algorithmically. As argued by Lindebaum et al. (2020), algorithms may trigger a new period of hyper-rationality that envisages people as an impediment to an efficient society. Additionally, by promising greater efficiency, algorithms are expected to entail the realization of both goals and strategies in exceptional ways. Hence, algorithms are positioned to influence both the processes and outcomes in organizations and societies. AI algorithms are more and more being utilized in organizational decision-making and, as Pasquale notes, "authority is increasingly expressed algorithmically" (2015, p. 8). Organizations have endeavoured to figure out the brains of outstanding CEOs onto algorithms for more efficient decision-making (Copeland and Hope 2016), monitor job applications via algorithms, and set up AI systems as members of boards (Libert et al. 2017).

The imperfect nature of human decision-making implies that it is also bound by cognitive biases in terms of rationality that may also pave the way to suboptimal decisions. AI transforms how businesses make decisions and interact with other stakeholders. As a multi-agent system, AI can be utilized to support individual and/or group cognition in decision-making. Furthermore, it can permit a human-agent team to better perform collective cognitive tasks than robotic agents alone. To illustrate, IBM has set up a cognitive room that aids merger and acquisition decisions. The AI system therefore forbids decision-makers to collectively interact with huge amounts of information using data visualization techniques in evaluating merger and acquisition options (Gil et al. 2019). The use of "algorithms in organizational decision-making is perpetuated by the striving for an ideal state of reality that is impacted by the ambition of reaching perfect rationality in decision-making" (Lindebaum et al. 2020, p. 7).

The current literature has mainly focused on the ways in which decision-making enabled by AI is incorporated into organization structure (Raisch and Krakowski 2020). In this regard, Shrestha et al. (2019) proposed a typology of arrangements that can be executed, going from full human–AI designation (commonly utilized for automatically detecting fraud or publicizing proposals) to crossover AI–human or human–AI consecutive decision-making (utilized for recruiting or well-being checking, for instance), and, at last, amassed human–AI decision-making (e.g., utilizing AI as a counterbalance of other board individuals' choices). Moreover, Bader and Kaiser (2019) revealed that human interaction with AI detaches the former from decision-making in terms of spatial and temporal separation, as well as facilitating the displacement of humans from decisions in cognitive terms. They challenged the prevailing notion that humans continue to be attached to decision-making because of infrastructural proximity and imposed engagement stemming from their access to contextual dynamics and their emotions. Algorithmic decision-making is, on the contrary, argued as an assemblage of algorithms and humans. They demonstrated that a user interface that introduces algorithmic decisions activates both human detachment and attachment, as they refined the classification of users as either detached from or attached to technologies.

Together with decision-making, task variety has been taken as a contingency factor influencing the adoption of AI. Organizations have benefited from AI-based solutions which automate routine operational tasks. Technological advances and machine learning enable organizations to benefit from AI-based solutions for managerial tasks (Brynjolfsson and McAfee 2017). Studies have argued that the nature of the task defines whether organizations choose automation or augmentation. AI systems learn from repetition and/or feedback from their environment to perform tasks. These tasks encompass performing analyses to grasp patterns or achieve a structured goal. This has enabled AI to do relatively better in highly structured tasks where clear rules are set (von Krogh 2018, p. 405). However, AI is constrained in understanding the context and fails to respond effectively to contextual changes. In the case of AI assisting in the carrying out of tasks, it has been suggested that a contextually sensitive practitioner is still needed to judge whether AI is relevant to a problem and, if so, to undertake reflective action (von Krogh 2018, p. 406).

It is possible to automate relatively routine and well-established tasks, while more complicated and uncertain tasks cannot, but the latter can be addressed through augmentation (Brynjolfsson and McAfee 2014; Davenport and Kirby 2016). This is because the increased learning of complex tasks is based on experts' tacit knowledge, which cannot be easily codified (Brynjolfsson and Mitchell 2017). Most managerial tasks are more complex, with a lack of rules and models, rendering automation impossible. In that case, managers could rely on the augmentation view to discover the problem and collaborate closely with machines on these tasks. In line with the augmentation thesis, AI in the workplace pinpoints the need for generating new skills that would reap the benefits of AI while retaining individuals' capacity for situational discretion both in the deployment of AI and the use of AI-generated outputs (Hadjimichael and Tsoukas 2019).

14.4 Consequences of AI at the Organizational Level: Opening the Black Box

It has been argued that AI provides benefits to organizations by enabling better organizational performance and creating competitive advantages. AI technologies are identified with benefits going from more noteworthy effectiveness and quicker and more precise outcomes to better strategic results at the organizational level (Davenport et al. 2020). In a similar vein, current scholarly work has sought to plot the brains of CEOs into algorithms to entail more competent decision-making (Copeland and Hope 2016), and instal AI systems as board members (Libert et al. 2017).

The common discourse on the positive influence of algorithms in terms of economic value and greater efficiency has recently begun to shift towards the discriminatory and exploitative nature of AI whereby algorithms may allow employers to reconstitute the employer–employee relations of production. In this regard, managers are viewed as transforming organizational control relationships in substantial ways by implementing new control mechanisms that would take full advantage of workers' labour (Kellogg et al. 2020). Among these and different uses of AI-based algorithmic dynamic are additionally various instances of "data harm", some of which might be deliberate while others are unintended. It can be argued that there is a growing concern about the "automation of society" (Helbing et al. 2017). Lindebaum et al. (2020) asserted that automation may prompt a totalitarian system enabled by technology along with oppressive guidelines mirroring the end of human decision. Birkinshaw (2020) argued that AI is forcing companies towards a more limited set of choices in terms of competition and functioning than their managers would opt for. Those restrained choices enabling incremental improvements in efficiency might curtail the ultimate strategy of gaining a competitive advantage.

The development of new technologies has been coupled with increasing concern about the ethical implications and impacts on the workforce. More specifically, there has been a lively debate about a jobless future and rising unemployment rates as humans are no longer needed for certain types of jobs, while the rise of a precarious workforce is deemed inevitable (Özkazanç-Pan 2019). While the general trend is to assume that AI is likely to eradicate jobs, others argue that the economic data do not reflect a job-killing effect of automation (Bruhn and Anderer 2019). Other studies showed a decline in available jobs coupled with a solid spill-over effect in such a way that there is an emergence of new jobs that did not exist before, which compensates for at least some of the losses (McKinsey Global Institute 2017). This trend is expected to bring about both a need to upskill workers and also high levels of unpredictability and uncertainty.

Complementing Raisch and Krakowski's (2020) argument that organizations should adopt a comprehensive perspective containing both augmentation and automation for positive organizational outcomes, others also argued that a one-sided emphasis on automation could lead to job losses and end with the deskilling of managers who hand over their tasks to machines, which could entail increasing rates of unemployment and societal inequality (Brynjolfsson and McAfee 2014). On the contrary, one-sided augmentation may also lead to another "digital divide" and "social tensions between the few who currently have the capabilities and resources for augmentation and those who do not" (Raisch and Krakowski 2020, p. 23).

As the organization studies scholarship is recently immersed into grand challenges (George et al. 2016) and more specifically inequality in organizational settings (Amis et al. 2020), the use of AI in management could also be assessed for its implications for social equality. At one extreme, it has been argued that automation takes humans "out of the loop", "reducing human biases and, in turn, promising greater equality and fairness. For example, using automation for credit approval could reduce bankers' biases that might previously have kept people from qualifying for credit due to their ethnicity, gender, or postal code" (Daugherty et al. 2019, p. 167). Correspondingly, computerized candidate assessment dependent on pre-decided rules and reliable machine processing could aid to eradicate people's hidden predispositions in recruiting choices.

In contrast to the potential equalities that AI could generate, other scholars (Brynjolfsson and Mitchell 2017) have argued that the influence of new technologies is bound by an "implementation lag". As AI implementation advances, it is foreseen that "economic growth will accelerate sharply as an ever-increasing pace of improvements cascade through the economy" (Nordhaus 2015, p. 2). In a similar vein, AI agents, defined as "actors that have the ability to imitate, and outperform human intelligence, act[ing] upon their own, distinct from and without further human intervention" (van Rijmenam and Logue 2020, p. 5), have the capacity to change their behaviour and collaborate, make decisions independently and autonomously and change the context without being subject to further human action. Authors have mentioned three areas of concern: (i) objectivity, with calls for more human oversight, as automated forms of analysis and decision may augment inequality; (ii) the ways in which artificial agency enables both governance and mass surveillance; and (iii) ordering, whereby AI agents become involved in the ordering of social life and institutional conditions.

14.5 Methodology

We conducted a comprehensive search of prominent journals in the management field. Similar to other studies (see Phan et al. 2017), we included articles from the *Academy of Management Journal (AMJ)*, *Academy of Management Review (AMR)*, *Academy of Management Annals (AMA)*, *Academy of Management Discovery (AMD)*, *Academy of Management Perspectives (AMP)*, *Administrative Science Quarterly (ASQ)*, *Journal of Management*, *Journal of Management Studies*, *Organization Science*, *Organization Studies (OS)*, *Organization*, *Human Relations* and *Strategic Management Journal*. These journals are also in the *Financial Times* list of top 50 journals (except for *Academy of Management Annals*, *Academy of Management Discovery and Academy of Management Perspectives*). We searched for papers with titles and keywords including "artificial intelligence", "robot(ics)", "automation", and "algorithm" published between 2000 and 2020. This search resulted in 15 articles; Table 14.1 provides information about these articles and their key findings.

We coded each article with regard to three dimensions: (i) whether the article is extending the theory (theoretical) or testing the theory in an empirical setting (empirical); (ii) whether the article includes task input (data), process (algorithm), and/or output (decision-making) in its design; and (iii) whether the article proposes future research avenues. We also searched for common themes in the articles. In-depth analysis of the nascent body of literature yields themes and contributes to the understanding of how this research field is evolving. This systematic review intends to contribute to the emerging debate in organization studies literature by integrating the concepts and contemplating research opportunities in the field where AI and organization studies overlap.

14.6 Findings

Stemming from the field's nascent nature, most of the articles that we examined for this review chapter commonly refer to the "possible research agenda", where the authors provide future potential questions to be studied with regard to organization studies. In this respect, while some studies raise general questions such as how technological progress in the capabilities of AI may influence organizational design, decision-making, and power issues, some others classify potential research questions at micro-, meso- and macro-levels of analyses (Raisch and Krakowski 2020). Understanding the change in the role of managers as a result of AI-based solutions represents the micro-level, whereas cooperation between humans and machines on managerial tasks pertains to meso-level analyses. Macro-level research, on the other hand, pinpoints how the automation and augmentation in management bring about institutional actions and changes that may bear wide-reaching societal implications.

Secondly, these articles mostly underline contextual factors and the contextualization of AI-related knowledge in organizations. In contrast to the discourse on the superior characteristics of AI and algorithmic decision-making, the studies merely mention the contextual actors. For instance, Fleming (2018, pp. 8–9) highlighted the various categories of jobs to be automated. This study further elaborated that AI is limited by both organizational and socio-economic forces that impact its implementation such as price of the labour, organizational power relations and the nature of the job task. From these contextual boundaries, Fleming (2018) coined the term "bounded automation", similar to bounded rationality, which allows an explication of why increasingly low-skilled (unautomated) jobs are tended to expand while "good ones" become more challenging to obtain. Instead of fetishizing smart machines and treating them in isolation, the discussion should revolve around the organizational and socio-economic conditions that embed and guide computational intelligence (Fleming 2018, p. 10). In addition, Bader and Kaiser's work (2019) indicated that

Table 14.1 Categorization of articles

Author(s) of the article	Year published	Name of the journal	Theoretical/Empirical	Key findings and arguments	Suggestions for research opportunities	AI component (task input, process, or output)
Raisch & Krakowski	2020	*AMR*	Theoretical	Augmentation cannot be separated from automation; these dual AI applications are interdependent, creating a paradoxical tension	Yes	Input Process Output
Van Krogh	2018	*AMD*	Theoretical	Functioning of AI systems entails task input, processes, and outputs. AI provides grounds for phenomenon-based theorizing	Yes	Input Process Output
Bader & Kaiser	2019	*Organization*	Empirical (case study)	"Human decision-makers' confrontations with the essence of the algorithmic decision via the user interface show that AI has a dual role in workplace decisions by creating both human attachment to and detachment from decisions" (p. 22)	No	Process Output

(continued)

Table 14.1 (continued)

Author(s) of the article	Year published	Name of the journal	Theoretical/Empirical	Key findings and arguments	Suggestions for research opportunities	AI component (task input, process, or output)
Fleming	2018	*Organization Studies*	Theoretical	"The forecast of mass joblessness is unlikely to be realized given how AI and digitalization are constrained by socio-economic and organizational forces that shape its implementation (namely labour pricing, extant power relations, and the job task in question)" (p. 2)	Yes	Input Output

(continued)

Table 14.1 (continued)

Author(s) of the article	Year published	Name of the journal	Theoretical/Empirical	Key findings and arguments	Suggestions for research opportunities	AI component (task input, process, or output)
Murray et al.	2020	*AMR*	Theoretical	"Categorizing four forms of conjoined agency between humans and technologies: conjoined agency with assisting technologies, conjoined agency with arresting technologies, conjoined agency with augmenting technologies, and conjoined agency with automating technologies" (p. 2)	No	Input Output
Lindebaum et al.	2020	*AMR*	Theoretical	Problematizing the assumptions of rationality underlying algorithmic decision-making and implications of the latter for organizations. Algorithms are theorized as supercarriers of formal rationality	Yes	Process Output

(continued)

Table 14.1 (continued)

Author(s) of the article	Year published	Name of the journal	Theoretical/Empirical	Key findings and arguments	Suggestions for research opportunities	AI component (task input, process, or output)
Phan et al.	2017	*AMP*	From the Editors	A review of prominent journals yielded no publications with regard to AI, robot(ics), and automation (except for *AMJ*, *AMR*, and *SMJ*)	Yes	N/A
Kellogg et al.	2020	*AMR*	Theoretical	"Algorithmic control in the workplace operates through six main mechanisms; employers can use algorithms to direct workers by restricting and recommending, evaluate workers through recording and rating, and discipline workers by replacing and rewarding" (p. 2)	No	Process Output

(continued)

Table 14.1 (continued)

Author(s) of the article	Year published	Name of the journal	Theoretical/Empirical	Key findings and arguments	Suggestions for research opportunities	AI component (task input, process, or output)
Glikson & Woolley	2020	*AMA*	Theoretical	Presents existing research on the determinants of human trust in AI. The form of AI representation and the level of the AI's machine intelligence are important antecedents	Yes	Input Output
Gregory et al.	2020	*AMR*	Empirical	Theorizes how a new category of network effects (data network effects) has emerged from advances in AI and the growing availability of data. A platform displays network effects if the more that the platform learns from the data it collects on users, the more valuable the platform becomes to each user	No	Input Output

(continued)

Table 14.1 (continued)

Author(s) of the article	Year published	Name of the journal	Theoretical/Empirical	Key findings and arguments	Suggestions for research opportunities	AI component (task input, process, or output)
Shrestha et al.	2020	*Organization Science*	Theoretical	Researchers are yet to recognize the value of machine learning techniques for theory building from data. Machine learning techniques are argued to be useful in theory construction during the pattern detection stage of inductive theorizing	Yes	Input Process Output
Furman & Teodoridis	2020	*Organization Science*	Empirical	Examines "how the introduction of a new technology that automates research tasks influences the rate and type of researchers' knowledge production" (p. 1)	No	Input Output

(continued)

Table 14.1 (continued)

Author(s) of the article	Year published	Name of the journal	Theoretical/Empirical	Key findings and arguments	Suggestions for research opportunities	AI component (task input, process, or output)
Curchod et al.	2019	*ASQ*	Empirical	Reveals “the power asymmetries generated by customers’ evaluations in online work settings. Algorithms reproduce power asymmetries among the different categories of actors, constraining human agency” (p. 1)	No	Input Process Output
Alaimo & Kallinikos	2020	*Organization Studies*	Empirical	Unpacks the work of algorithms in the process of categorization. As “key organizational activities are rearranged by algorithms, organizations can no longer be separated from the technologies that they deploy” (p. 3)	No	Process Output

(continued)

Table 14.1 (continued)

Author(s) of the article	Year published	Name of the journal	Theoretical/Empirical	Key findings and arguments	Suggestions for research opportunities	AI component (task input, process, or output)
Newlands	2020	*Organization Studies*	Empirical	Discusses the implications of surveillance with an algorithmic observer. “Relegation of surveillance and management tasks to algorithms render platform organizations heavily reliant on the reliability of algorithms” (p. 3)	No	Input Output

relying upon the user interface, AI isolates people from their choices while simultaneously reassuring their connection. They additionally uncovered that the conflicted character of algorithms is controlled by both autonomy and reliance.

Third, these articles mostly elaborate on general broad questions deemed to provide grounds for novel research. For instance, the interaction between AI and people has been approached by most of these studies by questioning how we can bring AI into organizations and successfully integrate systems and employees to create a sustainable competitive advantage (Murray et al. 2020; Makarius et al. 2020; Fleming 2018; Haenlein and Kaplan 2019). In the context of big, fundamental and mostly ontological questions, there has been a tendency to discuss "AI actorhood". Articles highlight the need for management scholars to acknowledge that "humans are no longer the sole agents in management even though most theories focus on human agency" (Raisch and Krakowski 2020, p. 28). AI systems are thus depicted as active agents in advancing problem-solving and strategic decision-making rather than as passive recipients of human inputs.

In developing AI actorhood, AI is no longer seen as a contingency factor but rather as possessing human actors' abilities, such as collaboration, learning and adapting to employee interactions. In this context, the evolution of AI agency and actorhood is deemed to be more than just a technological development, also reflecting challenges for organizational theorizing (van Rijmenam and Logue 2020). While former technological progress "focused on altering or replacing routine manual tasks, AI involves cognitive, relational and structural complexities" (Makarius et al. 2020, p. 263). In contrast to the separation between humans and machines, recent theorizing suggests a focus on the interdependence of these two actors interacting on the same or closely related tasks. For scholars to overcome human bias and to opt for augmentation, they need to adopt a relational ontology that maintains that "human and machine agents are so closely intertwined in hybrid collectives that their relations determine their actions, and the interactions between these actors should be the unit of analysis" (Raisch and Krakowski 2020, p. 31).

14.7 The Future of Organization Theory and Future Research Avenues

In this subsection, we briefly discuss the conceptualization of the research agenda on AI and organizational theorizing with regard to the two different theoretical lenses of socio-materiality and institutional theory, the latter of which has come to dominate the organization studies field (Alvesson and Spicer 2019). The introduction of artificial agents also implicates changes in the ways that humans work across individual, group and organizational levels. This, in turn, requires a change in our understanding of these multi-level processes (von Krogh 2018). As technology is not only embedded in and shaped by socio-organizational forces but also impacts those forces (Fleming 2018), it enables socio-materiality as a theoretical lens to understand AI agency.

Information technology enables human actors to understand their world, offers a tool for the construction of their social reality, and adds to human actions by objectifying knowledge (Orlikowski and Robey 1991).

In this view, technology is deemed to be the result of interactions among human actors, actions, choices and institutional contexts; hence, materiality is both socially defined and only relevant to the people engaging with it (Orlikowski 2009). Human agency has been defined by actors of different institutional environments as temporally constructed engagement which both generates and changes these frameworks through the interplay of habit, imagination, and judgement (Emirbayer and Mische 1998). Van Rijmenam and Logue (2020) viewed these definitions as failing to fully account for understanding AI agency; rather, they argued that artificially intelligent entities can exercise agency through their performativity, by doing things that are outside the control of other agents (i.e., human or artificial), and when agents' actions materialize through their intentionality, objectives can be attained. In line with the tradition of socio-materiality, the authors defined AI agency as "coordinated artificially intelligent intentionality formed in partial response to perceptions of human agency, material agency and/or other AI agency" (p. 9).

From this perspective, it can be argued that the integration of AI into organizations raises important implications. For instance, how the entanglement of the social and material would take place if AI creates AI and how this interaction could be conceptualized when no human actions are involved in the technology creation but rather an AI agent creates technology itself are very timely questions to consider. Van Rijmenam and Logue (2020) argued that AI agency challenges the concept of entanglement. As technological artefacts are created by social action, the material influences the social and vice versa, and all organizational aspects are bounded by the material (Orlikowski 2007). According to this perspective, the social and material are entangled; however, artificially intelligent agents have the capacity to act autonomously in response to human and material agency. AI is both social and non-social; it is social because it is developed by humans, yet it is also non-social because AI artefacts are now created by other AI artefacts. Building on the extant research on socio-materiality (Leonardi and Barley 2010), a potential question could be how we can answer for the emergence of new actors or dislodgment of other actors by AI.

Rapid developments within the field of AI increasingly result in autonomous AI agents displaying reflexivity that can act with intentionality. When AI creates AI, it is increasingly further removed from human design or interaction. Van Rijmenam and Logue (2020) argued that this looming form of AI challenges our assumptions of agency, structure, materiality, actorhood, and intentionality across many perspectives of organizational, management, and innovation theorizing.

To continue with institutional theory as a theoretical lens to understand AI, recent work has established that digitally enabled institutional arrangements such as new organizational forms are creating significant changes in many industries (Hinings et al. 2018). From the institutional theory perspective, AI agency can be theorized as an actor, as a mechanism that contributes to (de-)institutionalization, as a form of institutional infrastructure, or as a diffusion mechanism.

The concept of actors has been one of the central constructs in institutional theory, but its specification and use are contested (Hwang and Colyvas 2019, p. 2). Hwang and Colyvas (2019, p. 5) theorized actors as involving three elements: (1) the level of society that claims about actors inhabit; (2) the degree of generality that claims about actors possess; and (3) the ontology, or the essential features of an actor that determine the inclusion of social entities into the construct. From this conceptualization, institutional theorists may answer the question of what theoretically relevant features of AI actors will provide cognitive adequacy and generalizability across many empirical contexts. Humans are no longer the only actors in management, although most theories focus exclusively on human agency. The emergence of novel actors and agency may also be taken as potential research by asking the following questions: How can non-human modes of agency be theorized in institutional contexts? How does the infrastructure affect the process of institutionalization? How do the actors use their dominant roles to control these infrastructures?

At the micro-level, how the advent of AI-based solutions transforms the role of managers in organizations is a potential direction of research. Management theories have already stressed the domain knowledge of managers, which has given them expert power and influence in their organizations. However, as automation and augmentation are expected to lead to institutionalized knowledge, it will become superior to individual managers' expert knowledge. At the macro-level, it is important to discuss how the advent of automation and augmentation in management contributes to institutional change. Broader networks of stakeholders (i.e., companies, governments, international organizations, public institutions) work together to build institutions, and contributions from these agents within and outside the organization have an effect on the process of automation and augmentation, which can have wide-reaching societal consequences.

AI agency bears the significant theoretical potential to be studied in institutionalization processes. These processes render practices, forms, ideas and meanings taken for granted. In this regard, the roles that AI agents may play in this process, institutionalizing certain practices and further institutionalizing bias or inequality, are potential directions of research. For instance, the questions of what role AI agents might now play in institutionalizing certain practices further institutionalizing inequality (Amis et al. 2020), how AI shapes the direction of institutional change, and what institutional conditions are at stake when AI agency is introduced may be significant research directions. Other valuable questions may regard institutionalization mechanisms, such as how new digital institutional arrangements centred on technologies such as social networking, blockchains and AI reconfigure institutionalization mechanisms and processes, or how leveraging AI affects the process of (de)-legitimation of a new venture, might be other useful concerns.

Moreover, theorizing on institutional infrastructure (Hinings et al. 2017; Zietsma et al. 2017) may also illuminate how to conceptualize AI agency. "Institutional infrastructure" refers to "cultural, structural, and relational elements that create the normative, cognitive, and regulative forces that reinforce field governance" (Hinings et al. 2017, p. 163). As these elements maintain the stability of the social environment, they also impact how organizations should interact and exchange. Possible questions may be as follows: Could AI agents provide a new form of relational infrastructure in fields? While field boundaries may be created and reinforced by the activities of AI agents, how might the same agents deinstitutionalize field boundaries and professional jurisdictions? How does AI agency change the understandings of negotiation processes within fields, if AI agents can make their own decisions independent of humans, and the interaction and mutual dependence between and across fields and subfields?

The role and impact of digitalization has also been addressed by institutional theorists where digitally enabled institutional arrangements permeate and reshape fields, challenging power structures and meaning systems (Hinings et al. 2018; Hinings and Meyer 2018). Future research can therefore delve into how actors leveraging digital technologies can change the ways in which institutions are created or destroyed. The interplay of novel digital technologies and institutional processes may provide insights into institutional emergence, change, and institutionalization and deinstitutionalization. Empirically we witness platform-based organizations disrupting existing institutional processes, organizations as a part of the ongoing institutionalization process of digitalization and organizations in established fields that are changing institutional processes (Hinings et al. 2018).

14.8 Conclusion

As AI is outperforming human effort in a variety of tasks and cognitive acts, its ability to act autonomously separates it from most technologies historically used in organizations. This also results in new forms of organizing and challenging existing conceptualizations of technology in organization theory (van Rijmenam and Logue 2020). In this view, workplaces where humans once engaged in social interactions have paved the way for robots and AI assistants that will emerge as new intermediaries impacting these relationships. Organization theorists are urged to include these non-human elements into their organizational analysis with relation to cultures, norms, practices, agency and organizational policies. AI's growth can thus involve a novel period of organization theory scholarship that aims to comprehend how organizational outcomes affect different categories of employees beyond humans.

In this review chapter, we first aimed to synthesize the findings of the extant research through a systematic review of articles in top management journals about the impact of AI on organizations. We then identified knowledge gaps and provided several possible research questions regarding the future research directions for AI in organization studies. Through this systematic review, we have synthesized the knowledge from earlier research with the current scholarly work in order to structure future research avenues around the evolutionary phenomenon of AI in management. In particular, we have delineated between conceptual (theory-building) and empirical (phenomenon-based) articles, adopted a further classification with regard to aspects of AI (i.e., AI as task input, task process, or task output) addressed in the articles, and identified the common themes raised in these articles. This thematic framework ultimately served as a basis for identifying potential research streams in the emerging field of the interplay of AI and organization studies. We have aimed to contribute to the emerging scholarly discussion by systematically reviewing the research that has been conducted in the management and organization studies field.

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