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Artificial intelligence in the work context

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Abstract

Artificial intelligence (AI) reconfigures work and organization, while work and organization shape AI. In this special issue, we explore these mutual transformations and how they play out across industries and occupations. We argue that, to truly appreciate this transformative power, the use of AI should be understood in relation to key dimensions of the work context. In this editorial, we discuss the sociotechnical dynamics of AI implementation, the research landscape of AI in the context of work, and key contextual factors on the macro- and micro-level that help understand the AI-work nexus. We then provide directions for future research at the intersection of work and AI.

1 | TECHNOLOGY (AI) MATTERS (SELF-LEARNING AND OPACITY)

Artificial intelligence (AI) systems exhibit unique characteristics that may contribute to or hinder work practices; these characteristics may also set AI systems apart from the previous waves of information systems at work. Recent generations of AI systems, empowered by deep learning, differ from previous generations of information systems (even prior AI systems) because of their self-learning capacity (Jarrahi et al., 2022). That is, these systems can expand their intelligence and learning outside of prespecified structures and logics, as opposed to previous systems in which the logic was embedded into the code by human contributors. This can be a double-edged sword. On the one hand, the system can make inroads into some knowledge-intensive tasks that necessarily required human inputs in the past. For example, AI systems can now parse and interpret languages and create text much more dynamically or they can provide unprecedented image recognition capacities (Brynjolfsson & Mitchell, 2017). On the other hand, the logic of the AI system may not be transparent to human operators, users, or even developers (Felzmann et al., 2019). The system may not explain how and why inferences are made. These characteristics define the power of deep learning systems and their unique affordances for transforming work as well as the impediments for widespread adoption outside of the lab and experimental environments.

While technological features matter, the transformative power of AI systems in the work context lies in three elements (see Figure 1): (a) their descriptive and predictive models, (b) leveraging big data, and (c) changing work practices (Østerlund, Jarrahi, et al., 2020). These three elements do not operate individually but are tightly entwined. In other words, scrutinizing the predictive models that go into AI will illuminate data flows and

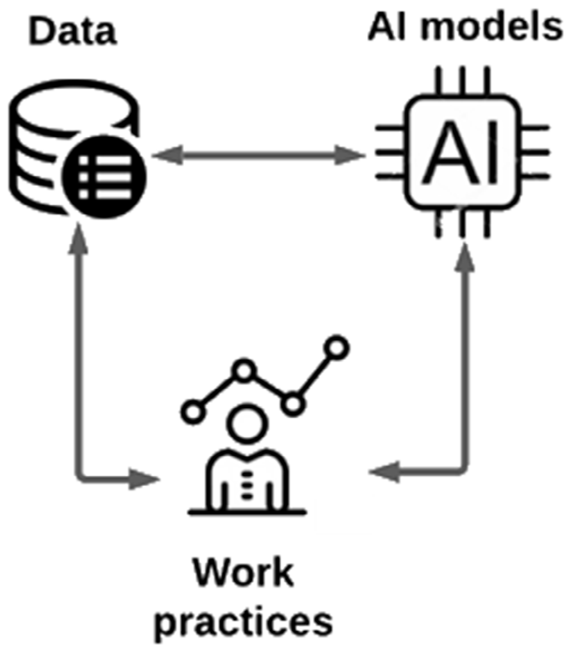

FIGURE 1 Three intertwined elements, defining AI performance in work context

work practices that nurture these models and are driven by them. Likewise, following the data feeding the AI models will reveal the work practices that produce and are incentivized by the data. The interplay between data flows, the organization of work, and AI model predictions spotlight the ongoing and emerging organizational practices. It is through these practices that data in various forms (e.g., abstract, quantified, unstructured, visualized) can be compared, converted, and given authority as a meaningful project of the future (Leonardi et al., 2021; Mazmanian & Beckman, 2018; Østerlund, Crowston, & Jackson, 2020). In short, one can only understand AI's implications if it is placed in the recursive relationships between data, work practices, and AI models. AI performance is therefore complicated and is only realized through an understanding of the work context, practices, and how AI interacts with it.

2 | THE CONTEXT OF WORK MATTERS

Like previous technologies, AI's true impacts are realized outside of the lab and in the context of daily work practices. A contextual study examines the technology at work not in isolation but in conjunction with organizational policies and routines. In this section, we highlight some of these contextual factors at different levels of analysis, including the macro- and micro-level.

2.1 | Macro-level contextual factors

2.1.1 | Regulation and policies

If we approach AI models, data, and work practices as interdependent, it has consequences for how we bound our approach to AI regulations and policies. AI policies are now emerging in different countries, regulating how benefits can be maximized and risks minimized. For example, the OECD AI principles[1] focus on the rights of different stakeholders (e.g., privacy) and how trustworthy AI can be reinforced in practice. Similarly, the Artificial Intelligence Act in Europe (European Commission, 2021) is in the regulatory process. It would use a risk-based approach to AI regulation, prohibiting certain applications deemed manipulative or exploitative, with high-risk applications having to undergo strict scrutiny. More generally, policy frameworks within industries, organizations, or occupations define how AI systems can be used. For instance, the lack of transparency in many AI decision-making tools is at odds with regulatory requirements of medical practice and has hindered the extensive roll-out of these systems in hospitals (Kahn, 2022).

It would be insufficient to narrowly regulate AI models. Policies must consider the data flows and work practices in regard to the AI models as well. Thus, AI regulation and policies touch upon other legal areas such as data protection law (e.g., GDPR, COPPA, HIPAA), competition and antitrust law (e.g., Digital Market Act), consumer protection law (e.g., Digital Services Act), and labor and employment law.

2.1.2 | Field and institutional logics

Different social fields and industries operate under different institutional logics, which has important bearing on how AI is put into use. The work contexts of AI research often share the knowledge-intensive nature of the work but have important idiosyncrasies and demarcations to conflicting institutional logics. For example, Sirén-Heikel, Kjellman and Lindén (this special issue) investigate both competing and assimilating logics at the intersection of journalism and AI developers (tech industry), spotlighting the latter's viewpoints. The technologists framed journalistic logics as sometimes unfocused, inefficient, and misinterpreting the role of AI and their own intentions. At the same time, they also acknowledged aspects of journalistic logics and integrated parts of them into their daily workflows.

In certain contexts, and situations, organizations (and therefore the individuals connected to them) will embrace AI and engage in meaningful ways with it, prospering and benefiting from it. In other contexts, they will confront, resist, and potentially suffer from AI systems. Maintaining contextual integrity, as respect for context-specific information norms, is a key tenet of the influential theory of privacy as contextual integrity (Nissenbaum, 2009). For AI and work, this means a critical awareness of how the specific work context or situation is amenable or resistant to AI implementation. Such awareness can mean, for example, to forgo AI technologies that clash with the lived experiences of workers and employees, are misaligned with organizational values or end up being purely performative and symbolic.

2.2 | Global events and historical transitions (Covid-19)

Beyond organizational, interpersonal, and individual aspects, the role of AI and work is shaped by more societal or macro-developments, such as global developments (e.g., climate change), and large-scale ruptures. Regarding the latter, the ongoing COVID-19 pandemic stands out as a pivotal moment for AI and work. It has come with a strong shift towards digitalization and remote work in general (Jarrahi, Newlands, Butler, et al., 2021) as well as increased use of AI across many industries and sectors in particular, including education (Krishnamurthy, 2020), hospitality and tourism (Li et al., 2022), knowledge work (Jarrahi, Newlands, Lee, et al., 2021), and public services (e.g., citizen monitoring and contact tracing; Newlands et al., 2020). Some of these implementations might be temporary but many are likely to shape the future of work in years to come, showing the ability to flexibly adopt relevant AI and adapting to rapidly changing circumstances to be a key asset.

2.3 | Micro-level contextual factors

2.3.1 | Work practices

A practice-centered approach (e.g., Feldman & Orlikowski, 2011; Østerlund & Carlile, 2005; Swartz, 2012) offers a helpful approach to explore the entwined relationships between AI models, data and work practices (Figure 1). Four shared properties of practice-based theories can shed light on AI in the workplace in particular: relational focus, process perspective, blurred boundaries, and historically constituted versus emergent relations.

First, AI models and data sets gain their properties through relations to one another and these relations emerge through people's work practices. Big data sets and complicated models do not have inherent qualities, properties, or identities, but they emerge through the work practices that produce and reproduce them. For example, building AI models that deal with organ transplant priority lists inevitably requires distinctions between certain categories in the data set and such distinctions are most likely anchored in medical work practices. This could involve relationships between the age of patients and the status of specific organ systems.

Second, practice theories build on process-thinking. The relations among AI models, their data, and work practices change over time. An organ transplant priority list should not be static but change as patients change and we learn more about the differences and dependencies among patients. This is often a big problem for AI models and data. Key features in the data set might change, requiring updates to the AI models. As such, process-thinking involves questions such as "How quickly do things change?" or "What relations might be more dynamic while others remain relatively static?"

Third, boundaries often blur in practice: given that relations among entities get produced and reproduced through people's work practices, the relations among them can get fuzzy. Even medical diagnoses come with soft edges: it might not be completely clear where one diagnosis begins and another ends. Such boundary issues often point to important ethical questions or power dynamics associated with specific data or AI models or their relationship to work practices. In the organ transplant priority list example, one could explore what distinctions in the data set determine people's position on the list and if certain work practices or groups of people hold more power in making changes to the priorities than others.

Fourth, how do the data and AI models deal with historically-constituted versus emergent relations? AI models tend to be conservative. They build on data gathered in the past, but exist in a world where the data structures and work practices constantly change. Keeping a keen eye on the emerging work practices associated with data and AI models will help us understand some of the critical issues that can emerge if our historically constituted models lose track of emerging and changing relations in work practices. A practice-centered perspective therefore helps us pay attention to such problems by prompting us to ask what relations are analytically central and what the temporal organization of the practices that produce and reproduce such practices is.

2.3.2 | Group work

As You and Robert in this volume show, AI systems can transform group work in organizations. The article demonstrates how introducing AI systems can affect subgroup formation and teamwork quality. AI implications for teamwork can be more profound than previous information technologies that only support communication between team members or act as memories or repositories for the team. For example, researchers suggest that taking the self-learning capabilities of AI seriously requires elevating it to an equal member of the team with a distinct role to play (Jarrahi et al., 2022; Malone, 2018). Some may disagree with such predictions and conceptualizations, arguing people and intelligent systems are inherently different actors and should not be treated as equal partners or teammates. For example, in his recent work on human-centered AI, Ben Shneiderman dismisses the "teammate fallacy" and contends: "[such a] fallacy lies in the belief that computers should become our teammates, partners, and collaborators. Psychologists point out the difficulty in accomplishing this goal because human teammates have such distinctive ways of coordinating with each other" (Shneiderman, 2020, p. 113). Despite these differing opinions on the role of AI systems in the future of teamwork, the unique nature of learning algorithms means practitioners and researchers may need to re-envision organizational functions and processes to facilitate relationships among human and synthetic team members (Larson & DeChurch, 2020).

2.3.3 | Communication

It is important to focus on how humans and AI systems not only communicate in dyads and one-on-one, but in larger groups, configurations, and assemblages inside and outside organizations. Studying dynamics between several humans and several (types of) AIs and their interplay requires further scrutiny. Here a network perspective or even actor-network (ANT) perspective can be fruitful (Lutz & Tamò, 2018). Information systems and management research might find inspiration in communication research and the emerging field of human–machine communication in particular. Scholars in that area highlight how AI systems are increasingly not only used as a medium through which communication takes but an interlocutor on its own (Guzman & Lewis, 2020; Sundar, 2020), coming with functional, relational, and metaphysical questions and implications that are highly relevant in a work context.

In *functional* terms, how human–human collaboration is different from or similar to human–AI collaboration requires scrutiny. For example, we are used to interacting with people under a small set of temporal or spatial terms, but human–AI collaboration may require or allow new arrangements. Such inquiries also may reveal new forms of symbiosis or antagonism. In *relational* terms, AI systems at work come with potentially new role configurations and understandings, including public image of and discourse about the technology (Nader et al., 2022), which is often polarized between overinflated hype, as characterized by the emergence of a whole ecosystem of AI consultants and advocates, or complete doom, as in horror stories of AI ruining the very fabric society. In *metaphysical* terms, "the 'borders' surrounding communicative AI, or any AI, [...] are important areas of study" (Guzman & Lewis, 2020, p. 79). Applied to a work context, this means investigating whether fundamental tenets of work are transformed with and through AI. For example, will the identity-providing and structuring functions of work be reconfigured through AI, fundamentally changing what it means to work or not work? What is the role of AI in affecting informal economies (i.e., dark jobs)? Similar fundamental questions that touch on the metaphysical aspects of AI and work will only gain in importance going forward.

3 | FUTURE RESEARCH DIRECTIONS

Based on our reflection of the current research landscape and current sociotechnical issues of AI adoption in the context of work, we provide a forward-looking research agenda for AI and work.

3.1 | New divisions of labor between humans and machines

Our current conceptualizations on how intelligent systems may support decision-making do not necessarily align with capabilities of emerging AI systems (Paul et al., 2022). Articles in this special issue, together with evidence from other research, show that many workers, particularly knowledge workers, are not easily replaceable by smart technologies. However, their role and contributions may shift as AI takes over certain facets of their work: the integration of AI systems may mandate new divisions of work between the worker and the intelligent system. This would require a different set of conceptualizations of new relationships and division of work, like for example the concept of "supermind," which more effectively recognizes the potential roles played by AI agents (as teammates) (Malone, 2018).

We encourage future research on AI and work to use established sociological, psychological, and organizational theories, testing their applicability to AI systems in work. Scholars will need to carefully consider existing theoretical and conceptual approaches to better for the specificities of AI and its application context. Even more promising is the application of theories from analogous disciplines in the area of AI. Such an endeavor might be highly generative. For example, theories of symbiosis (from biology), symbolic interactionism, labor process theory, or Bourdieu's habitus and class theory could be applied and tested in the context of AI and work.

3.2 | Power dynamics (power imbalances)

Research indicates that AI systems can reinforce existing power imbalances in organizations (Jarrahi, Newlands, Lee, et al., 2021). Such systems are hardly neutral and can act as purveyors of certain interests. As more AI systems are employed to coordinate tasks, research is needed to examine how they may reflect or change power dynamics among various players within and across organizations. For example, the use of algorithms for managing workers (i.e., algorithmic management) can allow managers to exploit algorithmic opacity to their benefit and consolidate more organizational power (Jarrahi, Newlands, Lee, et al., 2021). As another example, collecting training data in the workplace, storing that data in accessible or permeable storage, and acting on estimates inferred from workplace-collected training data can constitute surveillance that violates employee privacy, contributes to data colonialism, and further blurs the boundaries between employer control and employee autonomy (e.g., Boyd & Andalibi, 2022).

Future research is needed to illuminate how AI systems have consequences for multiple stakeholders and their relationships (beyond AI's impact on work process and efficiency goals). For example, observing the selection, deployment, and use of AI-driven workplace surveillance technology could reveal the priorities of decision-makers, interests and impacts on workers, refractive surveillance on customers or other unwitting parties (e.g., Levy & Barocas, 2018).

3.3 | Shifting boundaries

Introducing new technologies in the workplace often blurs boundaries (Gregg, 2013). For example, where a boundary might have existed at the door of the office or at 5 p.m., a laptop or a work phone may blur that boundary. Similarly, introducing AI in the workplace may blur boundaries. A small example of this comes from AI-enabled chatbots: if a user normally has the freedom to edit their correspondence before it is seen by people at their workplace, and a chatbot has access to, acts on, or passes along to human readers text as the user types, they lose privacy over their incomplete and developmental writing. Emotion recognition technology, increasingly in use in interviews, call centers, and intra-office communication, claims to detect workers' internal state, extends employers' reach beyond the boundary between emotional expression and workers' thoughts and feelings (Boyd & Andalibi, 2022). Future work may explore the ways that AI compromises worker privacy and autonomy by blurring boundaries in the workplace; and new forms of "boundary work" that are needed to bring one's work to a new functional equilibrium.

3.4 | Ethics of AI

The ethical dimensions of AI are and will continue to be central in implementation and adoptions of these systems. For example, research must continue exploring AI consequences for Diversity, Equity, Inclusion, & Access (DEIA). If a facial recognition model struggles to recognize dark-skinned faces because it has been predominantly trained on images of white people (a pattern that has been documented, see, e.g., Buolamwini & Gebru, 2018), that points not only to the importance of considering diversity, equity, inclusion and access in system performance, but throughout system design (Benjamin, 2019). It also draws our attention to the co-constitution of AI models, the data that feeds them and the work practices that drives them along. To address DEIA concerns associated with AI models we must explore the data flow and work practices entwined with these models.

When considering deploying AI in the workplace, even in a hypothetical use case where the design is totally aligned with the interests of workers, data subjects, and other impacted groups, AI with biased outcomes or unequal performance among groups can cause hidden inequities at work. For example, imagine an AI system that helps customer service workers communicate or helps assess job candidates in interviews (Zetlin, 2018). It may rely on language models and emotion detection software to read interlocutor's preferences and affect, make suggestions to a worker about how to communicate, and save insights about the employee's performance. Even if the worker finds these insights helpful and the system has good overall performance measures, bias in the language or emotion models could quietly rate women, workers using minority dialects, and other marginalized groups as performing less well (Gorrostieta et al., 2019; Tatman, 2017). Future work can explore effective ways for AI-driven systems to surface the uncertainty inherent in their outputs.

3.5 | Interdisciplinary collaborations

Finally, future research on AI and work should engage more in transdisciplinary collaboration (Bailey & Barley, 2020). AI is increasingly a general purpose technology that not only affects many occupations and industries but also constitutes a pressing topic of research across many disciplines. This happens in at least three ways. First, as outlined in this special issue, AI is an important area or topic of study as it is used in practice (e.g., in sociology, IS, communication, STS, law, political science). Second, AI is an application and development domain itself (e.g., in applied computer science and applied machine learning, where AI models are developed or improved). Third, AI serves as a methodological toolkit for studying other phenomena (e.g., language models in linguistics, AI tools for medical diagnostics, NLP methods for large-scale text analysis). However, disciplinary silos and conventions as well as funding constraints often prevent researchers from studying AI at work in a holistic manner that might combine these perspectives. Future research should see more scholars from different disciplines working and coauthoring together, for example computer scientists who are deeply familiar with AI technologies and their design, with social scientists who are domain experts and have in-depth knowledge of relevant theory, and ethical and legal scholars who can bring in the needed expertise to derive meaningful policy recommendations. Beyond just academia, industry partnerships and multistakeholder collaborations could be promising in furthering AI and work research if they allow the critical scrutiny of AI systems (e.g., are not drastically hampered or burdened by NDAs) and are not used simply as AI ethics-washing or PR exercises (Hao, 2019).

4 | ARTICLES IN THIS SPECIAL ISSUE

The articles in this special issue offer different but valuable perspectives into the interplay between different work contexts and intelligent machines. In "*Locating the Work of AI Ethics*," Slota et al.(2022) explore the challenges of anticipating the ethical, legal, and policy implications of AI by focusing on work that goes into exploring and understanding these sociotechnical dynamics. Drawing on interviews with AI researchers, law professionals, and policy makers the authors explore ethic work associated with a range of different AI tools including, autonomous vehicles, algorithmically determined organ transplant priority lists, the use of automated agents in call centers, algorithmically informed decisions on bank loans, use of AI in medical diagnoses and treatment, and the use of AI to determine sentencing in the criminal justice system. The authors insist that the work of AI ethics takes place not solely during the actual system design, but also before and after. Leading up to building the systems important meaning-making work considers resource availability and initial data collection. Equally important, AI ethics work entails not only the more visible legislation, regulation, and policy, but also the often invisible articulation work that goes into making the system applicable to a specific context, identifying available data, and recognizing appropriate opportunities for data reuse. In other words, when considering the work of AI ethics, attention must extend to the broader ecology of implementing, designing, and using AI in context and not just the technical system development and specifications. To become prevalent, this type of AI ethical work needs to be recognized, legitimated, and rewarded.

In "*Subgroup formation in human–robot teams: A multistudy mixed-method approach with implications for theory and practice*," You and Robert (2022) combine an experimental study of 44 human–robot teams with qualitative research from 112 managers and employees to shed light on group dynamics of working together with embodied AI. You's and Robert's experimental study shows that identification—both as robot identification and team identification—has an important role in affecting subgroup formation as well as teamwork quality. Subgroup formation has contingently positive or negative effects, depending on how humans identify with robots and the team. A major strength of the article is that it does not stop there but derives meaningful recommendations for teamwork quality in human–robot teams, based on a qualitative online survey. Key suggestions are to provide human workers with sufficient training, to conduct team-building exercises, to facilitate communication between human coworkers, and to establish strong leadership. From these contextualized and rich qualitative statements, the authors conclude that "as AI and the world of work are reshaping the meaning of work, employees would rather not lose what it means to be a human."

In "*Artificial intelligence changes the way we work: A close look at innovating with chatbots*," Wang et al. (2022) investigate disembodied AI in the form of chatbots. Like (social) robots, chatbots are a core application of AI and have gained great research interest in recent years (e.g., Følstad & Brandtzæg, 2017; Schanke et al., 2021). Wang, Lin and Shao investigate the crucial aspect of trust in implementing chatbots among employees. Their research model highlights the role of knowledge support and work-life balance in fostering trust in chatbots, which is itself understood multidimensionally (trust in functionality, trust in reliability, trust in data protection). Trust, in turn, is hypothesized to enhance the innovative use of chatbots. A structural equation model of survey data among 202 US-based employees shows how trust in chatbots is indeed positively influenced by knowledge support benefits and work-life balance, and how trust in chatbots does relate positively to innovative use. Countering discourses on AI automation, knowledge workers' thriving in a well-designed workplace (good work-life balance, good knowledge support) shapes their trust and innovative use of novel technologies, which themselves could result in even more thriving, thus describing a virtuous cycle of AI in the workplace.

In "*At the crossroads of logics: Automating newswork with AI (Re)defining journalistic logics from the perspective of technologists*," Sirén-Heikel et al. (2022) show how the logic of AI systems may diverge and even mitigate journalistic logics and institutionalized norms, practices, and values in journalism. Building on interviews with firms that provide AI solutions for newsrooms, the article represents the perspective of the technologists on the unique role that AI tools (i.e., natural language processing) could play in transforming and automating tasks in journalism, an industry long mediated by information technology. The authors argue that the firms included in the sample share some collective logic to rationalize AI in newswork: "a frame of AI technology optimizing newswork, and a narrative of newsrooms as misinterpreting the technology compared to other industries." The article provides an important contribution to the field of journalism as news organizations are considering ways to optimize news production through algorithmic journalism or AI-empowered news automation. Beyond this context, the article also contributes to our understanding of how the logic of AI systems articulated and presented by the technology developers could compete with the underlying logic of the work context.

"*How artificial intelligence (AI) might change academic library work: applying the competencies literature and the theory of the professions*" by Cox (2022) uses the frameworks of competencies, jurisdiction, and hybridity to outline the potential impacts of AI on librarianship as a profession, especially as it may be applied in knowledge discovery. The author generates and evaluates 11 possible approaches that libraries may take, considering how internal and external factors might influence them, and reviews different applications of ML within the library, speculating about what skills would be needed among users and how ML would impact the work of librarians. Then, the paper takes the application of AI to knowledge discovery as its focus, describing libraries' potential reactions to the application of AI to knowledge discovery. The paper relies primarily on features of the *profession* to think about the implications of AI at work, rather than features of the technology. The paper discusses how these features of librarianship shape the options and likelihoods for different approaches to integrating AI in knowledge discovery and also predicts how that approach to AI will impact how libraries jurisdiction conflicts in knowledge discovery will be settled.

We hope that these papers offer readers insightful and future-looking perspectives of AI at work, inspiring new inquiries, especially interdisciplinary and ethically aware ones, into how AI changes the division of labor, power dynamics, and boundaries in the workplace.

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ENDNOTE

[1] https://oecd.ai/en/ai-principles

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