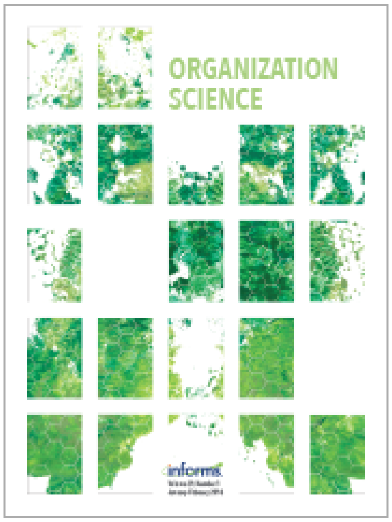

Organization Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

“Collaborating” with AI: Taking a System View to Explore the Future of Work

Callen Anthony, Beth A. Bechky, Anne-Laure Fayard

https://pubsonline.informs.org/journal/orsc

ORGANIZATION SCIENCE
Articles in Advance, pp. 1–23
ISSN 1047-7039 (print), ISSN 1526-5455 (online)

"Collaborating" with AI: Taking a System View to Explore the Future of Work

Callen Anthony,[a,*] Beth A. Bechky,[b] Anne-Laure Fayard[c]

[a] Department of Management and Organizations, Stern School of Business, New York University, New York, New York 10012; [b] Graduate School of Management, University of California, Davis, Davis, California 95616; [c] NOVA School of Business and Economics, 2775-405 Carcavelos, Portugal

*Corresponding author

Contact: canthony@stern.nyu.edu, https://orcid.org/0000-0002-1970-0264 (CA); bbechky@ucdavis.edu, https://orcid.org/0000-0003-0096-294X (BAB); annelaure.fayard@novasbe.pt, https://orcid.org/0000-0001-5274-3760 (A-LF)

Received: September 7, 2021
Revised: August 12, 2022
Accepted: November 21, 2022
Published Online in Articles in Advance: January 9, 2023

https://doi.org/10.1287/orsc.2022.1651

Abstract. In the wake of media hype about artificial intelligence (AI)/human collaboration, organizations are investing considerable resources into developing and using AI. In this paper, we draw on theories of technology in organizations to frame new directions for the study of what it means to work "with" AI. Drawing on prior literature, we consider how interactions between users and AI might unfold through theoretical lenses which cast technology as a tool and as a medium. Reflecting on how AI technologies diverge from technologies studied in the past, we propose a new perspective, which considers technology as a counterpart in a system of work that includes its design, implementation, and use. This perspective encourages developing a grounded understanding of how AI intersects with work, and therefore ethnography, building on thick descriptions, is an apt approach. We argue that relational ethnographic approaches can assist organization theorists in navigating the methodological challenges of taking a counterpart perspective and propose several strategies for future research.

Keywords: work • technology • ethnography • collaboration • AI

> The most promising uses of AI will not involve computers replacing people, but rather, people and computers working together—as "superminds"—to do both cognitive and physical tasks that could not be done before (Malone et al. 2020).

The promise of artificial intelligence (AI), algorithmically based applications that perform the cognitive tasks associated with humans, often incorporating some form of machine learning,[1] pervades popular imagination about the role of technology in the future of work. Previously heralded as a tool for automation and increased efficiency, narratives about AI now make a broader claim: that humans and AI will "[join] forces" (Wilson and Daugherty 2018). Indeed, humans and AI will create "super teams," ushering in a new era of human-AI collaboration (Wilson and Daugherty 2018, Schwartz et al. 2020). Commentators envision AI as a complementary actor in work collaborations, describing how AI (and other digital technologies) will accomplish the "routine" tasks of information processing (Brynjolfsson and McAfee 2014, Frank et al. 2017, Hess and Ludwig 2017, Koebler 2017, McAfee and Brynjolfsson 2017), allowing professionals to take on "higher-order" forms of work (Susskind and Susskind 2015, Davenport and Kirby 2016).

Despite casting AI in a new role, this emerging narrative is in line with previous deterministic narratives about AI that position the technology as a solution to human shortcomings (Miller 2018, Polli 2019). Such positive views of AI have been challenged by critical theorists, sociologists, and other like-minded skeptics who point to the dangerous outcomes that AI might drive. For instance, scholars have shown that the use of algorithms can have a disparate impact on the outcomes of disadvantaged groups in establishing creditworthiness, healthcare treatment, and criminal sentencing (Starr 2014, Barocas and Selbst 2016, O'Neil 2016). As these critics have shown, the objectivity of AI is questionable. AI may not, in fact, be a solution to human shortcomings and may even increase inequality and bias.[2] These critiques question the objectivity of AI and show how its use and effects do not deliver on espoused promises. Although these studies have demonstrated how AI continues to obstruct fairness and justice for the marginalized groups in our society, because of their focus on societal-level impact, they have not tackled the claims about the influence of AI at the workplace.

Although critics of AI have largely overlooked its impact on work within organizations, the management literature has a well-developed body of research on technology and organizing that can inform our understanding of this problem. These studies have demonstrated how technology serves as a tool for getting work done (Barley 1986, Nelson and Irwin 2014, Anthony 2021), as well as a medium for collaborating and facilitating interactions across roles (Bechky 2003a, Kellogg et al. 2006). To avoid taking claims about technology use at face value, organizational scholars within these tool and medium perspectives have embraced ethnographic methods, disentangling the symbolic and material dimensions of technology. These studies show that when technologies are heavily valued for what they symbolize, claims about them may not reflect use. For instance, Beane (2020) found that surgical robots were not used by hospitals and were abandoned in storage closets. However, these hospitals still touted their robots in promotional materials and digital media, attracting students and patients, as well as driving fundraising efforts. Similarly, firms, and especially startups, may exaggerate the effectiveness of AI, even when it does not yet work, to secure venture capital funding (Shestakofsky 2017). Ethnographic studies enable in-depth examination of how technologies are used in practice and how use can shape and is shaped by different groups within organizations (Orlikowski 2000, Orlikowski and Scott 2008). Taking a grounded perspective on how AI is integrated into organizations is particularly important because of deterministic narratives about AI in the popular press: even just using the words "artificial intelligence" has meaning and symbolic value. Ethnographic approaches thus may help to counter superficial narratives about AI by illustrating how it is used on the ground.

However, despite their use of ethnography, our current perspectives on technology, as a tool and as a medium, may struggle to counter the hype about human-AI collaboration because of the way they conceive of technology and how people work with it. One reason for these struggles is that AI diverges from past technologies and might require a different perspective on technology and some creative twists on traditional ethnographic approaches. Indeed, AI has three specific material characteristics, constant change, invisibility, and inscrutability, that may challenge traditional approaches to the study of technology and work. This combination of characteristics, although not individually novel or definitively problematic, in degree and combination limit the applicability of the management literature's typical focus on technology as a tool and a medium. Furthermore, the production and use of AI involves a broad swathe of stakeholders in and across organizations whose assumptions and interests influence design, development, implementation, and use. It thus calls for a broader view, tracing interactions across contexts and expanding analysis upstream from use, to develop the much needed rich and deep understanding of how AI is developed and used in practice in organizations.

Therefore, examining AI and work may require scholars to take a different perspective and approach than the tool and medium perspectives, which focus predominantly on practices shared by users in getting their work accomplished. Building on literature from cognitive anthropology and science and technology studies, we propose researchers consider AI as a counterpart by treating it as an actor within a system of relations that extend outside of its immediate context. Such a perspective examines AI's role in an ecosystem of interactions and relationships with and across the multiple actors involved in its creation and deployment. Building on the rich constructivist positions and ethnographic approach of the tool and medium perspectives, we argue for close study of the interactions that actors within different occupations and organizations have with AI to develop the much-needed grounded understanding of AI and work.

Such an approach requires that researchers experiment with traditional practices of ethnography, which face limitations when it comes to studying AI as a counterpart and exploring the system-level dynamics of AI at work. The ethnographic approaches associated with tool and medium perspectives tend to focus on local implementation and user groups, which constrains researchers' ability to uncover the broader dynamics among stakeholders that influence collaboration and work. Although the growing number of ethnographic studies of AI (Elish and Watkins 2020, Sachs 2020, Lebovitz et al. 2022) have generated important insights into its effects on work in organizations, they are mostly still taking a tool or medium perspective. To take a counterpart perspective to study AI, developing a grounded and system-level understanding of how it intersects with work, requires extending our methodological reach. We argue that relational ethnographic approaches (Desmond 2014, Clarke 2015) provide useful strategies for scholars who want to use ethnography to examine how AI shapes work and collaboration in organizations. Relational ethnography enables exploration of the dynamics between and across actors in a field (or in the case of AI, a system of work) by focusing on "processes involving configurations of relations" among those actors (Desmond 2014, p. 547). Expanding our methodological reach through a relational approach will require some broadening of our research strategies and development of additional skills, which we discuss.

Challenges of Working with AI

Organizations rely on technologies to accomplish work: a reality that has only intensified with the exponential rate and pace of technological change over the past half century (Barley 1996, Leonardi and Barley 2010, Cohen 2016). Thus, perhaps not surprisingly, the study of workplace technologies has a long and rich tradition within organizational theory (Barley 1986; Bechky 2003a, 2020; Mazmanian 2013; see Zammuto et al. 2007, Orlikowski and Scott 2008, and Leonardi and Barley 2010 for reviews). These studies embrace a definition of technology understood as a "bundle of material and symbol[ic] properties packaged in some socially recognizable form, e.g., hardware, software, techniques" (Orlikowski 2000, p. 408). They depart from early research that treated technologies as objective, their features determining patterns of use. Instead, this research highlights the social construction of technology showing that interpretations and meanings held by users impacts the ways technologies figure into tasks (Edmondson et al. 2001, Leonardi and Barley 2010, Nelson and Irwin 2014, Fayard et al. 2016). Indeed, scholars have found that the use of technologies is highly situated, such that the same technology may be interpreted and used differently (Orlikowski and Gash 1994, Benner and Tripsas 2012, Mazmanian 2013).

We believe that the prior literature on technology and organizing has much to contribute to our understanding of AI. Technologies in the workplace are understood broadly and include generic software like spreadsheets, PowerPoint, and email, as well as more targeted devices like computed tomography (CT) scanners and robots. Scholars have shown how these technologies may underpin expertise (Nelson and Irwin 2014, Anthony 2021), enable coordination (Bechky 2003a, Beane and Orlikowski 2015), define roles and organizations (Weick 1993, Tripsas 2009, Cohen 2013), and challenge interaction patterns across well-established hierarchies (Barley 1986, Edmondson et al. 2001, Leonardi 2013). Thus, when considering the claim that AI might work together with users, we have considerable theory from which to unpack such a premise.

However, important aspects of AI, namely its constant change, invisibility, and inscrutability, call into question the applicability of prior findings about technology and work. Although these properties may not be exclusive to AI, their nature, degree, and combination raise questions about the appropriate approach to take to studying AI. First, due to machine learning, AI applications may constantly change, without direct instruction by an actor. Prior literature notes that features of technologies can change (Tyre and Orlikowski 1994, Nelson and Irwin 2014), yet in existing studies, such changes tend to be episodic and made intentionally by designers and/or vendors. As a result, prior studies tend to focus on the impact of discontinuous technological change on social relations, but the material features of technology are otherwise treated as stable in their ongoing effects on users.

Additionally, the materiality of AI may not be visible. It may be difficult to literally "see" the technology and observe it. The shift to digital work has already made much work less visible (Riopelle 2013), but when machine learning underlies digital technology, the materiality of the application is opaque. AI applications may not have clear digital interfaces for different groups to interpret and make sense of. Because AI may be running in the background, users may even be unaware of it. Even when users are aware of applications using machine learning, these applications may be inscrutable, meaning that both users and designers encounter AI as a black box. Although many technologies may be black boxed by users, including computers, cars, and even mechanical pencils (Anthony 2018), these can be "unpacked" by users who have relevant expertise. By contrast, rules that govern inputs and calculations may shift such that even designers may not be able to understand the relationship between variables.

In practice, these material properties often coexist, which can lead to cascading effects that amplify challenges. For instance, when a technology is invisible, then it is not questioned or examined, which reinforces its inscrutability and allows constant change to continue unnoticed. The consequences of such combination depend on the context of the AI system and thus must be attended to by researchers.

Beyond these material properties, AI also has extreme symbolic value: It is a general-purpose technology with espoused vast application that has captured public imagination. Although many technologies may have symbolic value, including DNA profiling techniques (Bechky 2020) and engineering tools (Elsbach 2003), this value tends to be much more localized within specialized contexts. By contrast, the stories about AI and what it symbolizes seemingly implicate the entire economy: from individual workers to consumers to organizations and whole industries. This has fueled considerable hype, including about how humans can collaborate with AI.

In the following sections, we review prior literature on technology and organizing by focusing on two perspectives that each take a different analytic focus on the role of technology in work: technology as a tool and technology as a medium. We discuss how AI's characteristics may present distinctive challenges for these dominant perspectives. We then build on literature from cognitive anthropology and science and technology studies to propose a third perspective, technology as a counterpart, which embraces a system lens and may help overcome the challenges that AI poses for existing literature. Table 1 provides a summary of the three perspectives for studying AI and work.

Technology as a Tool: How Technologies Support Tasks and Work

Literature that takes a tool perspective examines how technologies are used to accomplish tasks, focusing on the skill and expertise of users (Kaplan 2011; Mazmanian 2013; Nelson and Irwin 2014; Anthony 2018, 2021; Beane 2019). When scholars apply this lens to the study of technology, they tend to focus on the repeated interactions between users and technologies after they "arrive" in a

Table 1. Summary of Perspectives for Studying AI and Work

	Traditional perspectives for studying technology and work		Proposed perspective to study AI and work
	Technology as a tool	Technology as a medium	Technology as a counterpart
Description of perspective	Technology enables the performance of tasks: How individuals interpret and interact with technologies in their daily work	Technology facilitates interactions between people across boundaries: How people use technologies to accomplish joint work	Technology is an actor within a system: How interactions between multiple individual and organizational actors shape work
Key literature(s)	Social construction of technology	Coordination and collaboration	Distributed cognition and ANT
Unit of analysis	Interactions with and around technologies	Interactions within and across groups	Interactions within a system across actors (human and technological)
Temporal scope	Moments of interaction once technology has arrived within an organizational context	Moments of interaction once technology has arrived within an organizational context	Intertemporal focus on past, present and future; includes history of actors, including development, implementation and evolution of technology within system
Role of technology	Supporting/influencing the expertise of users	Boundary object in people's work	Actor in a system of organizational processes
New key questions with AI	What are the consequences of AI for expertise? How might stories about how AI works coevolve with AI?	How does using AI for collaboration affect negotiation and meaning making across groups? What are the qualities of AI as a boundary object?	How do interests of different groups and power differences across actors shape design, implementation and use of AI? What invisible work is involved in the production and use of AI? How can we trace the consequence of AI across different parts of an organizational system?
Challenges with this perspective when studying AI	Left censoring Focuses only on users Ignores social and political context of work Constrained by AI's constant change, visibility and inscrutability	Left censoring Focuses only on users Ignores broader organizational and institutional context of work Constrained by AI's constant change, visibility and inscrutability	Requires new ethnographic strategies and skills Depth/breadth trade off when designing what to focus on within a system of relations Observational challenges of studying multiple stakeholders within an AI ecosystem Drawing boundaries around the system: risk of studying everything Getting at focused theoretical contributions

workplace. In particular, researchers focus on how interpretations and practices impact the ways in which technologies and their material properties figure into tasks. For example, a tool perspective taken to the study of spreadsheet technology would consider how users interpret and unpack the features of spreadsheets to perform key aspects of their work. Knorr Cetina (2010), for instance, found that financial analysts often use spreadsheets to support how they gather, transform, and interpret data. Their matrices of rows and columns allow analysts to sum and analyze data, allowing "deepening and enrichment of the analyses by making it easy to register and compare relevant numbers over time and across similar entities" (Knorr Cetina 2010, p. 190). Scholars who take this constructivist perspective on the study of technology have uncovered that users' expertise and skill are often formed in relation to tools (Knorr Cetina 1999, Myers 2008, Kaplan 2011, Nelson and Irwin 2014).

A tool perspective highlights that the way users work with their technologies is shaped by whether they rely on them without questioning or understanding how they work. In some instances, technologies are treated as trustworthy even if their users do not understand their inner workings (Barley et al. 2018). For example, one does not require an understanding of how pistons fire within an internal combustion engine to start up and drive a car; we trust those who have designed, built, and regulated the car. As a result, the functioning of technology can become taken for granted as working a certain way without direct understanding and observation. Scholars have referred to this as the black boxing of technology (MacKenzie 1990; Marx 2010; Anthony 2018, 2021).

Although some of the literature agrees with a lay intuition that tools do not have to be examined to be used (Simon 1947), other studies of the construction of knowledge and expertise have demonstrated that experts have a strong desire to understand and unpack their tools (Bailey and Barley 2011, Anthony 2021). Many expert users avoid black boxing tools, or trusting them without understanding how they work, by engaging in considerable effort to unpack and develop understanding of materially embedded features that might shape work outcomes. These include strategies of comparing data and features of the technology to other sources of information and technologies (Dodgson et al. 2007, Bailey and Barley 2011). For instance, physicists may run multiple scenarios in an analytical tool and compare variance in their data plots (Knorr Cetina 1999). Through these comparisons, users "[unravel] … the features of physical and technical objects, of their details, composition, hidden sequences, and behavioral implications" (Knorr Cetina 1999, p. 71), which can shape ongoing patterns of use. Studies that take a tool perspective have found that whether users black box technologies or seek to unpack their inner workings often rests with the expertise and practices of users: the more expert a user, the more capable they are in questioning their tools. Novices may find technologies obscure or difficult to understand, but expertise with a technology develops hand-in-hand with its exploration (MacKenzie 1990, Bailey et al. 2012).

However, although the desire to unpack technologies has historically reflected users' skill and social position, with AI, this may not be the case. First, unpacking how technology works presumes that users can see the tool and recognize that they are interacting with it. AI, however, may be invisible to users, running in the background without signaling its presence (Gillespie 2012). Even if they "see" it, because of AI's inscrutability, users, regardless of their expertise, may struggle when trying to figure out how AI actually works (Burrell 2016, Faraj et al. 2018, Christin 2020). For research that takes a tool perspective, the inability to unpack how AI works may disrupt interactions between users and technology: More expertise may not necessarily afford users understanding of how their AI tools function. Furthermore, prior literature suggests that when those working with technology confront problems or misunderstandings, they may tweak the tools (Von Hippel 1976, 1986, 2005). Yet because AI's materiality is inscrutable, users cannot necessarily do so. Thus, although prior literature within the tool perspective considers black boxing as a set of actions and approaches that derive from users, AI's inscrutability may make it a black box even to those who seek to unpack it. Functions may be so complex that "no human can understand how the variables are jointly related to each other to reach a final prediction" (Rudin and Radin 2019, p. 3), meaning that users may have little choice but to trust AI, including both its equations and the database used to train it. Using and trusting an AI tool without understanding how it works may open experts up to professional risk and status threat and raises the question of who or what holds authority over ultimate outcomes. This may have profound consequences for our understanding of expert work, the use of technologies, and accountability, all which stem from the fundamental question: How do people work with an inscrutable technology that is encountered as a black box?

The inscrutable nature of AI therefore raises new questions for research that takes a tool perspective and looks at how experts develop skill and understanding in relation to their tools due to the difficulty to unpack and examine technologies. One possibility is that when experts encounter an AI recommendation, they may not necessarily trust or defer to it, especially if it conflicts with their own expectations. For instance, Lebovitz et al. (2022) found that when radiologists could not discern how a diagnostic algorithm was arriving at its conclusions, doctors decided to override the tool and rely on their own professional judgement. This suggests that experts may choose not to use a technology that they encounter as a black box and raises new yet unanswered questions: When and how might users choose to not use AI? Under what conditions does any benefit of using a black box outweigh the risk of professional threat? Furthermore, who, or what, is accountable for outcomes when an expert user cannot verify how an AI tool is coming to its conclusions?

Yet when AI is encountered as a black box, instead of learning about how users unpack technology, researchers instead may be studying narratives and stories that emerge through superstitious learning. Because traditional practices for directly examining the technology's material properties are not possible due to its inscrutability, stories may play a unique and privileged role in compelling the use of AI. Scholars have found that users often configure social interactions to question tools and avoid black boxing them (Anthony 2018, 2021). For instance, users may engage in informal interactions and conversations, have formal meetings, and draw on stories of best practices to help others learn and to question and inspect tools and their outputs (Barley 1988, Lave and Wenger 1991, Orr 1996, Owen-Smith 2001, Kaplan et al. 2017, Bechky and Chung 2018). Through these interactions, users can develop and maintain deep understanding of technologies.

Users' stories may rest on magical reasoning, as it is hard to test and verify that they reflect how an AI application actually works, and yet they still can shape patterns of use. When users struggle to discern how technologies function, they construct stories based on their prior experiences with other technologies, regardless of whether these stories are correct. For instance, Barley (1988) observed that technicians drew on their experiences with other technologies like record players and computers when trying to diagnose problems with their CT scanners. This resulted in claims about problems with the CT scanner to help stabilize and normalize technology problems, even when claimed causes (like burnt-out circuit boards or short wires) were not present. Moreover, because the logical sequences of AI applications are constantly evolving, the technology might change unbeknownst to users, and a working story may become further disconnected from technological reality. This combination of inscrutability and constant change may further amplify the disconnect between the "rhetoric" and "reality" of narratives and AI's materiality. Therefore, taking a tool perspective to study AI might constrain scholars to focus on symbolic narratives of the technology, including questions like: What are the consequences of AI use driven by unconfirmed and outdated stories? Furthermore, how might stories coevolve with AI?

Although scholars taking a tool perspective may wind up studying the construction of narratives and stories, these stories are still consequential to action. Indeed, it is possible that stories about how AI algorithms work, regardless of their accuracy, may shape outcomes. For instance, the study of Elish and Watkins (2020) of Sepsis Watch, an AI-based tool that predicts the risk that a patient develops sepsis, found that nurses had to engage in considerable effort to explain the tool's sepsis risk score to attending physicians. However, because the tool's AI was a "noninterpretable algorithm" that did not explain how it arrived at its risk scores, often times the nurses misunderstood the algorithm. As a result, their explanations and stories misrepresented how the model actually worked. These healthcare workers treating sepsis patients were lucky that emerging stories about how AI worked, despite incorrect interpretations, coincidentally led to positive treatment outcomes. In other cases, users may not be so lucky. Incorrect stories and beliefs about how technologies work that are rooted in the material properties of AI might lead to actions that exacerbate problems and result in unexpected outcomes. This suggests that we need more understanding about what people *do* when they are telling stories about AI. How do users form their beliefs in the first place? How do they convince others their emerging understanding is correct? What enables collective agreement?

As discussed, taking a tool perspective to the study of AI surfaces tensions for our theories about how experts develop skill and use technologies in their work due to AI's invisibility, inscrutability, and constant change. Although these tensions lead to important questions about expertise and AI adoption for users, they ultimately focus on the struggle users may have in their sensemaking of AI tools. Because of this focus, these studies tend to ignore the social dynamics underpinning the construction of AI before it arrives in the workplace. As a result, the role of developers who design and train AI applications and managers who choose to purchase and implement AI within an organization are broadly overlooked. Furthermore, by approaching AI as a tool, we sacrifice developing an understanding of the broader social and political context of work, ignoring dynamics across actors. Indeed, this perspective on technology misses the role that those in the local environment of users, such as other occupational groups and even clients, might play in shaping how AI and humans work together. These dynamics are particularly important if we want to investigate the collaboration implications of AI in organizations. We therefore turn next to theories that focus on technology as a medium of collaboration, as these provide ideas about how AI fits with our existing understanding of how collaboration processes unfold.

Technology as a Medium: How Technologies Enable Collaboration Between Groups

Collaboration between groups in organizations often relies on technology, because groups are working with technologies to get their tasks done and to communicate. When scholars conceptualize technology as a medium for collaboration, they take the perspective that machines and technologies help people to make sense of their joint work and develop the knowledge needed to solve their problems (see Table 1 for a summary of this perspective). Given narratives that AI will be a supportive collaborator, interrogating how AI might be used as a technology for collaboration requires thinking about how AI helps people solve problems and accomplish joint tasks in organizations.

Organizational studies of collaboration focus on the practices that enable different groups to work together. Studies of collaboration have found that structural mechanisms (Okhuysen and Bechky 2009) and dialogical processes (Tsoukas 2009, Fayard and Metiu 2014) enable the incorporation of multiple perspectives into solutions (Hardy et al. 2005) and help develop common understandings about the work (Bechky 2003a). Technology plays a particularly important role as a medium for building common ground by supporting knowledge-sharing, facilitating communication, and making it easier to span boundaries across groups with different expertise, interests and power (Carlile 2002; Bechky 2003a, b). By contrast to the tool perspective, which is focused primarily on individual and shared collective interpretations of technologies as they use them, the medium perspective stresses the "interpretive flexibility" of technologies across parties and shows how people use them to collaborate in their work.

Spreadsheets continue to be a useful illustration here, as scholars have not only shown how individuals interpret them as a tool in their work but also have examined how members of organizations collaborate to solve problems using spreadsheets. In fact, some early studies of spreadsheet use noted that, although they were initially expected to be a calculative tool for individual users, most of the actual use of spreadsheets in organizations emerged collectively between people (Nardi and Miller 1990). Organizational members with different levels of interest and technical acumen with the spreadsheet worked together to share domain knowledge, building models based on their local expertise in areas such as product sales or budgeting and refining the spreadsheet calculations in discussions that spanned the organization. Hence, considering spreadsheets as a medium highlights the varied interpretations of disparate groups and reveals how their use enables members to coordinate their work across these groups.

The way groups work with technologies creates a variety of different meanings and practices, enabling groups to use technologies as boundary objects (Star and Griesemer 1989) to mediate their collective work. Because boundary objects are interpretively flexible, groups that come from different thought worlds (Dougherty 1992) can relate these technologies to their own work practices (Bechky 2003a) while using them to better understand the work of other groups. Information technologies are one example of boundary objects in organizations, as they can be used by boundary spanners to create shared meanings and practices across communities to collaborate (Levina and Vaast 2005).

How groups flexibly use technologies to mediate joint work is challenged in the context of AI, because it is less visible, constantly evolving, and more inscrutable than prior technologies studied by scholars of collaboration. The features of AI algorithms are frequently unobservable, and people thus can only use the output. This can make problem-solving difficult. For instance, when Medicaid changed its algorithm for funding home healthcare assistance, all that was communicated was that coverage should be denied (Hao 2020). Because the logic of AI was invisible, neither patients nor healthcare providers could make sense of this algorithmic decision. The invisibility and inscrutability of AI means that it can be difficult to ground in organizational practices: The people using it can have trouble anchoring understandings of algorithms to their work. Moreover, given that the algorithm can change over time, as in the Medicaid case, interpretations are further destabilized. In instances such as this, where the implementation of AI combines invisibility, inscrutability, and constant change, it is not surprising to see a cumulation of problems and many barriers to coordinating the work. Thus, the use of AI in organizations invites us to reconsider how collaboration across groups unfolds. It opens up questions regarding what the negotiation of meaning might look like between people collaborating using AI, whether and how common ground might be established, and how AI might be used as a boundary object.

How can meaning be negotiated around the use of AI? Usually, establishing common ground entails a confrontation between the context and the multiple perspectives of the people collaborating: active meaning-making, disagreement, and back and forth dialogue (Gittell 2002, Gittell et al. 2010, Anthony 2018). Sharing knowledge and communicating openly can become complicated when collaborators cannot understand or unravel the assumptions of the technology they are using. Implicitly, building common ground necessitates that assumptions and knowledge can be surfaced and, once visible, be negotiated. By encoding decisions invisibly, AI does not offer a means for people to confront assumptions and expose the nuances of the surrounding social context.

AI may not only complicate meaning-making dialogues between collaborators using it, but by incorporating AI into decision making, some conversations may be completely elided. For instance, consider the use of AI applications for hiring, which are promised to offer increased efficiency (speed, increased number of applicants screened, etc.) and the reduction or even removal of individual human resources (HR) manager's biases (Dastin 2018, Harwell 2019, Raghavan et al. 2020). Hence, organizations often adopt them without considering the risks of reinforcing biases and reducing diversity (Ajunwa and Greene 2019, Kellogg et al. 2020). If adopted, these technologies rank resumes or videos of candidates, often without anyone in the organization ever seeing unselected applications. This is problematic because hiring decisions create better employee fit when recruiters and managers have collaborative discussions about desired employee characteristics (Cohen and Mahabadi 2021). Moreover, these types of algorithms potentially eliminate any consideration of characteristics that candidates might exhibit in interviews that were not anticipated by the algorithms' designers. As in hiring, other collaborations using AI for decision making may not ever get to a moment of negotiation.

However, scholars have demonstrated that in situations where dialogue is not possible, people can often be quite creative in working around the constraints of rigid technologies (Leonardi 2011, Pine and Mazmanian 2017). Therefore, it makes sense to consider whether AI algorithms might be used as boundary objects between different groups, even though they can lack the flexibility that is necessary for groups to fit them into their regular work practices and be useful as a medium of collaboration. A set of recent studies suggests that rather than develop common ground around AI, different groups engage in "repair work" to integrate AI into organizations (Sachs 2020). Algorithmic output does not always seamlessly fit with organizational practices, and multiple groups may participate in the repair of these issues. For example, Valentine and Hinds (2021) found that buyers at an online retail organization overrode AI's suggestions based on their own understanding of customer taste.

Yet, with repair work, AI's inscrutability may constrain problem solving, as the groups end up correcting and explaining AI to make it possible for the organization to use the algorithm at all (Elish and Watkins 2020). This is not a type of collaboration in which groups solve problems and learn more about one another's work but rather a way to integrate output effectively into organizational processes. Moreover, if AI is inscrutable to these groups, the explanations they make may spread the magical narratives of AI described earlier to others in the organization, rather than being grounded in reality.

These studies show the tensions between the different interpretations developed by multiple groups engaging with AI. Scholars who consider technologies as a medium for collaboration note that the work around these objects is shaped by status differences and can impact the social dynamics of groups. Technologies can be a source of symbolic authority and legitimacy and shape the status hierarchies of their users (Barley 1986, 1988; Bechky 2003b). Status relationships between collaborating groups can also change when AI is introduced. In a study of algorithmic policing, Waardenburg et al. (2022) show the emergence of a new role, information system officers, who were in charge of creating documents to translate algorithms' recommendations to police officers. By using these documents to explain the algorithm's output to police officers, information officers became the voice of the algorithms while gaining power.

Therefore, when thinking about AI as a medium for collaboration between groups in organizations, we need to investigate how AI is being constructed, interpreted, and used by those groups. What are the qualities of AI as a boundary object? Does it change the practices by which groups develop common understandings that enable them to work together? How might it alter the status dynamics of the groups who use it in their work? How might the use of AI for collaboration serve as a barrier to negotiation and meaning-making? Alternatively, how could the development of AI trigger processes within organizations that open up discussions and create shared understandings?

Considering AI as a medium surfaces the ways in which AI's inscrutability, invisibility, and constant change may affect how groups establish the common understanding necessary for effective collaboration. This perspective, much like the lens of technology as a tool, foregrounds the practices and choices of users as they develop expertise and work with one another. Because analyses of technology within the medium perspective are bounded to the ways AI is used during collaboration, it does not engage with questions of where the technology comes from and does not give us enough leverage to examine the complexity of organizational decision making around AI. Moreover, although the medium perspective engages with power and status distinctions in a more substantive way than the tool perspective, it focuses on distinctions between roles and/or groups rather than engaging with the broader organizational and institutional contexts of the work. Thus, this perspective also does not provide a broad enough lens to contend with the power relations that shape the development and implementation of algorithmic technologies. As some organizations take seriously media claims about AI as a collaborator and try to implement AI as a "magic" element of "super-teams," it is important to think about what this implementation might mean: what are the relationships that impact how AI will be adopted and used inside organizations? This requires revising our ideas about our relationship to technology and considering its role in the broader system level of work. To do so, we will draw on theories that have taken a system view on the development and use of technology and consider how AI might be conceptualized as a counterpart in collaborations within and across organizations.

Technology as a Counterpart: How People and Technologies Interact Within a System of Work

As we discussed, tool and medium perspectives are limited when trying to understand how AI and humans might work together. Because of AI's invisibility, inscrutability, and changeability, perspectives that focus narrowly on users and local interactions may end up studying emerging narratives about how AI works and struggle to observe how AI is used in collaboration. By focusing on local practices, scholars embracing a tool or medium perspective risk exacerbating the challenges that AI's particular material aspects may pose, overlooking the multiple actors (including producers, audiences, and regulators), structures, and interactions that shape these very properties in the first place. In addition, because of their focus on local action, these perspectives struggle to capture the power and politics involved in AI development and implementation.

To overcome these challenges, we leverage theories outside of organizational studies and management, including distributed cognition (Hutchins 1991, 1995) and actor network theory (ANT) (Callon 1984; Latour 1987, 2005). We propose conceptualizing AI as an active counterpart in a system of interactions to unpack and understand its role in organizational processes, as well as the unintended consequences that might emerge from all stakeholders working "with" AI (see Table 1 for a summary of our proposed perspective). Systems are a set of related components that work together to perform whatever functions are required to achieve the system's objective (Meadows and Wright 2008). We argue that a system view allows us to better account for different stakeholders and components involved in the creation, implementation, and use of AI within organizations. In a system view, the focus is not on individual actors but on how knowledge creation and work result from interactions between different agents. Such other agents do not need to be human agents. Taking a system lens and acknowledging the role of AI as an actor in that system allows us to attend to broader consequences when it comes to unpacking the power dynamics between producers, implementers, and users of AI and the ethical issues that might arise. This proposed perspective does not assume that a technology is only in one location, but rather is actively implicated at each point of interaction, which may help to overcome challenges posed by AI's invisibility and inscrutability. In addition, studying technology as embedded in a system and constantly emerging through interactions presumes the technology is in constant change.

Take the case of spreadsheets, which as we have illustrated can be understood through tool and medium perspectives for collaboration. They can also be analyzed as a counterpart involved in a system of work which includes multiple actors and where spreadsheets have agency. Since spreadsheets' creation in 1978, they very quickly became authoritative, enacting a narrative of numbers where "businessmen are not telling but letting the spreadsheets do the talking" (Levy 1984). Many spreadsheet users take the accuracy of their figures and formulas at face value, forgetting that they rely on assumptions made by the model makers. A system view of spreadsheets invites us to deconstruct the authority of the figures produced by spreadsheets, their users and model makers (who might not be the end users), to highlight the power relationships between these different actors, and to question the quantitative view of the world embedded in and enacted through spreadsheets (Levy 1984). Moreover, because spreadsheets enable users to contemplate and explore scenarios in a relatively simple, ubiquitous fashion, they allow everyone in the organization to engage with modeling tasks (Levy 1984), which suggests their role in distributed decision making rather than individual calculating.

We draw on theories from cognitive anthropology and science and technology studies, – specifically, distributed cognition (Hutchins 1991) and ANT (Callon 1984, Latour 1987), to propose an analytic perspective to study AI and work in organizations. In this systemic view, technology acts as an active counterpart. Hutchins' conception of distributed cognition (Hutchins 1991, 1995) suggests that cognition is not an individual activity taking place in one's head but a set of interactions and relations among different elements of a socio-technological system. In his study of the navigation of a Navy ship, Hutchins (1995) defines navigation as a cultural activity system that has cognitive properties in its own right that cannot be reduced to the cognitive properties of individual sailors who participate in the navigation system. From a distributed cognition perspective, technological artifacts are more than tools or a medium. Navigation is enacted through the interactions between different elements of the ship's system: humans and nonhumans. Bearing recording, a crucial activity for maneuvers to enter a harbor, involves multiple human actors (the bearing recorder, several pelorus operators, and the officer) and multiple artifacts (including the chart table, alidade, the ship's clock, a log book, and the landmarks), all located at different places on the ship (the pilothouse and platforms on each wing of the ship). Across these different actors, information is encoded, interpreted, transformed, and acted upon. Recognizing the agentic role of technological devices suggests how introducing additional artifacts radically changes the flow of information and the work practices, thus potentially creating the need for new structures. In the context of AI, recognizing the agentic role of AI invites us to be aware of the material consequences it can have on work practices by making some of the information used in decision-making processes invisible and thus inhibiting the interpretation process.

ANT (Callon 1984; Latour 1987, 2005) also offers a system perspective for conceptualizing technology as a counterpart. ANT highlights the importance of developing system-level understandings of technological innovation and knowledge creation, which are described as networks involving human and nonhuman actors. Not only does ANT assign agency to both human and nonhuman actors (e.g., artifacts), but it also rejects ontological differences between humans and objects and makes the relationships between these actors central to the analysis. In this paper, we sidestep debates regarding the ontological differences between humans and objects but embrace a system lens that draws on ANT's acknowledgment of the diversity of relationships and multiplicity of actors (individual, organizational, institutional; human and nonhuman) involved in the development, implementation, and use of technology. We believe that ANT still provides a useful lens even if one remains agnostic about the ontological nature of objects and technology. For example, in his analysis of Pasteur's success in changing behaviors in France when it came to health and sanitation, Latour (1988) argued that Pasteur's success could not be reduced to his scientific discoveries. He highlighted the importance of surrounding factors such as Pasteur's collaborators' work, his ability to capture the attention of multiple interest groups, and his connections with the public hygiene movement and the medical professions, as well as artifacts and the details of his laboratory, including his decision to extend his experiments outside of the traditional laboratory. Artifacts allowed Pasteur to simplify, make visible, and create evidence that were used to convince different audiences (Latour 1983).

Putting artifacts in the forefront and giving them agency in a system opens up important discussions about power. Indeed, if we consider that artifacts have agency, this suggests that they also have politics (Winner 1980, Latour 1988). Latour showed how artifacts and inscription devices can influence public debates about innovation. For instance, Pasteur used statistics on anthrax epizootic microbes to make the microbes visible and push his work on the vaccine forward (Latour 1983). In other words, artifacts play a decisive role in the process that leads to particular technological outcomes. By highlighting the political nature of the processes involved in technological innovation, Latour uncovered how the interests of different groups involved shaped the design and implementation of technology. Although some scholars of sociomateriality have embraced a similar ontological stance to ANT vis-à-vis artifacts (Orlikowski and Scott 2008, Oborn et al. 2013), they usually do not adopt the system-level approach of ANT. Indeed, studies of sociomateriality zoom in on the level of practice (Scott and Orlikowski 2012) and interaction (Barrett et al. 2013, Mazmanian et al. 2014, Bailey et al. 2022) in their attempt to understand the entwinement of the material and the social. In doing so, they have also sacrificed the study of power (Leonardi and Barley 2010). To discern the relationships and power dynamics between actors involved in the development, implementation, and use of AI, we borrow the analytical focus of the system lens of distributed cognition and ANT.

Recognizing the politics of artifacts and technology reminds us that technology is never "neutral." Technologies are created by people, human engineers or designers, who have assumptions about users, including their mental models and needs, which are reflected in design decisions (Norman 1988, Suchman 2007). This resonates with recent observations which show that biases in AI-based algorithms not only reflect the politics of designers, engineers, and companies alike, but also that they influence and reproduce societal prejudices and inequalities. For instance, journalists have uncovered the biases of Apple designers "deflecting" questions about feminism and the #MeToo movement in the development of Siri (Eadicicco 2019), and scholars have demonstrated how engineers developed biased facial analysis algorithms with respect to phenotypic subgroups such as dark-skinned women (Buolamwini and Gebru 2018).

These examples suggest that the creators of AI have a great deal of power that may be unobtrusive to users, which can create power differentials between designers and users. Biases inscribed in algorithms in turn influence users' decision making. Drawing on the distinction of Weber (2013) between formal and substantive rationality, Lindebaum et al. (2020) argue that AI encodes a particular set of values into a reified formal model. As the algorithm acts, humans rely on its outputs instead of making plans based on their reflection about goals and possibilities, shifting the distribution of decision making (Murray et al. 2021, Balasubramanian et al. 2022). At an extreme, by privileging formal rationality and suppressing substantive rationality, AI encodes values in advance of decision making, which Lindebaum et al. (2020, p. 249) worry implies "the end of choice." The notion of biases and their reproduction opens up questions about the invisible work involved in the production of the machine learning–based algorithms and argues for exploring the actions of all of the different actors involved in the system, including the algorithms themselves.

By unveiling the role of developers and designers of AI, these studies generate new paths for inquiry. They show that if we want to better understand collaboration with AI-based algorithms, we need to understand their design and implementation, which requires studying the elaborate systems of relational dynamics between engineers, designers, organizational decision makers, and users, including important differences in power across these actors. Take the example of COMPAS (Correctional Offender Management Profiling for Alternative Sanctions), an algorithm widely used in the United States to predict the likelihood of recidivism, which was reported to be racially biased (Angwin et al. 2016). COMPAS's risk scores are calculated based on the answers to a questionnaire that aims to assess a defendant's criminal history and attitudes about crime. An analysis of the decisions made by judges in one Florida County using COMPAS made visible the influence of the algorithm on judges' decisions. It showed how COMPAS determined which defendants were released on bail made reflected disparities in outcomes across race. The algorithm predicted that black defendants had a higher likelihood of recidivism than they did, whereas white defendants were assigned a lower risk than they actually had.

Taking a system view highlights how the assumptions embedded in the algorithm are questioned or reinforced over time by the other actors in the justice system. Hence, if we unpack the system within which the COMPAS algorithm is embedded, we can trace the relationships between the data from the questionnaire, the proprietary algorithm, the company that developed the algorithm, the designers and engineers, the defendants, their lawyers, and the judges.

The COMPAS algorithm is inscrutable and makes decisions based on assumptions that are not necessarily clear to the judges using the system to make decisions. These assumptions reflect different understandings of fairness encoded by the designers: either the algorithm aims to identify as many people who are at high risk of committing a crime, even though this goes along with the risk of a high number of false positives, or it aims to reduce the chance of false positive but this goes hand in hand with an increase of false negatives (Spielkamp 2017). It also highlights the unobtrusive power that these designers have on outcomes relative to other actors in the system. For instance, when judges use COMPAS to make decisions, they may reinforce some of the assumptions embedded in the algorithm. As Spielkamp (2017) notes, this raises questions about who should be involved in making tradeoffs and prioritizing considerations for society as developers create the algorithm and courts implement it: Lawmakers and an informed public become critical constituents.

As designers can have power, the participatory design literature has focused on incorporating multiple stakeholders, and especially users, in the design of sociotechnical systems involving work (Henderson and Kyng 1991, Muller and Kuhn 1993, Bødker 1996). By doing so, participatory design aims to engage workers in the development of informal systems and their workplace (Bødker et al. 1987, Clement and van den Besselaar 1993). Similarly, engaging multiple actors to consciously design algorithms that include the views and meet the needs of multiple stakeholders can affect how AI impacts work. For instance, Dove and Fayard (2020) organized a design workshop to explore the use of AI to support student mental well-being. They invited data scientists, professionals working with students, and the students themselves to work together to create the process for checking the classifications that machine learning algorithms make against what they know in reality. This process uncovered considerable differences, across groups and individuals, in the interpretations of the sources of data and what kind of recommendations they might generate. Approaches that account for different stakeholders might help to reveal the relations between different actors within a system and how they shape the ways AI and people work together.

Taking a system view allows us not only to explore the nature of relationships between different actors and uncover underlying assumptions, but it also allows us to raise questions regarding who is doing the work. Recent widespread adoption of AI algorithms builds on the persistent assumption that technology helps people perform their tasks. Yet, some studies suggest that AI systems do not always help people perform tasks or work together. This research exposes what happens underneath the surface of the "magical" narrative of technologies: Algorithms are not truly functioning as advertised. Instead of the computational power of machine learning, people provide the knowledge and labor to power the AI.

The example of Amazon Mechanical Turk, with its reference to the historical Mechanical Turk, is evocative of this positive narrative while at the same time illustrates the true dynamics between human labor and the algorithm. The metaphor of the "Mechanical Turk" provides a resonant historical image of the context of labor power in the service of a "thinking" machine. The Mechanical Turk, constructed in 1770, was a machine that appeared to be able to play chess against a human opponent, and for nearly 84 years, it won many of the games played during its demonstrations. It was, in fact, an illusion: The Turk was operated by a skilled chess player hidden in the technical apparatus. This example illustrates how the "augmented intelligence" sometimes heralded by technologists and practitioners may in reality be powered by humans who become computational labor, where people "collaborate" with AI, or more accurately, work for AI, to improve the performance of algorithms (Burrell and Fourcade 2021). In the light of the story of the Mechanical Turk, Amazon Mechanical Turk (AMT) is an apt name for the way the platform operates. Irani (2015) shows how the work done by workers on AMT is menial labor that replaces the work that originally was supposed to be done by AI algorithms. As Irani (2015, p. 771) notes, "Like 'cloud computing' services more generally, AMT offered immediate, on-demand provisioning of computational power accessible through computer code. In this case, however, the computational power was human." Irani shows how AMT proposed "humans as a service" to complement or replace AI and support a separate, higher-paid creative class of workers.

Shestakovfsky (2017) discovered a similar relationship between the promised capabilities of technology and its working capabilities. His ethnographic study of a tech startup developing AI algorithms to match services and providers explored the relationship between workers and the evolving technology and found that workers engaged in computational labor to support the algorithms, or in some cases, fully carry out the matching work the algorithms purportedly performed. In both Irani's and Shestakofsky's studies, human-AI collaboration was characterized by people engaging in forms of labor that propped up the AI. In other words, these two studies highlight how new work divisions are produced in organizations where algorithms, and their promise, define and structure the tasks done by people.

The recent scholarly work on AI use and implementation in organizations paints a somewhat grim picture of the role of workers who substitute for under-performing AI algorithms. As Irani (2015) and Shestakofsky (2017) demonstrate, workers who end up "working for" AI typically are precarious contingent or outsourced workers with low status in their organizations, despite the criticality of the work that they do for the organization. This is not without precedent: scholars studying outsourced work demonstrate that often outsourced workers are given low status tasks and treated as nonexperts by those in the United States (Metiu 2006, Leonardi and Bailey 2017). Indeed, outsourced workers supporting and repairing AI to maintain the illusion of AI-run products and services offered by their employing organizations belong to the general population of precarious workers and are intended to be "disposed of" once the algorithms they are repairing begin working. These examples question the promise of AI as a counterpart and highlight the need to examine all the actors involved in AI as a system, including the invisible human actors who might be laboring behind the scenes to make sure that the algorithms appear to "work."

More broadly, these studies point to the fact that most of AI today is powered by humans. Indeed, machine learning algorithms need to be trained, and for this, humans are essential. According to a study by Cognilityca, 80% of the time of AI projects involves collecting, cleaning, and labeling data to be used to train algorithms (Schmelzer 2020). The central role of humans for the success of AI projects leads to this somewhat antinomic expression of human-powered AI, reminiscent of the Mechanical Turk. Yet, such examples also remind us to be wary of the power relationships existing between different actors: AI, engineers, data scientists, designers, workers, users, and managers. Not all humans are turned into computational labor; some (managers, venture capitalists) benefit from human-powered AI. For instance, some recent studies have shown how AI-based algorithms control workers, serving as a managerial tool rather than a means to collaborate (Rosenblat 2018, Kellogg et al. 2020, Fayard 2021). As Burrell and Fourcade (2021) argue, this power differential may actually result in a divide between "coding elite, who hold and control the data and software, and the cybertariat, who must produce, refine, and work the data that feed or train the algorithms, sometimes to the point of automating their jobs and making themselves redundant" (p. 215). Taking a system perspective will allow us to fully trace the dynamics of AI implementation to understand who gains and who loses.

Echoing Suchman (2007), we argue that the development of AI and the idea of human-AI collaboration also requires us to interrogate our view of shared understanding, a central dimension required for effective collaboration, as being accomplished solely by human beings interacting with each other. As discussed previously, most studies of collaboration refer to humans *using* artifacts or machines, where a clear demarcation between humans and artifacts is made. The notion of human-machine interactions that surfaced in the 1980s to refer to the use and design of computers presumes a different type of relation between humans and machines than one of use, opening up questions regarding shared understanding (Suchman 2007). These questions are becoming more salient with the development of AI and recent narratives of human-AI collaboration, which tend to erase the role of human actors, and the power and politics in which different actors are involved and engaged in the design and implementation of AI algorithms. Instead, AI is presented as a rational actor, under the guise of the magical narratives developed around computing, data science, and digital technology.

The latest narratives around AI as a collaborator rather than simply a tool for automation have reinforced these beliefs. Indeed, assuming that humans and artifacts collaborate tends to diminish, and to a certain extent, abolish differences and asymmetries between humans and artifacts. As we noted earlier, organization studies scholars with a sociomaterial view (Orlikowski and Scott 2008, Barrett et al. 2012, Mazmanian et al. 2014, Bailey et al. 2022), following studies in sociology of technology and science (Pickering 1993, Goodwin 1995, Knorr Cetina 1999), agree that "humans and artifacts are *mutually constituted*" (Suchman 2007, p. 268). However, Suchman argues that relationships between humans and artifacts in organizations need to be explored further and suggests that we cannot simply "equalize" humans and artifacts. On the contrary, it is important to explore asymmetries, "recovering certain subject-object positionings–even orderings–among persons and artifacts and their consequences" (Suchman 2007, p. 269). Furthermore, "the particularity of human actors" (Suchman 2007, p. 270) has become more acute with the development of AI and robots.

Research exploring the roles and relationships between algorithms and different human actors, including engineers, designers, decision makers in technology companies developing AI, and decision makers in organizations (public or private) implementing AI programs, is therefore important and timely. Indeed, taking a counterpart perspective to the study of working with AI in organizations requires researchers to develop a deep understanding of the system of relations that AI is embedded within. Ethnographic approaches used in previous studies of technology may be difficult to draw on when taking a system view on AI. This difficulty is exacerbated by the very properties of AI: constant change, visibility, and inscrutability. In the next section, we will discuss the methodological questions raised by this new theoretical perspective.

Taking a Counterpart Perspective: Methodological Challenges

We know the value of ethnographic methods from previous studies looking at technology and work in organizations: They allow us to understand "technology-in-use" (Orlikowski 1992, 2000) and investigate how technology and practices influence each other within organizations. Because ethnographers develop "thick descriptions," they can unpack the "web of meanings" represented in the details of experiences and interactions (Geertz 1973, p. 5), including how different actors use and interpret artifacts. Moreover, because these studies are immersive, they enable researchers to unpack assumptions and see evolution, as well as delineate the variations between what people do and how they describe and interpret their activities (Forsythe 2001, Van Maanen 2011). For example, Orlikowski (1992) found that despite management buying and deploying Lotus Notes licenses to encourage collaboration, people did not engage with the collaborative features of groupware technology because of the competitive and individualistic organizational culture they worked in.

Further, ethnographic studies allow us to go beyond symbolic narratives about technology (Zbaracki 1998, Beane 2020). Relying on indirect measures of adoption and use, such as dollars spent, binary presence/absence of technology, and even claims about use, may misrepresent use. Ethnographic studies reveal that we should be leery of making assumptions about what technology adoption actually means for organizations and their members. This research has found that narratives and practices may not cohere, particularly when technology is infused with symbolic values like progress, the future, and rationality (Zbaracki 1998, Orlikowski 2000, Zilber 2006, Bailey et al. 2012, Barrett et al. 2013). Without observation, our research may reflect and perpetuate positive, deterministic technological narratives rather than offer a more complete picture of the phenomenon from which to build theory. Indeed, the relationship between what organizations say, what members think they do, and what they actually do is complicated: There are robots in closets (Beane 2020), and underused technology licenses abound (Orlikowski and Gash 1994). In the context of studying AI and collaboration, thick descriptions can highlight variations among different groups of users, across contexts, and the differences in interpretations between what the designers or managers intended and how the people doing the work use them. Ethnographic methods are also the best approach to developing a rich understanding of the complex and fluctuating division of labor and roles that characterize the future of work in the era of AI.

Despite the considerable progress ethnography has made in our understanding of how technology and organizing unfolds, scholars of technology and organizations have largely confined their focus to studying intraorganizational dynamics. In some sense, this reflects the very intersection of the phenomena of technology and organizations. Consequently, previous research taking tool and medium perspectives prioritizes studying users and groups that are nested within organizations. Their ethnographic toolkit, including the way observations and interviews are structured, mirrors the research designs that enable studying intraorganizational technology use and makes it difficult to study AI as a counterpart in an ecosystem of relations. The aspects of AI that make it different from technologies studied in the past, including the degree and nature of constant change, visibility, and inscrutability, as well as its symbolic value, may further challenge traditional approaches to local observation and interviews.

The recent grounded studies of AI and organizations (Shestakofsky 2017, Sachs 2020, Brayne and Christin 2021, Watkins 2021, Cameron 2022, Lebovitz et al. 2022) illustrate both the value of ethnography and the need to experiment with our current toolkit. Indeed, their focus on the interpretations, practices, and interactions of users and groups has the empirical grounding that many commentaries of AI lack (Susskind and Susskind 2015, Davenport and Kirby 2016, Wilson and Daugherty 2018, Malone et al. 2020). Although these initial studies have helped to shed light on the complexity of collaboration between humans and AI, most of them take a more traditional view of AI as a tool and medium and thus tend not to fully explore the system of relations that are implicated in its design, implementation, and use.

Taking a system perspective to the study of AI requires focusing on a broader system of work, as the division of labor across humans and AI is complex and contingent on the multiple actors involved in the development, management, and use of the technology. This approach highlights the problems of power and status facing those who work with AI (or in its shadow) as they encounter barriers given their position relative to other roles and occupations. However, ethnographers may face particular challenges in the study of AI. Especially when considering AI as a counterpart, researchers need to get at the complexity of a full system. To study how humans and AI might work together requires focus on a considerable number of relationships: between designers and users, between human actors and AI, across different users, and between groups of users and other groups. This may require ethnographers to improvise in their data collection (Van Maanen 2011, 2020; Fayard 2017).

Hence, being willing to methodologically experiment and improvise is important for researchers who try to develop thick descriptions of work contexts where AI is involved. For instance, they need to consider where they sit, how to shift their seat, and when and where to move around the system. They could extend the temporality of their fieldwork, looking earlier at decision making and implementation, and following through to regular use. Yet such movement might also create a tradeoff of depth and breadth. Because studying these different relationships requires involvement with a broader set of informants, researchers must move across multiple parts of a system. Yet doing so might not yield enough data on any one set of actors. This is complicated further by problems of visibility: Although AI may produce outputs, it is distributed, digital, and inscrutable. This may make it difficult to "see" AI and how it impacts work. Instead, what we usually see is the outcome, for example, a suggested decision, and we cannot ask the algorithm for a rationale for that decision. Moreover, machine learning algorithms are constantly evolving, meaning that any understanding may be temporary. Although much of the research on technology in organizations draws on ethnographic methods, these challenges require us to revisit our traditional approaches. We therefore need a broader ethnographic toolkit to do justice to a system perspective on AI and collaboration. In the following section, we discuss how relational ethnography allows us to leverage the power of ethnography while taking a system lens.

A Relational Approach to Ethnography and Studying AI

Although studies that take a tool and medium perspective have mastered uncovering in-depth processes and interactions, their narrow focus on local practices reflects how ethnography has been used in studies of technology and organizing. However, other fields that also use ethnographic approaches, including urban sociology and science and technology studies, have been successful in studying broader systems and communities, which is something we can leverage to study working with AI in organizations. Specifically, we propose that researchers adopt relational ethnography (Desmond 2014), which is an ethnographic approach that foregrounds the relationships between and across actors in a field, or in our case, in a system of work. Our analysis revealed AI is always embedded in a system of relationships between different actors across different occupations, organizations, and fields. Therefore, understanding AI in the workplace requires studying the relations within which it is created, developed, implemented, and used by different groups (i.e., data scientists, designers, managers, and workers).

Relational ethnography invites us to focus on "processes involving configurations of relations among different actors and institutions" (Desmond 2014, p. 547). It encourages scholars to look at AI not simply as a technology but as a field involving multiple actors, institutional and individual. For example, in his urban ethnography of eviction, Desmond traced relationships across multiple actors (tenants, landlords, and lawyers) and various locales (homes, courtrooms, and homeless shelters). This allowed him to provide a fuller picture of eviction as a complex process that involves more than tenants and landlords and also unfolds across multiple settings beyond the home. In a similar relational approach, scholars within science and technology studies work to map the many players and institutions, human and nonhuman, involved in the production and use of technology (Latour 1996, Dumit 2012). Clarke (2015) suggests that researchers engage in a situational analysis, which allows them to take into account "non-human actors and implicated actors and/or actants" and to explore "less powerful actors and the consequences of others' actions for them" (p. 93). For example, in her study of RU486, also known as the French abortion pill, Clarke (2015) uncovered how silent actors including women as users, stem cell researchers, and genetic scientists; more visible players such as Congress, the U.S. Food and Drug Administration (FDA), prochoice and antichoice groups; and adjacent technologies like surgical abortion techniques, all affected the pill's regulation process and outcome in the United States.

Although it may not be possible for researchers to be embedded in all the relations at play (Desmond 2014), it is nevertheless important to map the larger system of relations around an AI system, tracing the relations between the AI under study and the other actors in the field in which it sits. Clarke (2015) provides useful guidelines on how to map "the situation of inquiry" (p. 99) by developing situational maps that lay out the major human, nonhuman, discursive, historical, political, and other elements involved in the study context and their relationships: "These maps are intended to capture the messy complexities of the situation in their dense relations and permutations" (Clarke 2015, p. 100). Developing a map of the different actors (human and nonhuman) and contexts of the research questions will allow researchers to analyze their data in light of this broader system and will provide directions for research that other researchers might explore.

A potential challenge with mapping a system is delineating the boundaries around it: in other words, deciding who or what to include in the system or leave aside. This is not always obvious. One risk is for researchers to end up trying to study everything and then struggling to identify potential theoretical contributions. This is why, once the system of relations and the different actors are mapped out, it is important for scholars to pick a focal point guided by a particular research question to start their study of relations and dynamics between actors. One can start with a specific group such as developers or users, a moment in time such as the design or the implementation, or a specific field of use such as healthcare or finance. Although researchers have to choose a focal point to start analyzing the system, it is also essential to be aware of the anchoring provided by this focal point. Researchers may also draw into their study those actors who both shape and are implicated in the use of AI at work. Scholars have shown that drawing on study of various actors around a technology, including producers and users, can help to reveal pivotal moments, demonstrating what shapes how meaning and technology evolve. For instance, the ethnographic study of Mol (2002) of the disease atherosclerosis drew her fieldwork through a hospital system, allowing her to unpack the evolving definitions, associated practices, and consequences of different thought worlds surrounding the "same" disease. By drawing on AI to help define the boundaries of a field site, decide on an ethnographer's position in the field, and guide disengagement from the field (Christin 2020), researchers may be thus better positioned to tease out key actors, issues of power and status, differences in meaning, and evolving role structures. This may also help to ensure that scholars are better able to match theory to their emerging phenomena of focus. Beyond providing a starting point for designing a relational ethnography, these practices may also prompt ethnographers taking a tool or medium perspective to better contextualize their own studies and help them avoid "zooming in" too closely to local explanations for patterns in action and interactions they may observe.

Implementing a relational ethnography may require scholars of technology and organizations to broaden their approach. In particular, we see two areas in which scholars may benefit from rethinking their traditional ethnographies: first through broadening research design and strategies and second by broadening the ethnographer's skill set.

Strategies for Relational Ethnographic Study of AI

To study AI using relational ethnography, we suggest scholars might follow several strategies, studying multiple parts of a system, settings, time periods, and narratives, to help disentangle key questions of how actors collaborate with AI. To illustrate these strategies, we draw on the example of Kensho, a FinTech AI firm recently acquired by S&P Global, whose products use machine learning to aid market and financial analyses (Popper 2016, Gara 2018).

Kensho creates machine learning engines that search financial data sets to compile data on events that bankers, analysts, and investors can use to develop market insights. Initially, Kensho struggled to find banks who were interested in the product, given banking culture and entrenched legacy computer systems. "There were probably a hundred 'no's' in the first 18 months" said Daniel Nadler, the firm's chief executive officer (CEO) (Gara 2018). However, the chief information officer (CIO) of Goldman Sachs was interested and became Kensho's largest initial investor. Goldman partnered with Kensho to refine the technology for the firm's traders, and other large banks followed Goldman's lead and implemented the AI. Meanwhile, Goldman and Kensho continued to collaborate to develop additional applications of the technology to be used in other parts of the bank. In the following sections, we present four strategies for relational ethnography and illustrate how they could be used to study the Kensho example.

Study Multiple Parts of the System. In studies of AI, capturing multiple perspectives may help develop new theory about how humans and AI might work together. Although most recent studies have taken a tool or medium perspective, they offer hints that systems of relationships matter for how humans and AI work together. For instance, AI is being increasingly adopted in hospitals, which are complex organizational systems. In her study of the use of AI by radiologists, Lebovitz (2020) describes how, contrary to narratives about the changing nature of machine learning algorithms, the AI applications in her settings did not evolve because any changes had to be approved by the FDA given their classification as medical devices. Although this was a passing description of her context, it suggests that scholars taking a system view should think about how studying developers, managers and regulators could reveal the importance of their assumptions to how AI takes shape, with implications for use. By gathering data across multiple perspectives, scholars would be well equipped to answer several key questions. For example, they might study how unverified stories about AI emerge and shape role relations; how the framing of AI producers might influence patterns of use; who is doing the work and how divisions of labor unfold across actors and AI; and whether AI really is subsuming more menial tasks or if narratives about AI are being propped up by ventriloquism (i.e., Mechanical Turk).

A relational ethnography of Kensho would require the study of the many different actors involved throughout development, implementation, and use of AI algorithms. For instance, Kensho developed its products in collaboration with banking clients' top management and end users. Ethnographers could expand the temporal context of technological change "beyond a single moment in time or a discrete episode of change" (Thomas 1994, p. 12). They could begin by studying how the original designers imagined its use and with what consequences for technological development. This construction phase would allow researchers to trace how original designers imagined the Kensho AI systems would be used, as well as its initial framing pitched to potential clients, tracing consequences for AI development, and eventual implementation practices. Exploring different actors and relations within the system, researchers could examine how the CIO of Goldman initially laid the groundwork for implementation and how the traders responded to it. Next, researchers could follow the implementation of the AI algorithm at Goldman and interactions with Kensho, examining how the traders used it in their daily work. Moreover, the long-term partnership and expansion into other areas of the bank would provide opportunities to see how different types of workers responded to and used the newly developing AI. For instance, investment bankers who provide advisory services already use some of S&P Global's other products: Rolling out Kensho to these other users, who sit on the other side of an information barrier from traders, may provide contrasts and tensions across different users within the bank. Finally, given the Security and Exchange Commission's interest in algorithmic trading (Security and Exchange Commission 2020), it would be critical to explore how they influence some of the conversations and decisions of different actors in the field.

Study Multiple Settings. When studying how AI affects collaboration within a system, an important question is how systems evolve and change when there are different actors in them. To address these questions, we suggest researchers study multiple settings. As Bechky and O'Mahony (2016) discuss, scholars might draw on a number of different strategies for cross-site comparison that help to match sites for key similarities and leverage differences important for building new theory. Because power dynamics within organizations may be salient in the study of AI at work, a matched approach can help researchers observe and disentangle how they might emerge and evolve. For instance, Barley (1986, 1990) found that the distribution of expertise across hierarchical and occupational roles shaped patterns of technology use and interactions when CT scanners arrived at two different hospital settings.

For scholars of AI, this might mean comparing different occupational groups or organizations contending with AI at work. Comparable to Barley's case, one might examine the same AI as it is used in different locales (organizations or units). It could also mean exploring similar types of AI in different industries or different cultures. For example, Christin (2018) found that national culture shaped how journalists in the United States and France interpreted the role of algorithms in their work. This study highlights how culture shapes the way AI is interpreted, and likely shapes how it is designed, developed, and implemented. Comparative studies such as these might help to reveal how differences like the nature of the work, role structures, status, and clients' relations can influence the role of technology within a system (Christin 2018, Bechky 2020, Anthony 2021).

Continuing the Kensho illustration, researchers could compare how the same technology was implemented and used across different organizations in the same industry. For instance, their AI was adopted by multiple banks, and Kensho also developed an AI application used by the Central Intelligence Agency (Forbes 2015). If researchers negotiated access to that partnership, a cross-industry examination of this AI system would also be a possibility. Scholars could ask questions like: How does the culture and structure of banking versus government intelligence shape the design of the AI application and how does it figure in how workers collaborate with AI?

Study Multiple Time Periods. As AI applications are produced and implemented, they are going to evolve and function in ways even their designers cannot fully articulate. This evolution will likely shift relations between actors, and therefore studying AI over time is important. Thus, we suggest researchers should consider the intertemporal nature of interactions between AI and actors within a system. Although ethnographers have traditionally anchored on the synchronous meaning and actions of participants within their field sites, considering the relationship between contemporary practices and prior key moments in time might help researchers to better tease out how AI and organizational members "work" together.

In addition to tracing material evolution, scholars should consider changes to the perspectives that organizational members take toward AI. As Nelson and Irwin (2014) found, evolution in the framing of search technology coincided with changes to the identities of librarians, which informed how librarians used search technologies in their work. Designing longitudinal field studies to observe how interactions between AI and decision makers, designers, users, and systems of work unfold over time may therefore be important (Barley 1990). One potential strategy for capturing change over time might be to leave the field and come back (Barker 1993). For example, Anthony (2021) staggered field observations eight months apart, allowing her to capture shifts in group members' relationships and subsequent changes to technology use. By leaving and coming back, ethnographers may be able to capture and trace important shifts in work, roles, groups, and even AI, and be more likely to notice changes across two points in time vs. observing the gradual day-to-day shifts that may be less obvious.

A temporal analysis of Kensho, for example, could reveal how its purchase by S&P Global in 2018 affected the evolution and use of the AI. Access to the S&P's data resources and client relationships could change both the design of AI and its uses, as Nadler claimed, "Overnight we have the global scale with every financial user in the world, and our system becomes exponentially smarter as a result" (Gara 2018). A relational ethnography could mean returning after this purchase to see not only what Kensho's developers were doing and the AI itself changed but see how it was being used in additional settings.

Study the Symbolic Narratives of AI. Thus far, we have highlighted the need to study action, practices, and take a system view of AI—importantly, not treating discourse as truth about action. Yet discourse and narratives are part of systems (Clarke 2015), and they can shape action and interactions (Zbaracki 1998, Leonardi 2008, Martin 2016). Although nonobservational methods struggle to distinguish symbolic action and rhetoric from the reality of AI, scholars who take a relational ethnographic approach may be uniquely positioned to actually study positive narratives about AI, tracing their origins and consequences, and how they shape practices (Pachidi et al. 2021). As anthropological study of myths demonstrates, stories situate action (Bloch 1977, Halbwachs 1992). This means scholars might find great analytic purchase in considering articulations of the past, for instance, why a firm adopted a particular technology, how and why an AI application was designed, or how the technology has evolved, as key units of analysis. In addition, given deterministic rhetoric about AI and progress, scholars could also consider constructions of the future in a similar fashion.

For example, the public narratives surrounding Kensho reveal both the excitement and fear of AI: It was named one of the most impactful and innovative early-stage firms of 2016 by the World Economic Forum (2016), and that same year, the title of a *New York Times* article about the firm read, "The Robots are Coming for Wall Street" (Popper 2016). Early on, the CEO often discussed possible implications of Kensho's AI for work alongside the usual disruption narratives, noting that "we are creating a very small number of high-paying jobs in return for destroying a very large number of fairly high-paying jobs, and the net-net to society, absent some sort of policy intervention or new industry that no one's thought of yet to employ all those people, is a net loss" (Popper 2016). Researchers could study how Kensho's internal rhetoric influenced the development of their products, how the firm's perspective has changed over time, and how it is influenced by the public narratives about their products and AI more broadly. Doing so would be particularly useful for disentangling issues of power and symbolic narratives around AI. Scholars could ask questions such as the following. Who is discursively constructing what? Which narratives are developed and/or contested and by whom? Who has developed the narrative of automation as offering opportunities instead of replacement, or who has developed the narrative of collaboration?

Broadening Skill Sets

The strategies we describe for taking a relational approach complement many of the core tenets of ethnography but also call attention to aspects of ethnographic practice that may require broader skills. In particular, researchers may need to develop new skills in team-based ethnography, alter interviewing practices, engage with archival data and surveys, and use digital traces.

Team-Based Approach. Ethnographies of technology and organizing are typically structured as a lone ethnographer focusing on one or two organizations and observing colocated actors. Instead, a team-based approach seems better suited for relational ethnographies exploring a system view of AI and collaboration. With this approach, researchers might collect their data independently and then engage in comparative analysis (O'Mahony and Bechky 2006, Bechky and Ohkuysen 2011, Fayard et al. 2016, Brayne and Christin 2021). For example, Brayne and Christin (2021) compared the predictive algorithms within the judicial system, with Brayne studying police and Christin following legal professionals. Alternatively, teams can collect data together, iterating with one another to ensure their collection and emerging interpretations align. Jarzabkowski, Smets, and Spee also used a team-based approach as they jointly studied the reinsurance industry by following 11 firms, staggering their fieldwork, remaining in constant written communication, and having one member participate in data collection at all firms (Smets et al. 2015, Spee et al. 2016). By working together in a team, ethnographers may be able to triangulate aspects of the system such as meanings across different actors or actions within different organizational locations or geographies. As ethnographers work in teams, issues regarding data collection, sharing, and analysis need to be designed and managed to provide a richer understanding of the system and best leverage the members of the team.

Deepening Interview Skills and Combining with Visual and Material Devices. However, even with a team in place in the field, studying AI and collaboration raises new challenges in terms of observation because of AI's invisibility and inscrutability. Even if we were to sit nearby data scientists or people using AI to perform their tasks, it might not always be obvious what we could observe. The difficulty of relying primarily on observations has been an increasing concern because of the growing digitalization of work and communication and the ubiquity of technology, which has made a large part of work invisible (Riopelle 2013). Thus, interviews become even more important in relational ethnographies of AI, and broadening our interview skills can address some of the concerns about the tricky observational aspects of AI. Although observations tend to be conceived as the primary data for ethnography, Weeks (2020) reminds us that interviews are not a peripheral technique but are at the core of the ethnographic project. Leveraging Spradley's guidelines for ethnographic interviews, Weeks encourages us to see interviewing as a "mix of informal questioning, conversation, and formal unstructured interviews" (p. 77).

In relational ethnography, to better understand the relationship between the different actors, we can ask our informants to map out the different actors (human and nonhumans) involved in the design, development, implementation, and use of AI. We can also borrow from other fields like design research. Techniques like cultural probes (Gaver et al. 1999), informant drawings (Crosina 2018), and building artifacts (Dove and Fayard 2020) can help informants articulate their perception of AI and how it might affect their work. For instance, Dove and Fayard (2020) asked participants of a workshop they organized to build monsters that evoked AI for them. They then gave them a series of visual materials to help them articulate the ground truth for an algorithm to be developed in a specific context. Because of their visual and material nature, these techniques provide great resources to help our informants discuss their perceptions and practices related to AI, despite its invisible and inscrutable properties. One risk with interviews is that informants may fall back on invoking symbolic narratives about the value and uses of AI. Instead, these kinds of tools enable researchers to evoke informants' underlying interpretations, constructions, and uses at a deeper level.

Drawing on Archival Data and Surveys. The use of archival data could help scholars capture data on what preceded their fieldwork, for instance, by triangulating interviews with archival data such as internal company documents (i.e., newsletters and posts; Zbaracki 1998). In addition, relational ethnographers could engage with archival documents to uncover and analyze the nature of relations among actors within a system. Within the networks literature, scholars draw on archival data such as public filings and databases to map organizational ties at the field level (Gulati 1995, Schilling and Phelps 2007, Shipilov and Gawer 2020). Network scholars also use surveys to capture relationships among actors through sociometric questionnaires, where respondents answer questions about who they interact with, seek advice from, rely on as an ally, and are friends with (Ibarra 1992). These approaches have allowed scholars to study not only the nature of relationships among actors but also the structure of relations and positions of actors within a network of relationships. Similarly, to study AI through relational ethnography, researchers could begin drawing a system of relations around AI through archival documents and surveys to surface connections between actors, for instance, producers, regulators, and funders, to capture both the existence of relationships and their nature.

Although the use of networks helps to expand the ethnographer's skill set, it is important to still incorporate observation instead of relying too heavily on these surveys as providing a full picture of relations. As scholars of technology have noted, when technologies become taken for granted, informants can struggle to articulate and identify accurately how they interact with technologies (Orlikowski 2000). Thus, researchers would be well served to triangulate survey responses, which represent perceived relations, with patterns of interactions in observations (Krackhardt 1992).

Using Digital Traces. As technology has become ubiquitous in organizations, information system researchers have explored the role of documents and in particular digital traces (Geiger and Ribes 2011; Østerlund et al. 2016, 2020; Leonardi 2021). As scholars studying medical and other systems of categorization have shown (Berg and Bowker 1997, Bowker and Star 1999), these traces help us to understand collaboration and how work gets done in systems. More recently, Østerlund et al. (2016) demonstrated how documents played a key role in the unfolding of work in distributed environments. When researchers follow documents and their traces, it makes visible some of the work that cannot be directly observed because of the distributed and digital nature of the interactions. Tracing documents includes not only the content exchanges but also the activity on the databases, email servers, and cloud-based systems, as well as the organizing practices that surround them (Østerlund et al. 2016). This is another method that could help to map the system of actors. Relational ethnographers could therefore collect all the different forms of communication (email, text, Slack, WhatsApp, etc.) exchanged by developers, implementers, and users.

Automatic tracking of digital traces might be particularly useful to the study of AI and work in organizations. At the same time, when you consider the properties of AI, this may cause difficulties for scholars. As many algorithms are proprietary and therefore inscrutable, scholars and even organizational participants may be unable to get access to some of the digital traces. Moreover, because AI is constantly changing, researchers need to keep careful track over time of the inputs and outputs. In addition, scholars must remember that in most organizations, digital traces are interwoven with real world interactions, and thus researchers need to explore the context around the digital trace (Lindtner and Nardi 2008, Østerlund et al. 2016). With respect to AI, this means tracking down who is creating inputs, implementing tools, or using outputs, and eliciting those participants' practices and interpretations of the data.

Digital traces also can help researchers to analyze interactions and relations among actors who are not colocated. Analyzing social media and online communication media like email and Skype allow scholars to map such relationships (Kozinets 2010, Akemu and Abdelnour 2020). For example, Massa and O'Mahony (2021) used message boards and the development and circulation of content such as memes and videos online to trace relations across actors over time within Anonymous. These approaches may assist researchers to uncover the relationships and the work of participants who are not easily observed.

By broadening the ethnographic skill set to include working in teams, incorporating new interview techniques, drawing on archival data and surveys to map relations, and using digital traces to follow patterns of collaboration, ethnographers may be better equipped to engage with informants in a new way. Developing these skills can enable scholars to triangulate their observations with alternative data sources and better study relations across a system.

Conclusion

Although positive narratives about how workers and AI will harmoniously collaborate continue to diffuse, these stories paint an abstract picture of the role of AI at work, glossing over the rich body of literature on technology and organizations that has theorized interactions between actors and technology for decades. As organizations (private and public) are heavily investing in developing, acquiring, and implementing AI, we need to develop better and richer understandings of AI, how it is designed, implemented, and used, and how it might reconfigure social and economic life. Yet our traditional perspectives of technology as a tool and as a medium might suppress important material, symbolic, and relational dimensions of AI.

We argued that a better understanding of AI, work, and collaboration requires a counterpart perspective that requires scholars to study a system rather than just users. By studying the system, scholars can analyze the interactions and relationships between different human actors in occupations and organizations as and AI algorithms and their outputs. Yet to do so, we need rich data collected through relational ethnography. Its focus on the multiple and evolving arrangements of relations among different actors and institutions is well suited for such an analysis. Furthermore, such an approach will help us to move beyond symbolic narratives and abstract representations of AI in organizations. Not only will these studies provide a more grounded and richer picture of AI, but they will also unpack the power dynamics underlying the creation, implementation, and use of AI and its unintended consequences.

Acknowledgments

The authors thank Siobhan O'Mahony and three anonymous reviewers for excellent feedback throughout the review process. The paper also benefited from the comments of seminar participants at ESSEC, University of California–Irvine, and New York University's Future of Work group. In addition, the authors thank Mark Zbaracki who provided helpful comments on earlier drafts of this manuscript. All remaining errors are our own. The authors are listed alphabetically and contributed equally to this work.

Endnotes

[1] Machine learning algorithms perform without explicit instruction, relying on inferences and patterns in the underlying data it analyzes. As a learning program, it "consequently builds its own representation of a classification decision" (Burrell 2016, p. 10). Although not all AI includes machine learning, many of these applications do.

[2] For further discussion, see Burrell and Fourcade (2021), Crawford (2013), and Pasquale (2015).

References

Ajunwa I, Greene D (2019) Platforms at work: Automated hiring platforms and other new intermediaries in the organization of work. *Res. Sociol. Organ.* 33:61–91.

Akemu O, Abdelnour S (2020) Confronting the digital: Doing ethnography in modern organizational settings. *Organ. Res. Methods* 23(2):296–321.

Angwin J, Larson J, Mattu S, Kirchner L (2016) Machine bias. *ProPublica* (May 23). December 3, 2022, https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing.

Anthony C (2018) To question or accept? How status differences influence responses to new epistemic technologies in knowledge work. *Acad. Management Rev.* 43(4):661–679.

Anthony C (2021) When knowledge work and analytical technologies collide: The practices and consequences of black boxing algorithmic technologies. *Admin. Sci. Quart.* 66(4):000183922110167.

Balasubramanian N, Ye Y, Xu M (2022) Substituting human decision-making with machine learning: Implications for organizational learning. *Acad. Management Rev.*, ePub ahead of print July 18, https://doi.org/10.5465/amr.2019.0470.

Barley SR (1986) Technology as an occasion for structuring: Evidence from observations of CT scanners and the social order of radiology departments. *Admin. Sci. Quart.* 31(1):78–108.

Barley SR (1988) The social construction of a machine: Ritual, superstition, magical thinking and other pragmatic responses to running a CT scanner. Lock M, Gordon D, eds. *Biomedicine Examined* (Springer, Dordrecht), 497–539.

Barley SR (1990) The alignment of technology and structure through roles and networks. *Admin. Sci. Quart.* 35(1):61–103.

Barley SR (1996) Technicians in the workplace: Ethnographic evidence for bringing work into organizational studies. *Admin. Sci. Quart.* 41(3):404–441.

Barley WC, Treem JW, Kuhn T (2018) Valuing multiple trajectories of knowledge: A critical review and agenda for knowledge management research. *Acad. Management Ann.* 12(1):278–317.

Barocas S, Selbst AD (2016) Big data's disparate impact. *California Law Rev.* 104:671–732.

Bailey DE, Barley SR (2011) Teaching-learning ecologies: Mapping the environment to structure through action. *Organ. Sci.* 22(1): 262–285.

Bailey DE, Leonardi PM, Barley SR (2012) The lure of the virtual. *Organ. Sci.* 23(5):1485–1504.

Bailey DE, Faraj S, Hinds PJ, Leonardi PM, von Krogh G (2022) We are all theorists of technology now: A relational perspective on emerging technology and organizing. *Organ. Sci.* 33(1):1–18.

Barker JR (1993) Tightening the iron cage: Concertive control in self-managing teams. *Admin. Sci. Quart.* 38(3):408–437.

Barrett M, Heracleous L, Walsham G (2013) A rhetorical approach to IT diffusion: Reconceptualizing the ideology-framing relationship in computerization movements. *Management Inform. Systems Quart.* 37(1):201–220.

Barrett M, Oborn E, Orlikowski W, Yates J (2012) Reconfiguring boundary relations: Robotic innovations in pharmacy work. *Organ. Sci.* 23(5):1448–1466.

Beane M (2019) Shadow learning: Building robotic surgical skill when approved means fail. *Admin. Sci. Quart.* 64(1):87–123.

Beane MI (2020) In storage, yet on display: An empirical investigation of robots' value as social signals. *HRI '20: Proc. 2020 ACM/IEEE Internat. Conf. Human-Robot Interaction*, 83–91. https://doi.org/10.1145/3319502.3374775.

Beane M, Orlikowski WJ (2015) What difference does a robot make? The material enactment of distributed coordination. *Organ. Sci.* 26(6):1553–1573.

Bechky BA (2003a) Sharing meaning across occupational communities: The transformation of understanding on a production floor. *Organ. Sci.* 14(3):312–330.

Bechky BA (2003b) Object lessons: Workplace artifacts as representations of occupational jurisdiction. *Amer. J. Sociol.* 109(3):720–752.

Bechky BA (2020) Evaluative spillovers from technological change: The effects of "DNA envy" on occupational practices in forensic science. *Admin. Sci. Quart.* 65(3):606–643.

Bechky BA, Chung DE (2018) Latitude or latent control? How occupational embeddedness and control shape emergent coordination. *Admin. Sci. Quart.* 63(3):607–636.

Bechky BA, Okhuysen GA (2011) Expecting the unexpected? How SWAT officers and film crews handle surprises. *Acad. Management J.* 54:422–459.

Bechky BA, O'Mahony S (2016) Leveraging comparative field data for theory generation. Elsbach KD, Kramer RM, eds. *Handbook of Qualitative Organizational Research: Innovative Pathways and Methods* (Routledge, New York), 168–176.

Benner MJ, Tripsas M (2012) The influence of prior industry affiliation on framing in nascent industries: The evolution of digital cameras. *Strategic Management J.* 33(3):277–302.

Berg M, Bowker G (1997) The multiple bodies of the medical record: Toward a sociology of an artifact. *Sociol. Quart.* 38:513–537.

Bloch M (1977) The past and the present in the present. *Man (London)* 12(2):278–292.

Bødker S (1996) Creating conditions for participation: Conflicts and resources in systems development. *Human Comput. Interaction* 11(3):215–236.

Bødker S, Ehn P, Kammersgaard J, Kyng M, Sundblad Y (1987) A UTOPIAN experience: On design of powerful computer-based tools for skilled graphic workers. Bjerknes G, Ehn P, Kyng M, eds. *Computers and Democracy: A Scandinavian Challenge* (Avebury, Aldershot, UK), 251–278.

Bowker G, Star SL (1999) *Sorting Things Out* (MIT Press, Cambridge, MA).

Brayne S, Christin A (2021) Technologies of crime prediction: The reception of algorithms in policing and criminal courts. *Soc. Problems* 68(3):608–624.

Brynjolfsson E, McAfee A (2014) *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies* (Norton, New York).

Buolamwini J, Gebru T (2018) Gender shades: Intersectional accuracy disparities in commercial gender classification. *Proc. Machine Learn. Res.* 81:77–91.

Burrell J (2016) How the machine 'thinks': Understanding opacity in machine learning algorithms. *Big Data Soc.* 3(1):1–12.

Burrell J, Fourcade M (2021) The society of algorithms. *Annu. Rev. Sociol.* 47:213–237.

Callon M (1984) Some elements of a sociology of translation: Domestication of the scallops and the fishermen of St Brieuc Bay. *Sociol. Rev.* 32(1):196–233.

Cameron LD (2022) "Making out" while driving: Relational and efficiency games in the gig economy. *Organ. Sci.* 33(1):231–252.

Carlile PR (2002) A pragmatic view of knowledge and boundaries: Boundary objects in new product development. *Organ. Sci.* 13(4):442–455.

Christin A (2018) Counting clicks: Quantification and variation in web journalism in the United States and France. *Amer. J. Sociol.* 123(5):1382–1415.

Christin A (2020) The ethnographer and the algorithm: Beyond the black box. *Theory Soc.* 49(5):897–918.

Clarke A (2015) From grounded theory to situational analysis. What's new? Why? How? Clarke A, Freese C, Washburn R, eds. *Situational Analysis in Practice: Mapping Research with Grounded Theory* (Routledge, New York), 84–118.

Clement A, van den Besselaar PAA (1993) A retrospective look at PD projects. *Comm. ACM* 36(6):29–37.

Cohen LE (2013) Assembling jobs: A model of how tasks are bundled into and across jobs. *Organ. Sci.* 24(2):432–454.

Cohen LE (2016) Jobs as Gordian knots: A new perspective linking individuals, tasks, organizations and institutions. Cohen LE, Burton MD, Lounsbury M, eds. *The Structuring of Work in Organizations. Research in the Sociology of Organizations* (Emerald Insight, Bingley, UK), 25–59.

Cohen LE, Mahabadi S (2021) In the midst of hiring: Pathways of anticipated and accidental job evolution during hiring. *Organ. Sci.* 33(5):1938–1963.

Crawford K (2013) The hidden biases in big data. *Harvard Bus. Rev.* Accessed December 2, 2022, https://hbr.org/2013/04/the-hidden-biases-in-big-data.

Crosina E (2018) Start me up: On becoming an entrepreneur in a shared workspace. PhD dissertation, Boston College, Boston.

Dastin J (2018) Amazon scraps secret AI recruiting tool that showed bias against women. *Reuters* (October 10). Accessed December 3, 2022, https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK08G.

Davenport TH, Kirby J (2016) *Only Humans Need Apply: Winners and Losers in the Age of Smart Machines* (Harper Business, New York).

Desmond M (2014) Relational ethnography. *Theory Soc.* 43(5):547–579.

Dodgson M, Gann DM, Salter A (2007) "In case of fire, please use the elevator": Simulation technology and organization in fire engineering. *Organ. Sci.* 18(5):849–864.

Dougherty D (1992) Interpretive barriers to successful product innovation in large firms. *Organ. Sci.* 3(2):179–202.

Dove G, Fayard AL (2020) Monsters, metaphors, and machine learning. *Proc. CHI Conf. on Human Factors in Comput. Systems*, 1–17. https://doi.org/10.1145/3313831.3376275.

Dumit (2012) *Drugs for Life: Growing Health through Facts and Pharmaceuticals* (Duke University Press, Durham, NC).

Eadicicco L (2019) Leaked Apple documents reveal that Siri was designed to deflect questions about feminism and #MeToo, report says. *Business Insider* (September 6). Accessed December 3, 2022, https://www.businessinsider.com/apple-designed-siri-to-deflect-questions-about-feminism-metoo-report-2019-9#:~:text=Leaked%20Apple%20documents%20reveal%20that,feminism%20and%20%23MeToo%2C%20report%20says&text=Apple's%20Siri%20has%20been%20re,movement%2C%20according%20 to%20The%20 Guardian.

Edmondson AC, Bohmer RM, Pisano GP (2001) Disrupted routines: Team learning and new technology implementation in hospitals. *Admin. Sci. Quart.* 46(4):685–716.

Elish MC, Watkins EA (2020) *Repairing Innovation: A Study of Integrating AI in Clinical Care* (Data & Society Research Institute).

Elsbach KD (2003) Relating physical environment to self-categorizations: Identity threat and affirmation in a non-territorial office space. *Admin. Sci. Quart.* 48(4):622–654.

Faraj S, Pachidi S, Sayegh K (2018) Working and organizing in the age of the learning algorithm. *Inform. Organ.* 28(1):62–70.

Fayard AL (2017) Bricolage in the field: Experimenting in ethnography. Mir R, Jain S, eds. *The Routledge Companion to Qualitative Research in Organization Studies* (Routledge, London), 141–153.

Fayard AL (2021) Notes on the meaning of work: Labor, work, and action in the 21st century. *J. Management Inquiry.* 30(2):207–220.

Fayard AL, Metiu A (2014) The role of writing in distributed collaboration. *Organ. Sci.* 25(5):1391–1413.

Fayard AL, Gkeredakis E, Levina N (2016) Framing innovation opportunities while staying committed to an organizational epistemic stance. *Inform. Systems Res.* 27(2):302–323.

Forbes (2015) Fintech 50: The future of your money. *Forbes* (December 9). Accessed December 3, 2022, https://www.forbes.com/pictures/ffgh45emeel/kensho/?sh =39e29e837e40.

Forsythe D (2001) *Studying Those Who Study Us: An Anthropologist in the World of Artificial Intelligence* (Stanford University Press, Palo Alto, CA).

Frank M, Roehrig P, Pring B (2017) *What to Do When Machines Do Everything: How to Get Ahead in a World of AI, Algorithms, Bots, and Big Data* (John Wiley & Sons, Hoboken, NJ).

Gara A (2018) Wall Street tech spree: With Kensho acquisition S&P Global makes largest A.I. deal in history. *Forbes* (March 6). Accessed December 3, 2022, https://www.forbes.com/sites/antoinegara/2018/03/06/wall-street-tech-spree-with-kensho-acquisition-sp-global-makes-largest-a-i-deal-in-history/?sh=2f95d6967b85.

Gaver B, Dunne T, Pacenti E (1999) Design: Cultural probes. *Interaction* 6(1):21–29.

Geertz C (1973) *The Interpretation of Cultures: Selected Essays* (Basic Books, New York).

Geiger RS, Ribes D (2011) Trace ethnography: Following coordination through documentary practices. *Proc. 44th Hawaii Internat. Conf. on System Sci.* 1–10.

Gillespie T (2012) Can an algorithm be wrong? Retrieved April 15, 2018, https://limn.it/articles/can-an-algorithm-be-wrong.

Gittell JH (2002) Coordinating mechanisms in care provider groups: Relational coordination as a mediator and input uncertainty as a moderator of performance effects. *Management Sci.* 48(11): 1408–1426.

Gittell JH, Seidner R, Wimbush J (2010) A relational model of how high-performance work systems work. *Organ. Sci.* 21(2):490–506.

Goodwin C (1995) Seeing in depth. *Soc. Stud. Sci.* 25(2):237–274.

Gulati R (1995) Social structure and alliance formation patterns: A longitudinal analysis. *Admin. Sci. Quart.* 40:619–652.

Halbwachs M (1992) *On Collective Memory* (University of Chicago Press, Chicago).

Hao K (2020) The coming war on the hidden algorithms that trap people in poverty. *MIT Technology Review* (December 4). Accessed December 3, 2022, https://www.technologyreview.com/2020/12/04/1013068/algorithms-create-a-poverty-trap-lawyers-fight-back/.

Hardy C, Lawrence TB, Grant D (2005) Discourse and collaboration: The role of conversations and collective identity. *Acad. Management Rev.* 30(1):58–77.

Harwell D (2019) A face-scanning algorithm increasingly decides whether you deserve the job. *Washington Post* (November 6). Accessed December 3, 2022, https://www.washingtonpost.com/technology/2019/10/22/ai-hiring-face-scanning-algorithm-increasingly-decides-whether-you-deserve-job/.

Henderson A, Kyng M (1991) There's no place like home: Continuing design in use. Greenbaum J, Kyng M, eds. *Design at Work: Cooperative Design of Computer Systems* (Lawrence Erlbaum Associates, Hillsdale, NJ), 219–240.

Hess ED, Ludwig K (2017) *Humility Is the New Smart: Rethinking Human Excellence in the Smart Machine Age* (Berrett-Koehler Publishers, Oakland, CA).

Hutchins E (1991) The social organization of distributed cognition. Resnick LB, Levine JM, Teasley SD, eds. *Perspectives on Socially Shared Cognition* (American Psychological Association, Washington, DC), 283–307.

Hutchins E (1995) *Cognition in the Wild* (MIT Press, Cambridge, MA).

Ibarra H (1992) Homophily and differential returns: Sex differences in network structure and access in an advertising firm. *Admin. Sci. Quart.* 37:422–447.

Irani L (2015) Difference and dependence among digital workers: The case of Amazon Mechanical Turk. *South Atlantic Quart.* 114(1):225–234.

Kaplan S (2011) Strategy and PowerPoint: An inquiry into the epistemic culture and machinery of strategy making. *Organ. Sci.* 22(2):320–346.

Kaplan S, Milde J, Cowan RS (2017) Symbiont practices in boundary spanning: Bridging the cognitive and political divides in interdisciplinary research. *Acad. Management J.* 60(4):1387–1414.

Kellogg KC, Orlikowski WJ, Yates J (2006) Life in the trading zone: Structuring coordination across boundaries in postbureaucratic organizations. *Organ. Sci.* 17(1):22–44.

Kellogg KC, Valentine MA, Christin A (2020) Algorithms at work: The new contested terrain of control. *Acad. Management Ann.* 14(1):366–410.

Knorr Cetina K (1999) *Epistemic Cultures: How the Sciences Make Knowledge* (Harvard University Press, Cambridge, MA).

Knorr Cetina K (2010) The epistemics of information: A consumption model. *J. Consumer Culture* 10(2):171–201.

Koebler J (2017) The rise of the robolawyers. Accessed December 3, 2022, https://www.theatlantic.com/magazine/archive/2017/04/rise-of-the-robolawyers/517794/.

Kozinets RV (2010) *Netnography: Doing Ethnographic Research Online* (Sage, Thousand Oaks, CA).

Krackhardt D (1992) The strength of strong ties: The importance of philos in organizations. Eccles R, Nohria N, eds. *Networks and Organizations: Structure, Form and Action* (Harvard Press, Cambridge, MA), 216–239.

Latour B (1983) Give me a laboratory and I will raise the world. Knorr Cetina K, Mulkay M, eds. *Science Observed: Perspectives on the Social Study of Science* (Sage, London), 141–140.

Latour B (1987) *Science in Action: How to Follow Scientists and Engineers Through Society* (Harvard University Press, Cambridge, MA).

Latour B (1988) *The Pasteurization of France*, English translation (Harvard University Press, Cambridge, MA).

Latour B (1996) *Aramis, or the Love of Technology* (Harvard University Press, Cambridge, MA).

Latour B (2005) *Reassembling the Social: An Introduction to Actor-Network-Theory* (Oxford University Press, Oxford, UK).

Lave J, Wenger E (1991) *Situated Learning: Legitimate Peripheral Participation* (Cambridge University Press, Cambridge, UK).

Lebovitz S (2020) Artificial intelligence in practice. PhD dissertation, New York University, New York.

Lebovitz S, Levina N, Lifshitz-Assaf H (2022) Is AI ground truth really "true"? The dangers of training and evaluating AI tools based on experts' know-what. *Management Inform. Systems Quart.* 45(3):1501–1526.

Leonardi PM (2008) Indeterminacy and the discourse of inevitability in international technology management. *Acad. Management Rev.* 33(4):975–984.

Leonardi PM (2011) When flexible routines meet flexible technologies: Affordance, constraint, and the imbrication of human and material agencies. *Management Inform. Systems Quart.* 35(1):147–167.

Leonardi PM (2013) When does technology use enable network change in organizations? A comparative study of feature use and shared affordances. *Management Inform. Systems Quart.* 37(3):749–775.

Leonardi PM (2021) COVID-19 and the new technologies of organizing: Digital exhaust, digital footprints, and artificial intelligence in the wake of remote work. *J. Management Stud.* 51(1):247–251.

Leonardi PM, Bailey DE (2017) Recognizing and selling good ideas: Network articulation and the making of an offshore innovation hub. *Acad. Managment Discovery* 3(2):116–144.

Leonardi PM, Barley SR (2010) What's under construction here? Social action, materiality, and power in constructivist studies of technology and organizing. *Acad. Management Ann.* 4(1):1–51.

Levina N, Vaast E (2005) The emergence of boundary spanning competence in practice: Implications for implementation and use of information systems. *Management Inform. Systems Quart.* 29(2):335–363.

Levy S (1984) A spreadsheet way of knowledge. *Harper's* (November 24). Accessed December 3, 2022, https://backchannel.com/a-spreadsheet-way-of-knowledge-8de60af7146e.

Lindebaum D, Vesa M, Den Hond F (2020) Insights from "The Machine Stops" to better understand rational assumptions in algorithmic decision making and its implications for organizations. *Acad. Management Rev.* 45(1):247–263.

Lindtner SM, Nardi BA (2008) Mixed realities in China's Internet cafes. Accessed December 3, 2022, https://www.ics.uci.edu/~lindtner/documents/Lindtner-Nardi_MixedRealitiesChina.pdf.

MacKenzie DA (1990) *Inventing Accuracy: An Historical Sociology of Nuclear Missile Guidance* (MIT Press, Cambridge, MA).

Malone T, Rus D, Laubacher R (2020) Artificial intelligence and the future of work. *MIT Work of the Future Research Brief,* RB17-2020. https://workofthefuture.mit.edu/research-post/artificial-intelligence-and-the-future-of-work/.

Martin SR (2016) Stories about values and valuable stories: A field experiment of the power of narratives to shape newcomers' actions. *Acad. Management J.* 59(5):1707–1724.

Marx L (2010) Technology: The emergence of a hazardous concept. *Tech. Culture* 51:561–577.

Massa FG, O'Mahony S (2021) Order from chaos: How networked activists self-organize by creating a participation architecture. *Admin. Sci. Quart.* 66(4):1037–1083.

Mazmanian M (2013) Avoiding the trap of constant connectivity: When congruent frames allow for heterogeneous practices. *Acad. Management J.* 56(5):1225–1250.

Mazmanian M, Cohn M, Dourish P (2014) Dynamic reconfiguration in planetary exploration. *Management Inform. Systems Quart.* 38(3): 831–848.

McAfee A, Brynjolfsson E (2017) *Machine, Platform, Crowd: Harnessing Our Digital Future* (Norton, New York).

Meadows DH, Wright D (2008) *Thinking in Systems: A Primer Paperback* (Chelsea Green Publishing, Hartford, VT).

Metiu A (2006) Owning the code: Status closure in distributed groups. *Organ. Sci.* 17(4):418–435.

Miller AP (2018) Want less-biased decisions? Use algorithms. *Harvard Business Review* (July 26). Accessed December 3, 2022, https://hbr.org/2018/07/want-less-biased-decisions-use-algorithms.

Mol A (2002) *The Body Multiple* (Duke University Press, Durham, NC).

Muller MJ, Kuhn S (1993) Participatory design. *Comm. ACM* 36(6): 24–28.

Murray A, Rhymer J, Sirmon DG (2021) Humans and technology: Forms of conjoined agency in organizations. *Acad. Management Rev.*, ePub ahead of print July 15, https://doi.org/10.5465/amr.2019.0186.

Myers N (2008) Molecular embodiments and the body-work of modeling in protein crystallography. *Soc. Stud. Sci.* 38(2):163–199.

Nardi BA, Miller JR (1990) An ethnographic study of distributed problem solving in spreadsheet development. *Proc. ACM Conf. on Computer-Supported Cooperative Work*, 197–208. https://doi.org/10.1145/99332.99355.

Nelson AJ, Irwin J (2014) "Defining what we do—all over again": Occupational identity, technological change, and the librarian/Internet-search relationship. *Acad. Management J.* 57(3):892–928.

Norman DA (1988) *The Psychology of Everyday Things* (Basic Books, New York).

O'Mahony S, Bechky BA (2006) Stretchwork: Managing the career progression paradox in external labor markets. *Acad. Management J.* 49(5):918–941.

O'Neil C (2016) *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy* (Crown, New York).

Oborn E, Barrett M, Dawson S (2013) Distributed leadership in policy formulation: A sociomaterial perspective. *Organ. Stud.* 34(2):253–276.

Okhuysen GA, Bechky BA (2009) Coordination in organizations: An integrative perspective. *Acad. Management Ann.* 3(1):463–502.

Orlikowski WJ (1992) The duality of technology: Rethinking the concept of technology in organizations. *Organ. Sci.* 3(3):398–427.

Orlikowski WJ (2000) Using technology and constituting structures: A practice lens for studying technology in organizations. *Organ. Sci.* 11(4):404–428.

Orlikowski WJ, Gash DC (1994) Technological frames: Making sense of information technology in organizations. *ACM Trans. Inform. Systems* 12(2):174–207.

Orlikowski WJ, Scott SV (2008) Sociomateriality: Challenging the separation of technology, work and organization. *Acad. Management Ann.* 2(1):433–474.

Orr JE (1996) *Talking About Machines: An Ethnography of a Modern Job* (Cornell University Press, Ithaca, NY).

Østerlund C, Crowston K, Jackson C (2020) Building an apparatus: Refractive, reflective, and diffractive readings of trace data. *J. Assoc. Inform. Systems* 21(1):10.

Østerlund C, Snyder J, Sawyer S, Sharma S, Willis M (2016) Documenting work: From participant observation to participant tracing. Elsbach K, Kramer R, eds. *The Handbook of Qualitative Organizational Research: Innovative Pathways and Methods* (Routledge, New York), 391–400.

Owen-Smith J (2001) Managing laboratory work through skepticism: Processes of evaluation and control. *Amer. Sociol. Rev.* 66(3): 427–452.

Pachidi S, Berends H, Faraj S, Huysman M (2021) Make way for the algorithms: Symbolic actions and change in a regime of knowing. *Organ. Sci.* 32(1):18–41.

Pasquale F (2015) *The Black Box Society* (Harvard University Press, Cambridge, MA).

Pickering A (1993) The mangle of practice: Agency and emergence in the sociology of science. *Amer. J. Sociol.* 99(3):559–589.

Pine KH, Mazmanian M (2017) Artful and contorted coordinating: The ramifications of imposing formal logics of task jurisdiction on situated practice. *Acad. Management J.* 60(2):720–742.

Polli F (2019) Using AI to eliminate bias from hiring. *Harvard Business Review* (October 29). Accessed December 3, 2022, https://hbr.org/2019/10/using-ai-to-eliminate-bias-from-hiring.

Popper N (2016) The robots are coming for Wall Street. *New York Times Magazine* (February 15). Accessed December 3, 2022, https://www.nytimes.com/2016/02/28/magazine/the-robots-are-coming-for-wall-street.html.

Raghavan M, Barocas S, Kleinberg J, Levy K (2020) Mitigating bias in algorithmic hiring: Evaluating claims and practices. *Proc. ACM Conf. on Fairness, Accountability, and Transparency*, 469–481.

Riopelle K (2013) Being there: The power of technology-based methods in Jordan, B. ed. *Advancing Ethnography in Corporate Environments* (Left Coast Press, Walnut Creek, CA), 38–55.

Rosenblat A (2018) *Uberland: How Algorithms Are Rewriting the Rules of Work* (University of California Press, Berkeley, CA).

Rudin C, Radin J (2019) Why are we using black box models in AI when we don't need to? A lesson from an explainable AI competition. *HDSR* (November 22). Accessed December 3, 2022, https://hdsr.mitpress.mit.edu/pub/f9kuryi8/release/6.

Sachs SE (2020) The algorithm at work? Explanation and repair in the enactment of similarity in art data. *Inform. Comm. Soc.* 23(11):1689–1705.

Schilling MA, Phelps C (2007) Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. *Management Sci.* 53(7):1113–1126.

Schmelzer R (2020) The human-powered companies that make AI work. *Forbes* (February 2). Accessed December 3, 2022, https://www.forbes.com/sites/cognitiveworld/2020/02/02/the-human-powered-companies-that-make-ai-work/?sh=6e21a54c670c.

Schwartz J, Mallon D, Van Durme Y, Hauptmann M, Yan R, Poynton S (2020) Superteams: Putting AI in the group. *Deloitte Insights* (May 15). Accessed December 3, 2022, https://www2.deloitte.com/us/en/insights/focus/human-capital-trends/2020/human-ai-collaboration.html.

Scott SV, Orlikowski WJ (2012) Reconfiguring relations of accountability: Materialization of social media in the travel sector. *Accounting Organ. Soc.* 37(1):26–40.

Securities and Exchange Commission (2020) Staff report on algorithmic trading in U.S. Capital Markets. *Staff of the U.S. Securities and Exchange Commission* (August 5). Accessed December 3, 2022, https://www.sec.gov/files/Algo_Trading_Report_2020.pdf.

Shestakofsky B (2017) Working algorithms: Software automation and the future of work. *Work Occupation* 44(4):376–423.

Shipilov A, Gawer A (2020) Integrating research on interorganizational networks and ecosystems. *Acad. Management Ann.* 14(1): 92–121.

Simon HA (1947) *Administrative Behavior: A Study of Decision-Making Processes in Administrative Organization* (Free Press, New York).

Smets M, Jarzabkowski P, Burke GT, Spee P (2015) Reinsurance trading in Lloyd's of London: Balancing conflicting-yet-complementary logics in practice. *Acad. Management J.* 58(3):932–970.

Spee P, Jarzabkowski P, Smets M (2016) The influence of routine interdependence and skillful accomplishment on the coordination of standardizing and customizing. *Organ. Sci.* 27(3):759–781.

Spielkamp M (2017) Inspecting algorithms for bias. *MIT Technology Review* (June 12). Accessed December 3, 2022, https://www.technologyreview.com/2017/06/12/105804/inspecting-algorithms-for-bias/.

Star SL, Griesemer JR (1989) Institutional ecology, 'translations' and boundary objects: Amateurs and professionals in Berkeley's Museum of Vertebrate Zoology, 1907-39. *Soc. Stud. Sci.* 19(3):387–420.

Starr SB (2014) Evidence-based sentencing and the scientific rationalization of discrimination. *Stanford Law Rev.* 66:803–872.

Suchman LA (2007) *Human-Machine Reconfigurations: Plans and Situated Actions* (Cambridge University Press, Cambridge, UK).

Susskind RE, Susskind D (2015) *The Future of the Professions: How Technology Will Transform the Work of Human Experts* (Oxford University Press, Oxford, UK).

Thomas RJ (1994) *What Machines Can't Do: Politics and Technology in the Industrial Enterprise* (University of California Press, Oakland).

Tripsas M (2009) Technology, identity, and inertia through the lens of "The Digital Photography Company." *Organ. Sci.* 20(2):441–460.

Tsoukas H (2009) A dialogical approach to the creation of new knowledge in organizations. *Organ. Sci.* 20(6):941–957.

Tyre MJ, Orlikowski WJ (1994) Windows of opportunity: Temporal patterns of technological adaptation in organizations. *Organ. Sci.* 5(1):98–118.

Valentine MA, Hinds R (2021) "Rolling up the leaf node" to new levels of analysis: How algorithmic decision-making changes roles, hierarchies, and org charts. Working paper, Stanford University, Stanford, CA.

Van Maanen J (2011) *Tales of the Field: On Writing Ethnography* (University of Chicago Press, Chicago).

Van Maanen J (2020) Withdrawal pains and gains: Exiting from the field. Mir R, Fayard AL, eds. *The Routledge Companion to Anthropology and Business* (Routledge, New York), 501–513.

Von Hippel E (1976) The dominant role of users in the scientific instrument innovation process. *Res. Policy* 5(3):212–239.

Von Hippel E (1986) Lead users: A source of novel product concepts. *Management Sci.* 32(7):791–805.

Von Hippel E (2005) *Democratizing Innovation* (MIT Press, Cambridge, MA).

Waardenburg L, Huysman M, Sergeeva AV (2022) In the land of the blind, the one-eyed man is king: Knowledge brokerage in the age of learning algorithms. *Organ. Sci.* 33(1):59–82.

Watkins (2021) The polysemia of recognition: Facial recognition in algorithmic management. PhD dissertation, Columbia University, New York.

Weber M (2013) *[1920] From Max Weber: Essays in Sociology* (Routledge, London).

Weeks J (2020) What good is the ethnographic interview? Mir R, Fayard AL, eds. *The Routledge Companion to Anthropology and Business* (Routledge, London), 64–79.

Weick KE (1993) The collapse of sensemaking in organizations: The Mann Gulch disaster. *Admin. Sci. Quart.* 38(4):628–652.

Wilson HJ, Daugherty PR (2018) Collaborative intelligence: Humans and AI are joining forces. *Harvard Bus. Rev.* (July-August): 114–123.

Winner L (1980) Do artifacts have politics? *Daedalus* 109(1):121–136.

World Economic Forum (2016) Who are the technology pioneers? Accessed December 3, 2022, https://widgets.weforum.org/techpioneers-2016/index.html.

Zammuto RF, Griffith TL, Majchrzak A, Dougherty DJ, Faraj S (2007) Information technology and the changing fabric of organization. *Organ. Sci.* 18(5):749–762.

Zbaracki MJ (1998) The rhetoric and reality of total quality management. *Admin. Sci. Quart.* 43:602–636.

Zilber TB (2006) The work of the symbolic in institutional processes: Translations of rational myths in Israeli high tech. *Acad. Management J.* 49(2):281–303.

Callen Anthony is an assistant professor in the Department of Management and Organizations at the New York University Stern School of Business. Her research examines the emergence and use of new technologies, expertise, and framing. She received her PhD from Boston College.

Beth A. Bechky is the Stephen G. Newberry chair in leadership and professor of management at the Graduate School of Management at University of California, Davis. She is an organizational ethnographer who focuses on technology and work. She received her PhD from Stanford University.

Anne-Laure Fayard is the ERA chair professor in social innovation at NOVA School of Business and Economics and visiting research professor at New York University. She is an ethnographer of work, whose interests involve collaboration, technology, and innovation. She received her PhD from the Ecole des Hautes-Etudes en Sciences Sociales (Paris).