Substance, Discourse, and Practice: A Review of Communication Research on Automation

Joshua B. Barbour

Jared T. Jensen

Shelbey R. Call

Nandini Sharma

The University of Texas at Austin

Forthcoming at *Annals of the International Communication Association*,

https://doi.org/10.1080/23808985.2023.2183232.

Joshua B. Barbour (ORCID 0000-0001-8384-7175) is an associate professor in the Department of Communication Studies at the University of Texas at Austin. Jared T. Jensen (ORCID 0000-0003-3602-6854), Shelbey R. Call (ORCID 0000-0001-9944-6368), and Nandini Sharma (ORCID-0000-0003-3596-5841) are doctoral candidates at the Department of Communication Studies at the University of Texas at Austin.

This material is based upon work supported by the National Science Foundation under Grant No. SES-1750731.

The authors report there are no competing interests to declare.

Correspondence concerning this article should be addressed to Joshua B. Barbour, Department of Communication Studies, The University of Texas at Austin, 2504A Whitis Ave. (A1105), Austin, TX 78712-0115, 512-471-5251, barbourjosh@utexas.edu.

Substance, Discourse, and Practice: A Review of Communication Research on Automation

Abstract

Echoing past waves of transformation, the public sphere is awash with anxiety about automation now driven by the rise of intelligent machines. Emerging technologies encompass a wider and wider range of work, and the disruptions that will accompany the transformation of work involve pressing problems for research and practice. Communication scholarship is distinctively well equipped for the study of automation today because communication itself is increasingly the focus of automation, because the automation of work is a communication process, and because deliberations about automation will shape how we manage those disruptions. This article reviews scholarship in communication that focuses on automation, highlighting research that focuses on communication as the substance of automation, discourse about automation, and communicative practice of automation.

Keywords: automation, future, work, practice, discourse, artificial intelligence

Substance, Discourse, and Practice: A Review of Communication Research on Automation

"The robots are coming!" This phrase has become a common trope in the public sphere amid growing interest in and apprehension about automation. For example, Chen (2019) argued, "while we might not have robot overlords anytime soon, changing technology is already making many of our workplaces increasingly dystopian" (¶ 1). As if to underline the concerns, stories about automation and the coming wave of robots run alongside lists of related articles automatically curated by algorithms (Wright, 2016). It is a common enough trope that Lepore (2019) joked, "Hide the WD-40. Lock up your nine-volt batteries. Build a booby trap out of giant magnets; dig a moat as deep as a grave" (¶ 1).

Automation and concerns about it have been around for as long as industrialization itself (Noble, 2011; Sennett, 2009; Weber et al., 2021), but recent coverage and research have emphasized that present-day technological advances will extend the reach of automation beyond its historical boundaries (Acemoglu & Restrepo, 2020; Brynjolfsson & McAfee, 2016; Morath, 2020; Wolf, 2019). The automation of work today increasingly involves intelligent machines, or "[artificial intelligence (AI)] and the suite of associated technologies that complement or contribute to it, such as machine learning, big data, robotics, smart sensors, the Internet of things, and analytics," (Bailey & Barley, 2020, p. 2). Intelligent machines are already ubiquitous in daily life and include AI-enabled mobile phones, automated thermostats, virtual assistants, chatbots, autocorrect, recommendation algorithms on streaming sites, auto-email completion, automated image search, and smart cars and the algorithms that drive them. Analysts have raised concerns about how these machines influence meaning making in medicine, criminal justice, and the hiring and management of workers (e.g., Crawford, 2021; Crowston et al., 2022; Graham, 2022; O'Neill, 2016; Topol, 2019a). Public opinion reflects a mix of hope and apprehension about the future of work (Johnson & Verdicchio, 2017; Liang & Lee, 2017; Lobera et al., 2020; Pew

Research Center, 2017).

The rise in discourse on automation in the public sphere coincides with increasing interest in automation in communication and allied disciplines (Bailey & Barley, 2020; Guzman & Lewis, 2020; Kellogg et al., 2020; Seeber et al., 2020). Murdock (2018) challenged communication scholars, writing that “research needs to match the scope and ambition of the companies…” “…constructing the new computing, network, and artificial intelligence architectures…” “and expand the range of areas and applications it addresses” (p. 365). Underscoring the value of existing communication frameworks for the study of automation, evidence suggests we may communicate with automated entities as we do with each other (Reeves & Nass, 1996; Westerman et al., 2020). However, changes in automated communication, communication about automation, or communication for automating point to the need for research and theoretical development that focuses on (a) the expanding capabilities of the technology (Laapotti & Raappana, 2022; Sundar, 2020) and (b) the complexity of the communication involved (Bailey & Barley, 2020; Gambino & Liu, 2022; Guzman & Lewis, 2020).

In this review, we build a case for communication approaches for the study of automation, arguing that communication is distinctively well-suited to the study of automation today. First and foremost, it is increasingly communication that is being automated. Unlike previous waves of automation, intelligent machines can complete more complex communication tasks (Acemoglu & Restrepo, 2020; Brynjolfsson & McAfee, 2016), and we also have more direct experience with automatic technologies (Fortunati, 2018). For example, we interact through AI-supported technologies and with AI-communicators, including AI content creators like virtual influencers, AI conversers such as digital assistants and chatbots, AI-curated content on platforms mediated by AI, and AI co-authors who recommend responses, correct us, and finish our sentences (Sundar, 2020; Sundar & Lee, 2022). Moreover, the importance of intelligent machines notwithstanding, the automation of communication can also include technologies that automate interaction such as algorithm-guided news production (Diakopoulos, 2019; Flyverbom, 2019), data-driven personalized news recommendations (Beam, 2014), electronic-health-record-based personalized medicine (Ratcliff et al., 2018; Scherr et al., 2017), or analytics-driven sales work, hiring, and leadership (Barbour et al., 2018; Berkelaar, 2017; Pääkkönen et al., 2020). Furthermore, communication also matters now more than ever because societal and organizational deliberations about automation will influence its effects and may moderate the disruptions feared of in the robots-are-coming discourse.

To make the case for communication approaches for the study of automation, the article begins with an explication of automation. As detailed below, the term has referred to processes of designing, implementing, and updating human and machine systems to do work that might otherwise be done by humans; the tools developed and deployed in those processes; and communication about the technology, work, and workers involved. Building on this explication, we focus our review of communication research on automation at the intersection of (a) automatic technologies, (b) specific tasks, work, and occupations, and (c) workers using or being subject to those technologies (see Figure 1). Through this review, we demonstrate the distinctive value of communication approaches, summarize key insights from this literature, and forward an agenda for future research.

After explicating automation and its implications for work and workers, we organize a synthesis of the literature by examining three clusters of research that emerged through our review: Communication as the **substance** of automation includes scholarship that focuses specifically on the automation of communication. Research on the **discourse** of automation examines communication about automation in the public sphere and among workers engaged in automation or subject to it. Research on the **practice** of automation investigates the development, implementation, and transformation of automated systems through communication. Key insights from the review include that automation is at once transformative and taken-for-granted, that it generates information and interaction, and that it unfolds in and through communication. Based on the review, we forward an agenda focused on three overarching recommendations for future communication research: We first argue that the intersections among the substance, discourse, and practice of automation provide rich opportunities for communication scholars. Second, we argue that communication research should include the study of data-intensive automation, the use of data generated by automation, and the changing nature of agency in the context of intelligent machines while taking care not to confound these related phenomena with automation itself. We conclude by arguing that communication scholarship should aim to empower choices about how we use automated technologies through empirical, critical, and design research. To focus the review, we now turn to an explication of automation.

Explicating Automation

Defining automation is difficult. The term is polysemous, and its many uses refer to different but related phenomena. “Automation” can refer to (a) specific technologies; (b) processes of design, implementation, and operation; (c) occupational and industry trends; (d) continua of human-machine relationships; and (e) focuses of discourse. Automation may refer to devices and algorithms doing “automatic” work or advances in the capabilities of these technologies to operate without human intervention (Kellogg et al., 2020). Automatic technologies vary in sophistication. For example, they include a relatively simple repeat-song function on a music player as well as complex machine-learning-powered calendaring systems. Klatzky (1970) referred to “the extent of automation” as the number of computers and “input-output units" involved in an organization's workflow (p. 143). "Bots" or "automata," for example, may follow "a well-defined recipe to compute some result" where the "will" of the bot, aims to "substitute procedural uncertainty with precisely defined routines" (Hilbert & Darmon, 2020, p. 672). Bots are used to scrape online data, automate product promotion, spread (mis)information, make friends, and influence deliberation online (Brandtzaeg et al., 2022; Duan et al., 2022; Seering et al., 2018; Shorey & Howard, 2016). Bots may also be capable of learning by themselves from the data they operate on and becoming unpredictable even for those who create them. It is not that this deviation from specific recipes is unanticipated, it is just that there are no set recipes for them to follow. They are meant to learn and evolve with time. Important to the conceptualization of automation as a specific technology is that the apparatus is usually perceived as a discrete entity, independent from its users, designers, and creators.

As a process of design, implementation, and operation, automation brings to mind the assembly line, valorized in presentations about factory productivity and caricatured in satire such as Chaplin's classic, *Modern Times* (e.g., the eating machine, Chaplin, 1936). In that same spirit, and as is often the case in the public sphere, automation refers to efforts to replace human work and workers. Indeed, automation should be of particular interest to communication scholars of work and organizing in part because automation like "many—perhaps most—workplace technologies are designed to save labor" (Autor, 2015, p. 5). Meyer (1968) defined automation as the use of computers in data processing to replace work that would have been done by hand, emphasizing efficiency gains. Bainbridge (1983) argued that the "classic aim of automation is to replace human manual control, planning, and problem solving by automatic devices and computers," while arguing that this definition obscures that automation requires human involvement and that "the more advanced a control system is, so the more crucial may be the contribution of the human operator" (p. 775). Furman and Teodoridis (2020) defined automation as measurable according to "the extent to which technology substitutes for specific tasks and affects the allocation of human effort across tasks within a personnel function" (p. 332). Indeed, many new technologies have been sold to adopters on promises of productivity gains (e.g., Sproull & Kiesler, 1991). These definitions of automation tend to emphasize it is "a process that reduces the cost of performing certain tasks" (Furman & Teodoridis, 2020, p. 331) while bringing into question the role of human oversight.

To make sense of automation along these lines, Parasuraman and colleagues (2000) defined automation as "a device or system that accomplishes (partially or fully) a function that was previously, or conceivably could be, carried out (partially or fully) by a human operator" (p. 287). Using this definition, they conceptualized levels of interaction between human and machine decision making that ranged from one extreme where the computer made all the decisions to another where the computer offered no assistance. Similar continua exist in the context of self-driving cars and automated/augmented medicine where applications range from no automation and the absence of "assistive features such as cruise control" to full automation and the "true electronic chauffeur" that "retains full vehicle control, needs no human backup, and drives in all conditions" (Topol, 2019b, p. 51). The varied balance of human and machine control in work is central as well in more recent theorizing of human-machine interaction (Glikson & Woolley, 2020; Guzman & Lewis, 2020; Hancock et al., 2020; Sundar, 2020).

A key point of this work is that automation should be conceptualized in terms of integrated processes of human and machine effort. Along those lines, automation may also be understood in terms of the communication it produces. Zuboff's (1988) germinal work emphasized that information technologies do not just automate work; they may informate it, meaning that automation involves creating information about work to mechanize or computerize it and that the ongoing functioning of automation produces a flow of information about that work

(Flyverbom, 2019; Flyverbom & Murray, 2018; Treem et al., 2020; Zuboff, 2019).

For example, algorithms are a principal engine of present-day automation and a key connection between human and machine effort in automation (Gibbs et al., 2021; M. K. Lee et al., 2015). Kellogg et al. (2020) defined algorithms as “computer-programmed procedures that transform input data into desired outputs in ways that tend to be more encompassing, instantaneous, interactive, and opaque than previous technological systems” (p. 366). The data that algorithms consume and the results they produce may be deployed in critical decision-making contexts such as search engine results, criminal justice sentencing, hiring, learning platforms, and teacher performance evaluations. The role of algorithms in shaping such decisions evoke questions of trust, bias, and transparency (Benjamin, 2019; Laapotti & Raappana, 2022; Obermeyer et al., 2019; O’Neill, 2016). Research has documented (a) systematic biases that suppress or distort minority representation in data for hiring, education, genomic research, clinical trials, and search engines and (b) the reproduction of those biases in the algorithms that rely on the data (e.g., Adamson & Smith, 2018; Eubanks, 2017; Popejoy & Fullerton, 2016; Sardar et al., 2014).

Studies of algorithms also make clear that automation refers to a category of discourse (Peña Gangadharan & Niklas, 2019; Shorey & Howard, 2016). “Automation” may refer to societal trends and deliberation about those trends. For example, Marshal argued for the need to be critical of ‘habitual’ tendencies and positioned Google Image’s algorithms as instantiating “a kind of visual ingenium or architecture of discovery,” explaining “we must curate image arrays for ourselves instead of relying solely on the mysterium of the results page” (p. 372). Velkova and Kaun (2021) analyzed Swedish design student Johanna Burai’s efforts to resist algorithmic power by campaigning to push images of non-white hands into the top of image search results. Through their analysis, they explored resistance as occurring alongside algorithms rather than in opposition to them, framing such efforts as “reformist rather than revolutionary” (p. 536), co-opting the algorithm for personal, philanthropic, and social good. Automation research includes study of the processes of designing and implementing algorithmic image search, the patterns the search produces, and how automation sparks deliberation as in Burai’s work.

Deliberation about automation is also central in studies of communication involved in workplace automation. For example, Bailey and Leonardi’s (2015) study of automotive, civil, and software engineers focused on how engineers incorporated automated tools into their work and deliberated about the efficacy of those tools. Workers in their study made choices about automation grounded in communication. Occupational factors such as professional mores and standards, safety regulations, the pace of occupational knowledge change, divisions of labor, task interdependence, and also local leadership framing and conversations with colleagues and vendors informed the choices engineers made about automation. In this example, “automation” was a focus of interaction regarding how they should work and with what specific tools. In their study of firms selling social media analytics, Pääkkönen and colleagues (2020) found that automation was a “technological means through which analysts and clients think they can reach the objectives set for social media analytics” (p. 793), emphasizing that automation was less a specific tool or process than it was an “idea that actors in different contexts can adapt to lend their expectations with credibility” (p. 806). Again, in this research, automation referred not just to technologies or processes of technology design and use, but to a focus of discussion among coworkers, managers, vendors, and clients.

Looking across its usage, automation can refer to a category of technological applications, processes of designing, implementing, and updating human and machine systems that do work that has been or might otherwise be done by humans, and a subject of organizational and societal deliberation. Across these conceptualizations, the study of automation involves an emphasis on changing relationships among (a) automatic technology, (b) specific tasks, work, and occupations, and (c) workers using or subject to those technologies (see Figure 1). In other words, although the term automation has varied usage, the emphasis of this review is that the study of automation is the study of work.

Automation, Work, and Workers

Existing research provides mixed evidence about the effects of automation on work and workers. In his analysis of the connections between thinking and making reflected in craftwork, Sennett (2009) argued that the history of work is the history of workers embracing "tools that eventually turned against them" (p. 81). This is a history common to weavers, steelworkers, and bakers, a history of the skilled artisan, become machine operator, become machine monitor (Faunce, 1965). It is not, by any means, a history only of the trades (Garson, 1988). Automation includes the work of architects as well as brick makers and bricklayers (Groleau et al., 2012; Sennett, 2009). Present day anxieties about automation inherit this history, but the broader point is this: The replacement of human with machine effort changes the work itself. For example, explaining the proliferation of computer aided design in architecture, Sennett argued that—its many virtues notwithstanding—the adoption of computer aided design did not merely speed up architectural work or make it more accurate; it supplanted physical observation and drawing with screen work (cf. Groleau et al., 2012). What may be most important about this sort of transformation is that those involved are often unaware of it or its implications. Workers may "come to see particular changes as inevitable because routine work dynamics obscure the processes through which those changes were decided" (Leonardi, 2012, p. 5). The implications or effects of automation can be easy to overlook and difficult to forecast. The form and effects of even the same technologies of automation can vary in use (Bailey & Barley, 2020), and the effects of automation in one industry can have complex, long-unfolding implications for others

(Acemoglu & Restrepo, 2020).

For example, Shestakofsky (2017) studied software automation and found that, rather than replace workers, the automation burdened their communication processes, namely through the emotional work involved in helping them adapt. Woolley et al. (2018) studied artists, teachers, investigative journalists, and computer programmers who used bots to automate parts of their social media work. They found that, although focused on "simple and direct functions," bots affect the "social spheres in which they operate" (p. 74). Automated, data-intensive digital tools also change work. They may alter the temporalities of work by making and implementing decisions more quickly (Andrejevic et al., 2020; Lange et al., 2018) and changing how we present our work selves to others (Endacott & Leonardi, 2022). Digital control systems may reduce opportunities for innovation and affect the organization of work across industries (J. Lee & Berente, 2012), but even in ostensibly mechanistic, clerical work, such as entering and approving invoices, the effects of automation can be complex (Pentland et al., 2011).

This complexity should not obscure the fact that automation does in fact replace work and displace workers (Acemoglu & Restrepo, 2020; Noble, 2011). Autor (2015) argued that automation has not replaced work altogether because previous advances in automation have tended to be complementary, adding value to labor markets flexible enough to absorb the changes while the demand for work increased. For example, the spread of automated teller machines (ATMs) coincided with an increase in the number of bank branches and tellers (albeit perhaps at a declining share of overall employment). ATMs lowered the cost of staffing a branch *and* made the customer-facing work done by tellers more valuable. Tellers could retool to do that work, and customer demand for it grew. Autor predicted that automation will continue to net gains for workers *if* educational systems provide access to middle-skill jobs that require "literacy, numeracy, adaptability, problem solving, and common sense" (p. 27) and policymakers work to ensure that the gains from automation are distributed across society. This insight suggests that we should be less concerned with work disappearing and more concerned with the difficulties of public and private sector deliberation about automation-related disruptions (Brynjolfsson & McAfee, 2016; Chui et al., 2015; Fleming, 2018; Hasan et al., 2015). Communication scholars are well positioned to study and intervene in the deliberations that will shape the form and effects of those disruptions.

Deliberations about automation also matter because the disruptions associated with automation disproportionately affect those with lower status and fewer resources. Disruptions occur via deskilling, as managers replace skilled work with machine work to increase productivity, and upskilling, as existing work gets augmented and requires new expertise and skills (Bailey & Leonardi, 2015). For example, Blauner (1964) found that factory workers who could hold on to craft autonomy or responsibility in the production process experienced less alienation. Barrett et al. (2012) studied the introduction of robotic dispensing in pharmacies and found that, while the pharmacists and technicians learned new skills, lower status assistants were marginalized and neglected (see also, Piercy & Gist-Mackey, 2021). Rawley and Simcoe's (2013) analysis of taxi fleets' adoption of automated technology found that upskilling and deskilling outcomes depended on worker skill: adopting automation that benefited lower skilled workers encouraged vertical integration and deskilling. Autor (2015) warned that job polarization may mean disproportionate decreases in low-paid jobs that are that involve skills undervalued by that markets, and increases in middle-skilled jobs and high-paying work that involves skills markets do value. Park and Humphry's (2019) study of automation in public assistance and social welfare services documented the shifting of work to those it was designed to help: "the onus to identify and respond to errors in calculating the debt was transferred to recipients of welfare," where, "lower levels of digital access, poor accessibility, inadequate user-testing and inability to dispute the matter further disadvantaged the recipients" (pp. 948-949). Advances in automation like these can be especially disconcerting for workers and users as they often depend on data gathered and coded by massive, invisible, global, and crowdsourced workforces (Alorwu et al., 2022).

When automation works well, the stakes of automation for communication work are still high. Oliver et al.'s (2017) study of the Air France 447 disaster provides a powerful example. The automation of so many work processes in long haul flying made it difficult for pilots to think and communicate how to recover when the autopilot failed:

> One of the shocking features of the AF447 story is that apart from the short, transitory loss of airspeed indications, there were no technical faults with the aircraft. It was a modern aircraft, operated by a reputable airline with a good safety record, flown by an experienced, well-trained crew. The information necessary to diagnose the situation was available to the crew and the situation was probably recoverable up until the last minute or so of flight. (p. 738)

The *success* of automation in replacing and augmenting pilots' effort meant that they did not receive much training on how to recover from a stall relative to avoiding one, suggesting an overreliance on automation by the larger professional and organizational systems. The flight crashed because of the insulating and obscuring functions of automation. These "automation surprises," where the technology malfunctioned or did not function as expected, degraded their cognitive and interactional capacities for meaning making (p. 732). The recent Boeing 737 MAX disasters saw similar break downs in possibilities for sense making due to communication shortcomings. Even though the pilots were trained to fly and maneuver aircrafts with automated software, its default settings caused the software to override pilot commands, miscalculate flying angle, and dip the aircraft's nose. Boeing failed to inform airlines and pilots, which meant they could have reasonably concluded that the settings had little import (Herkert et al., 2020). Automation transforms work through communication and through effects on communication processes.

Reviewing Communication Research on Automation

We contend that the study of automation today can benefit from a focus on communication. We forward a framework for the study of automation by focusing on (a) communication as the substance of automation, (b) discourse about automation, and (c) the communication involved in the practice of automation. These three emphases emerged as we sought to categorize different sorts of communication research on automation, and the following sections summarize existing research that involves one or more of these emphases.

To complete a holistic review, we gathered a corpus of scholarship identified in the course of our organic reading and a search of the literature. To bolster the corpus reviewed, we searched for articles using the term "automat*" where "*" refers to the journal-database-specific wildcard used to include terms such as automation, automate, automating. We limited the search to articles appearing between 2010 and 2021 in the *Annals of the International Communication Association*; *Academy of Management Journal*; *Administrative Science Quarterly*; *Communication Monographs*; *Communication Research*; *Communication Studies*; *Communication Theory*; the *European Journal of Information Systems*; *Information, Communication, and Society*; *Human Communication Research*; *Human Relations*; *the Journal of the Association for Information Science and Technology*; the *Journal of Applied Communication Research*; the *Journal of Communication*; the *Journal of Computer Mediated Communication*; *Management Communication Quarterly*; *MIS Quarterly*; *New Media and Society*; *Organization*; *Organization Studies*; *Organization Science*; *the Quarterly Journal of Speech*; and *Rhetoric and Society Quarterly*. We also included articles, books, book chapters, and proceedings relevant to this review that were cited in the articles identified or that emerged through organic reading, which incorporated publications outside the 2010-2021 window and beyond these outlets.

We focused on empirical, communication research that emphasized (a) automatic technology in changing relationships with (b) specific tasks, work, and occupations and (c) workers using or subject to those technologies. The research team examined abstracts to determine if an article included all three of these emphases or offered insights about one or more emphasis. The team then reviewed articles independently before discussing them to reach consensus about their inclusion or exclusion. The team read and summarized them in a table that captured the nature of each piece (i.e., empirical, framework, critique, review, or a combination), the research approach (e.g., framework, methods), what was being automated (e.g., calendaring, online posts, data transfers, management, customer support tracking), the definition of automation as explicit or implicit in the work, and a brief summary. In the synthesis that follows, we mention but do not focus on research that drew on automation methodologically, for example using automated discourse analysis. We also excluded articles that only mentioned automation tangentially; although, we highlight the existence of this literature in the following synthesis. The substance, discourse, practice framework emerged through our reading, and we eventually used this framework to categorize the literature. The framework situated the review as related to but distinct from emerging interdisciplinary efforts to understand human-machine communication more broadly.

Substance

The study of automation's effects on communication have a long history (Bailey & Leonardi, 2015; Shorey & Howard, 2016), but present day automation is remarkable because it is communication itself that is increasingly being automated. Examples include information seeking and meaning making, especially in organizational analytics and the automation of science (Bader & Kaiser, 2019; Barbour et al., 2018; Dougherty & Dunne, 2012; Leonardi et al., 2021; Leonardi & Contractor, 2018; Maiers, 2017), posting online and managing social media (Bolsover & Howard, 2019; Ringel & Davidson, 2020; Santini et al., 2020; Woolley et al., 2018), getting restaurant advice (Beattie et al., 2020), collecting, analyzing, and communicating customer feedback and managing customer relationships (Pachidi et al., 2020; Rahman, 2021), scheduling meetings and the correspondence that entails (Endacott, 2021; Endacott & Leonardi, 2022; Jensen et al., 2022; Wajcman, 2019), Wikipedia editorial work (Hilbert & Darmon, 2020), managing healthcare information (A. Barrett, 2020; Topol, 2019a), providing emotional support (Brandtzaeg et al., 2022; Laitinen et al., 2021; Meng & Dai, 2021), journalistic work like curating news feeds and content generation especially in the coverage of sports, financial markets, and elections (Beam, 2014; M. Carlson, 2018; Rydenfelt, 2021; Soffer, 2021), gathering information for hiring and promotion (Berkelaar, 2017), and communicating to manage others (Curchod et al., 2020; Darr, 2018). The automation of communication is not limited to information processing tasks or the work of virtual, automated chatbots, but also includes more tasks in the physical world at work and at home evident in what Taipale and colleagues (2015) described as a shift from industrial to social robotics (see also, Fortunati, 2018). Across these lines of inquiry, communication is the substance of automation.

Take, for instance, the automated generation of messages and the perceptions and effects of those messages. Research has focused on communicators' discernment and perceptions of automated communication delivered from bots in the public sphere (Hilbert & Darmon, 2020; Shorey & Howard, 2016) and in the context of therapeutic interventions and social support (Meng & Dai, 2021). The ability to discern human from bot communication and preferences for humans versus machine communicators depends on the task. For example, people tend to prefer human content moderation over AI or AI-assisted moderation (Wojcieszak et al., 2021) and human social support providers, but not in all situations (Meng & Dai, 2021). Automated moderation and support provision can have positive effects. For example, communicating with an automated therapist may decrease fears of being judged and impression management concerns while encouraging disclosure and the expressions of emotions (Lucas et al., 2014, 2017). Communicators make similar evaluations of the sophistication of bots' communication aimed at regulating a team members' behavior (A. Edwards et al., 2020) and bots' usage of emojis, which increases evaluations of social attractiveness, communication competence, and credibility for bots and humans alike (Beattie et al., 2020).

Automated communication can also have differing effects apart from users' preferences. For example, news personalization systems have tended to rely on machine- or user-tailoring or a combination. Beam (2014) found that machine-based recommender systems more effectively limited exposure to counter-attitudinal news. That is, the design of the recommending systems and how automation was incorporated affected participants' exposure to ideas. Hancock and colleagues (2020) defined AI-mediated communication (AI-MC) as "mediated communication between people in which a computational agent operates on behalf of a communicator by modifying, augmenting, or generating messages to accomplish communication or interpersonal goals" (p. 89). Pointing to examples such as predictive text, grammar correction, and auto-completion, they highlighted that the senders of these messages do not typically disclose that AI helped draft them. Building on this work, Endacott and Leonardi (2022) defined artificially intelligent communication technologies (AICTs) as "goal-directed, computational agents that use AI to make decisions about communication and communicate on someone's behalf" to distinguish between technology that mediate interaction between humans and those with "the capability to make consequential decisions about communication" (p. 463).

Automation can indeed change what is communicated. Groleau (2012) documented an architectural firm's adoption of automated tools for communicating designs to clients. The adoption created an occasion for the renegotiation of institutional logics of profession and markets, including changes in the work practices of architects and their interactions with clients. Senior architects no longer produced finished drawings but instead made sketches. An intern reproduced the sketches in software, adding his own details, which the senior architects might accept or not as evident in their feedback (e.g., "It has to look like a champagne cocktail at 5 o'clock," p. 611). The computerized drawings lacked the beauty of the hand drawings, but they looked more realistic and could be easily replicated. Clients saw the 3D renderings as a more realistic depiction of what could be, and they exhibited more comfort in their comments about the renderings, changing the communication between architect and client. However, architects worried that the more realistic depictions might give clients a false sense of the buildings to come and undermine their professional standing.

Along similar lines, Woolley et al. (2018) found that professional communicators used chatbots to "reveal, exploit and change aspects of digital systems that otherwise go unquestioned" (p. 60). They conceptualized bots as "proxies for their creators," which acknowledged that they act as surrogates, but they also found that "as bots interact with complex social systems, they do things beyond the expectations of their builders" (p. 61). The intertwined effects of the bots and communicators' usage of them in their work also depended on the unfolding interactions with the complex communication systems they sought to engage (e.g., collective, automated efforts to block bots, Geiger, 2016). Likewise, Hilbert and Darmon's (2020) study of Wikipedia editors who adopted automation to simplify their work found that the editors' straightforward choices to do so produced complexity in the aggregate. Jensen et al. (2022) found that individual workers' automation of routine correspondence tasks and scheduling undermined collective efforts to slow work to allow for greater focus and creativity. These threads demonstrate how communication is transformed and made more complex by automation in unpredictable ways that at times contradict the goals of the human actors deploying it. Communication may also be transformed in ways that are unexpected but beneficial. For example, Laitinen et al (2021) found that a social chat bot active in a team's instant messaging platform (Slack) fostered socioemotional conversations. They argued that such systems may "not just host or enable communication, but rather take part in and shape it," (p. 2).

Additional lines of research have focused less on perceptions of particular messages and messengers and more on work processes that integrate human and automated actors (Seeber et al., 2020). Much of this scholarship looks at AI "teammates," meant to augment the work of their human counterparts, but research again confirms that introducing automated communicators does not just replace work—it changes the conversations. Bader and Kaiser's (2019) study of the implementation and use of algorithmic decision support highlighted the importance of "humans' attachment to decisions," such that too much attachment encouraged deferred decisions, workarounds, and (data) manipulations (p. 667) (cf. Goodhart's law, summarized in Muller, 2018, which holds that metrics lose value as measures when used to judge performance). Automated scheduling tools promise to replace the drudgery of communicating to find a time to meet and to allow workers to focus on creative and fun tasks but such calendaring systems are also part of a larger ideology that emphasizes quantifying and mechanizing human thought following logics of productivity, efficiency, and commodifiable time with profound implications for work and workers (Endacott, 2021; Wajcman, 2019). Endacott and Leonardi (2022) found that users of autonomous, conversationally fluent AI-scheduling technologies sought to shape the impressions formed about themselves by framing the technologies and by monitoring and directing the interaction between the AI and the individuals it was interacting with on their behalf. They sought to regain control over the interaction they gave up as they augmented it.

Augmenting work and workers is a particular emphasis in healthcare, for example, in the development of clinical decision support systems (e.g., Gupta et al., 2014; Sholler et al., 2016; Topol, 2019a). Maiers (2017) studied the use of Horizon, a predictive analytics system that monitored patient data and identified those at risk. Maiers found that clinicians engaged in “conditioned” and “accumulative” reading by considering their own expertise and experience alongside the outputs rather than relying on the early warning as intended by designers. Horizon automated information gathering and analytical work and prompted information seeking and discussion among clinicians. Supporting clinical work with AI-powered, automated analytics does not just provide additional sources of information for clinicians, it reorganizes the work practices and meaning making of medicine (Henriksen & Bechmann, 2020).

Across research focused on how automated communicators work in tandem with humans, trust is a key concern (Y. K. Chen & Wen, 2021; Glikson & Woolley, 2020). Liu’s (2021) experimental study exemplifies much of this scholarship, which focuses on specific automation technologies out of the context of work. Liu tested a hypothetical fake news detection AI and found that social presence and uncertainty mediated the effects of machine agency on perceptions of trust. This research has direct applicability to the implementation of AI-driven automation in work contexts because it shows that the use of AI makes issues of trust central.

Trust is connected to issues of transparency and explainability, because the reasoning of AI teammates is not always clear (Glikson & Woolley, 2020; Kellogg et al., 2020). For example, trust was central in archivists’ incorporation, or lack thereof, of automation into their workflows in Ringel and Ribak’s (2021) study of scanning at the National Library of Israel. They found that digitization was not a straightforward process of converting analog to digital. Archivists rarely used a robot that automatically turned and scanned book pages into a database because old materials were too delicate and new materials were copyrighted. Although visitors loved to see the robot, it spent most of its time dormant at the archive.

The novelty of AI contributes to hype and anxiety about it, and the history of efforts to support work with technology can be important in specific organizations and industries. For example, most electronic health records (EHRs) meant to aid and automate medical recordkeeping are today reviled by healthcare workers who find the tools poorly designed and implemented but must use them, nonetheless. Indeed, the rapid adoption of EHR systems has produced entire lines of scholarship focused on providers' adaptations or workarounds including delegating documentation to others, relying on workers like scribes whose sole responsibility is documentation, continuing to use paper records, relying on technologies like faxing and scanning, and shallow usage that appears to fulfill requirements to use the technology but does not (A. Barrett, 2020). The development and implementation of automated healthcare technologies and the discussion of them in the public sphere references the poor track record of the EHR's history but also the industry's reliance because so many automated healthcare processes like billing depend on the data in the EHR, such as it is (Barcellos Almeida & Farinelli, 2017; Krumholz, 2014; Topol, 2019b).

Research also focuses on tools developed to automate or augment the communication work associated with key management tasks. For example, Berkelaar (2017) documented the supplementing (or supplanting) of resume review and background checks by automated cybervetting. Managers viewed cybervetting tools as time-saving devices but disregarded how they changed the nature of the hiring practice from interactive relationship building to extractive information seeking. Darr (2018) examined the mediation of managerial control through an automated sales platform. The platform conceptualized sales work as competitive and win-at-all-costs devaluing "good and moral salesmanship" that would be against selling a product the customer did not need, should not buy, or that the salesperson did not believe was any good (p. 905). These examples obscured managements' power and their ability to maintain affect in their work in and through automation by defining work in particular ways and by making work and workers visible to each other and to the management (see also, Newlands, 2020; Treem et al., 2020).

Research also documents workers' resistance and workarounds in response to these forms of control (Kellogg et al., 2020; M. K. Lee et al., 2015). For example, Curchod et al.'s (2020) analysis of the automated eBay platform found that it disempowered and isolated sellers. eBay had automated the oversight and processing of customer reviews, disciplinary decisions, and much of the communication towards sellers. In resisting these constraints and policing set forth by the algorithms, sellers' efforts took the form of (a) communication workarounds that enabled personal relationships with buyers, and (b) establishing their own rules of engagement to guide buyer behavior, and proactively screening for and blocking problematic buyers. Rahman's (2021) study of a freelancing platform that automated the collection, analysis, and communication of customer feedback similarly disenfranchised them, and they also responded by shifting interaction off the platform or avoiding relationships with new customers. Rahman summarized the workers' critique of algorithmic management as (a) unannounced, in that the change to the platform came without warning, (b) unexplainable, meaning it provided no sense of how ratings translated into scores, (c) unpredictable due to the speed of changes, (d) unfair because ratings from bad clients still hurt their scores, (e) unaccountable with no way to appeal or for a client to make corrections if they mis-clicked or reconsidered, and (f) useless because the feedback did not support learning and professional growth.

In sum, studies of the communication as the substance of automation have focused on automated messaging, teamwork, and supervision with particular concerns for (a) human versus machine sender effects, (b) the complex patterns produced in the aggregate by simple automation, (c) the importance of trust especially in automation meant to augment work, (d) the problems of the hype associated with these technologies, and (e) the implications for control and resistance. We now move to a review of research on discourses about automation. Whereas studies concerning the substance of communication tend to focus on specific examples of automation, studies of discourse tend to eschew specific technologies and focus instead on the construction and negotiation of automation more broadly in the public sphere and by specific communities of workers.

Discourse

Compared to previous waves of automation, the recent public discourse is remarkably similar regarding anxiety about the future of work (McGuigan, 2019; Vergeer, 2020; Weber et al., 2021). Even though the tenor of public discourse echoes the past, the need for deliberation may be even more acute now for directing civic and industrial attention and resources toward mitigating organizational and societal disruptions (Autor, 2015; Dodel & Mesch, 2020). Deliberation about automation will shape its implications, perhaps even more so than before, because of the increased accessibility of automation as a part of work and play (Bailey & Leonardi, 2015). Workers can deploy their own automation in occupations that have more power over the tools of work, and these occupations such as architecture, medicine, and engineering have also previously been insulated from automation because of the intellectual and creative nature of the work (Groleau et al., 2012; Topol, 2019a, 2019b).

Research on discourses of automation has examined the development of public and expert opinion about automation, collective action in response to automation, and public arguments about automation. Workers exercise power in automation in part through public critique of the technologies. Kellogg et al. (2020) identified workers organizing in response to algorithmic control and their framing of these technologies in terms of fairness, accountability, and transparency. Workers' "algoactivism" has made important contributions to the public sense of automation technologies (p. 395). Crowdsourced work is a particularly important and underexamined form of labor in automation because so many AI technologies depend on it in ways that are not clear (Alorwu et al., 2022). Likewise, research has also pointed to the underappreciated material costs and implications of present day automation, such as Crawford's (2021) analysis of the environmental costs of AI. Murdock (2018) casts choices about automation technology in moral terms arguing that "all economic transactions involve us in chains of connection to social and environmental relations that confront us with moral choices," which require we study "the organization of the production chains that manufacture communications infrastructures and devices and the resource, energy, and consumption preconditions for environmental sustainability and justice" (p. 366).

In studies of work that include but do not centralize automation, communication research has examined phenomena related to discourses about automation without focusing on work and workers per se. For example, Ohl (2015) mentioned automation offhand in an analysis of drone war rhetoric where drones "moved from the margins of Western arsenals to become the dominant logic of militarized automation" (p. 628). Pezzullo and Hunt (2020) positioned automation as contributing to the "magical" techno-scientific efficiency of agribusiness futurism that characterizes modern agriculture: "Advances in animal science and mechanical technology since the 1950s enabled livestock producers to confine greater numbers of animals in smaller spaces, increasing the need for synthetic hormones and antibiotics and automated feeding and cleaning systems" (p. 419). Kelly (2021) analyzed news stories of the 2016 election, writing that "Trump Country essays typically return to the interplay of physical and emotional pain to illustrate the unique particularity of white precarity" (p. 226). In these stories, automation (shorthand for replacing human workers with machine labor) alongside economic decline, social marginalization, offshoring, and globalization functioned to make white pain worthy of public sympathy. Witteborn (2022) highlighted quantification and automation as central themes in public discussions of migrants and migration. These research examples are about automation in a sense, but automation as defined for this review is not at the center per se.

A principal concern of research about communication focused on automation is the formation of public opinion about it, and as in studies of automated messages and teammates, trust recurs as a key theme. For example, trust in AI and the scientific community associated with AI has tended to correspond with trust in government and corporations generally (Y. K. Chen & Wen, 2021; S. Lee et al., 2020). Concerns about privacy, science, and robotization have been associated with opposition to AI, and these perceptions matter because “public debate about how to regulate AI in fields such as the workplace or electoral campaigns is heavily conditioned by people’s attitudes toward this new technology” (Lobera et al., 2020, p. 448). Fears of robots tend to be associated with exposure to fictional media portrayals of “bad robots,” and mitigated by contact with actual robots (Horstmann & Krämer, 2019).

Not surprisingly, many studies of perceptions of automation focus on anxieties about the future of work. Weber, Barley, and Kahn (2021) studied newspaper coverage of automation from the 1950s through 2020 and found that although technologies of automation may have changed, anxieties about the implications for work and workers had not. For example, a Pew Research Center (2017) study of American views of automation found “more worry than optimism about potential developments in automation” (p. 3) (see also, Liang & Lee, 2017). Those worries focused on the implications for work with broad support for policies that would limit the automation of work by restricting machines to dangerous jobs or capping the number of jobs machines could replace. Workers with greater education were more likely to report that automation might make their work more interesting or improve their opportunities for advancement. However, few reported direct experience with job loss (2%) or pay/hours reduction (5%) due to workforce automation with the youngest respondents (18-24) reporting the highest values (6% and 11% respectively) (see also, Horstmann & Krämer, 2019). Taipale and colleagues' (2015) study of European Union (EU) citizens across 27 member states found that respondents tended toward positive perceptions of robots in dangerous domains of work and domains with well-established histories of using robots such as space exploration, manufacturing, military and security, and search and rescue work. Fears focused on social robots, "designed to deal with human care, health, domestic tasks, entertainment and various other forms of immaterial and material tasks which aim to renew human capacities" (p. 12). The more positive overarching attitudes toward robots in general may also reflect the more widespread adoption of robots in some EU member states (Acemoglu & Restrepo, 2020).

Alongside general studies of public perceptions of automation, research has also considered the perceptions of technology in specific occupations, especially in industries seeing growth in automation (Miller, 2007; Peña Gangadharan & Niklas, 2019). For example, Piercy and Gist-Mackey (2021) surveyed pharmacists and pharmacy technicians and found that they experienced anxiety about automation notwithstanding previous research findings that more highly educated professions would be insulated from such concerns (M. Barrett et al., 2012). Their anxiety was associated with perceptions of the helpfulness of automation, predictions that their job would change, and that automation would increase in the future. However, Piercy and Gist-Mackey's findings underscored that workers' sense of automation developed from more than just their understanding of technology change and may have instead been "tied to outside anxieties" and "the relational power dynamics between organizational decision-makers and front-line workers" (p. 204). Indeed, a narrow focus on the technologies of automation themselves may obscure the broader dynamics of power that mobilize them. Speaking to this, Peña Gangadharan and Niklas (2019) argued that understanding the relationships among automation, marginalization, and fairness requires a holistic approach that decenters technology. That is, marginalizing automation technologies cannot be analyzed in isolation.

Communication research offers a particularly rich body of scholarship focused on journalists' deliberations and perceptions of these technologies, arguing that discussion of the effects of automation should go hand in hand with discussions of the changing conditions of work and associated labor processes, which are of particular importance in cultural media work (Murdock, 2018). For example, Soffer (2021) elaborated a two-step flow theory to contrast human and machine opinion leadership. The human gatekeeper frames mass media content through interpersonal contact over time in ways apparent to communicators, informed by their expertise, and grounded in relationships, and by extension, professional community. The algorithmic gatekeeper matches content based on automated, "neutral" procedures as a part of the consumption of mass media content. Exposure and gatekeeping occur simultaneously, less visibly, and without a grounding in community.

Research has also made sense of the construction of automation in the public sphere by examining news accounts of automation and related technologies (Weber et al., 2021). Vergeer's (2020) automated content analysis of news coverage of AI in 4,224 articles across 25 Dutch newspapers found generally positive coverage, picking up especially after 2014 in economic and national newspapers. The balance of negative and positive coverage remained stable with variation around specific topics such as the "singularity," which increased over time as did stories about robot football, deep learning, and AI playing games against humans. Vergeer noted the irony that "although diverging topics emerged from the data, one topic relevant to journalists themselves was surprisingly absent: robot-journalism" (p. 388). A similar observation can be made of communication researchers' own use of automated technologies in research that does not tend to engage the implications of its adoption and use.

Other research has problematized automation's role in the agency of marginalized populations through discourse related to specific industries or technologies. For example, Demo (2017) documented the construction of automated assistance in marketing claims made by autism apps. These apps tended to conceptualize agency as possessed by the individual but which the application could unlock. Demo contrasted these claims with the consensus in disability research that has emphasized agency as "denied, minimized, or hindered through interactions with other actors (human and nonhuman)" and argued for a conceptualization of agency as functioning "through a constellation of human and nonhuman actors" (p. 293). Al-Khateeb's (2021) analysis of progress-focused accounts of automated biometric identification systems contended that they obscured the inhumanity of the treatment of refugees. Al-Khateeb argued that the "narrative of progress that calls for celebrating biometric screening technologies for their affordances while effectively limiting a critical engagement with the role of such technologies" exacerbates "conditions of violence and control for refugees" (p. 16).

Key themes in this research underscore the hype surrounding automation as reflected in the discourse itself that overstates the power of the technology and obscures other concerns. For example, McGuigan's (2019) analysis of the history of the interest in automated media buying in advertising trade publications from the 1950s-1970s revealed fantastical hopes for technologies of automation. The historical analysis complicated the "received wisdom about Internet-driven disruption of commercial media" that reflects a "more gradual remediation of these industries" rather than automating advertising reps out of existence (p. 2368). Carter and Egliston (2021) examined materials produced by twenty-one virtual reality education technology companies. Their analysis revealed similar fantasies of "perfect" data collection, the promise of the complete automation of soft skills, and speculation about a coming gold rush of educational data. The discourse they examined made explicit and implicit claims on what ought to be valued in education by focusing on measures like clicks and page views. Yu and Couldry's (2022) analysis of the public discourse of publishing corporations, suppliers of learning analytics, and social media platforms for education found a similar characterization of automated surveillance and the data it produces. They found that even though digital technologies were depicted as neutral and used by forward-thinking teachers, their usage and this framing marginalized the relationship between student and teacher. As is evident in these exemplars, the discourse of automation may exaggerate the effects and capabilities of automated technologies, centering the technology itself in ways that overlook important questions about power. Whereas these studies of automation focus on anxieties, hopes, and predictions in the public sphere and in specific groups such as workers affected by automation, the workplace is itself a key site of deliberation about automation because automation involves distinctive communication practices (Bailey & Leonardi, 2015).

Practice

Automation itself involves communication. That is, automation is a communicative practice. The form that automation takes unfolds through technological and organizational change and involves conversations among workers, policymakers, technologists, and managers (Klatzky, 1970; Leonardi, 2009a; Orlikowski, 1992; Poole & Holmes, 1995). Leonardi's (2012) study of the development and use of CrashLab, an automotive crashworthiness simulation technology, contended that "developing, implementing, and using a technology are all parts of the process of organizing" (p. 19). That is, whereas early theories of technology implementation tended to take a view focused on managing the effects of the introduction of technologies, in fact, technology adoption, implementation, and use are bound up with the communication systems within and through which that implementation occurs.

Indeed, navigating technological/organizational change is a communicative accomplishment (Barge et al., 2008; Lewis, 2019). Early change management scholarship tended to emphasize a linear process of messaging to put technology in place. The current research consensus focuses on the need to manage change processes by intervening in existing conversations, introducing new ones, and offering communicative resources for sensemaking as well as highlighting the limits on the extent to which change can be managed (Bisel & Barge, 2011; Lewis & Russ, 2011). For example, Leonardi (2012) found that CrashLab's adoption, development, and use reflected a complex interplay between (a) the framing of the technology by and for managers, (b) deliberations about CrashLab among managers and those trying to use it, and (c) workers' experience with the technology. Leonardi (2009b) argued that the form and effects of implementation are not inevitable: "Managers and other invested parties may have a window of opportunity to enter into the communication environment, enroll stakeholders, and begin to shape communication about a new technology that will align this discourse with what people will experience in their material interactions" (p. 436). What may be most remarkable about these findings for the study of automation is that implementers themselves did not see the importance of the communication involved. Framing CrashLab in terms of cost savings and speed meant that it was evaluated in those terms to its detriment and to the detriment of those using the technology who rejected potentially useful innovations. The engineers' choices about work and automation were obscured by how they communicated to make these decisions. This insight highlights the stakes because efforts to structure and guide deliberations about change can stymie the very outcomes workers and managers hope to cultivate (Henderson, 1998; Lammi, 2020; Pachidi et al., 2020).

Implementers communicate to automate work, and how they communicate influences the form and effects of automation (P. A. Carlson, 2001; Henderson, 1998; Leonardi, 2012). The communication through which automation choices occur is important because automation involves the ongoing negotiation of values and norms about work (Applebaum & Albin, 1989; Chapanis, 1965) in ways likely to be overlooked. Influencing these processes depends on understanding how new technologies will interact with existing ones as well as the work and communication involved. Leonardi (2012) also highlighted communication practices involved in the development and adoption of automated technology by the workers themselves, including (a) workers' upward information seeking including finding out about the technology from managers, (b) technological benchmarking or asking each other questions about the technology and how to use it, and (c) technical teaching such as interactions with design engineers, especially around the results of simulations. He also highlighted (d) the rhetorical framing and pitching of the technology and (e) the policy-focused deliberations of the "Focus Group," the cross-functional team that made development decisions. The occupational and organizational factors important in automation choices are negotiated in these routine communicative work practices (Bailey & Leonardi, 2015). Key questions for research center on how to exert influence on the communication through which the automation of work occurs and how to cultivate preferred forms of communication.

These processes are of particular importance today because workers themselves increasingly guide the adoption and implementation of automation by collaborating with others, which further heightens the importance of communication. This insight points to blurring of the line between the automators and the automated. For example, Lammi's (2020) study of the automation of delivery of case files to caseworkers found that efforts to build "automated control" into existing ways of working failed as workers resisted control by "returning to teamworking," alienating workers who subverted the system and undermining the intent of designers and managers (p. 127). Belair-Gagnon et al.'s (2020) study of the development of chatbots in newsrooms found that as the developers joined the profession of journalism, they struggled to reconcile developer logics that emphasized experimentation, audience, and efficiency with journalistic logics that emphasized established workflows, formats, and a greater degree of professional autonomy in their practices of making automation.

Workers may control the adoption of automation by collaborating in ways that prioritize existing work practices, but collaboration may also pre-emptively facilitate change and encourage acceptance. In healthcare, collaboration between providers and stakeholders in the development and implementation of clinical decision support systems increases adoption and use (Sholler et al., 2016). This relationship matters because integrating automated technologies into complex workflows often requires moving work through multiple processes that involve more and less automation (Bailey et al., 2010). For example, Ringel and Davidson (2020) found that journalists used automated tweet deletion as a sort of proactive ephemerality to work around the limitations of the social media platform while realizing in their view the true spirit of it and their professions' use of it. The journalists deleted content to clear up their timelines, protect their futures, limit their tweets to the moment, avoid harassment, stay consistent with professional norms, and shape their identity for future employers or audiences. That is, their practice of automation centered on integrating automated tools into their existing work. Automation increasingly involves tools deployed by workers themselves (Endacott, 2021).

These studies can be contrasted with scholarship that documents design processes that take input from users to automate the technologies of work. For example, Lin et al. (2014) documented the development of Book Smile, a book-locating support robot. Their case study focused on the design work involved, especially the process of creating the robot via task analysis of behavioral data from children and librarians. This research tackles the role of existing work practice in the *creation* of Book Smile, whereas other research might try to understand librarian's use of the tool.

Research on automation as communication practice underscores the importance—and difficulty—of conversations central to the future of work with intelligent machines. Individuals with the technical skills needed for data-intensive automation are hard to find and the need for them is likely to grow. At the same time, leaders have also highlighted the need for those doing automation work to have, not just technical skills, but also (a) skills for effective communication and conflict resolution, and (b) competencies important for teamwork, change implementation, and work that crosses disciplines (Hsieh, 2016; Leonardi, 2011). Moreover, automation as communication is difficult precisely because it involves communicating across different domains of work. For example, Hemon-Hildgen et al. (2020) described the difficulty of integrating operational and developmental roles because navigating the boundaries between the doing of the work and the making of tools for work can have important implications for work satisfaction and identity negotiation. They argued that success in Agile development projects depends on the orchestration of communication.

The communication involved in automating work also reflects organizational and occupational dynamics. Professional standards and occupational norms provide established models for communication, supply goals for communication, and at times, even dictate the form and function of communication. Bailey and Leonardi (2015) studied communication about if and how to automate work in their observations of computer hardware engineers who (a) debated about the place and function of technologies in the "design flows" of their work; (b) communicated with vendors to influence the development of new automation technologies; and (c) talked with work colleagues, organizational experts, and peers at other organizations to understand and evaluate new technologies. In contrast, the structural engineers they observed engaged in almost no automation. In fact, senior structural engineers communicated with new hires about the need to limit their use of automation to avoid errors. In each case, managers or engineers made choices about how to communicate, what messages to send, what questions to ask, how to arrange their interaction, and so on, and their choices about communication were mediated by occupational forces. While communication is a cause and consequence of technology choices about automation, communication about automation provides a site for influencing how it unfolds.

Indeed, much automation involves not just changes to communication systems, but *making choices* about communication tasks and roles with implications for organizational power relationships (Gibbs et al., 2021). For example, Kellogg et al.'s (2020) review found evidence of algorithms in the direction, evaluation, and disciplining of workers and emphasized the growing comprehensiveness of the technologies, the instantaneity and opacity of algorithmic action, and the integration of multiple sources and types of data about workers ("algorithmic interactivity," p. 387). They found that, compared to other forms of control, algorithmic control disintermediated management, removing them from key workplace interactions: "The ability for workers to appeal to a human decision-maker means that bureaucratic systems, in many ways, allowed for more leeway than algorithmic systems that may remove human decision-making altogether from control structures" (p. 387). Their research agenda also emphasized communication because the curation of data and models involved greater interaction through engagement with more organizational stakeholders (see also, Leonardi et al., 2021). Likewise, the adoption and development of these algorithms involved brokers who specialize in interpreting their outputs and who "seek to communicate the logic and value of the algorithmic systems to various groups in the organization" (p. 389). These brokers do the work of trying to convince workers to implement algorithms and are unlike previous forms in that the power of the algorithm depends on how much “workers change their workflows to consume algorithmic outputs” (p. 389.) Moreover, these new systems have involved the rise of novel occupations that they described as “algorithmic articulation,” which is key in navigating the assemblages of technologies of which algorithms are one part, explaining when and how algorithms fail, and producing economic value for organizations. That communication work involves power as “algorithmic articulators have the opportunity to claim new jurisdictions and push back on employer control” (p. 390).

Henriksen and Bechmann (2020) also emphasized issues of power in their study of the development of algorithms to predict the likelihood of health conditions among patients in multiple clinical settings. They identified five practices through which developers “built truth” or constructed the empirical reality of patient status evident in data. Those practices included (1) the inductive negotiation of “data signals, human classification, and data selection” by “locating and evaluating signals in data by testing labels, relabeling data, and sometimes removing or adding data” (p. 808). The developers also (2) consulted with experts such as “medical specialists from the collaborating hospital” who they relied on to “define labels and evaluate cases” when the results were suspect (p. 809). They tried to (3) balance “contextualization and generalization” in the sense that they tailored predictions to the specific requirements of each context and medical condition. They (4) removed errors in predictions by judging them against outcomes. In doing so, they also had to “contextualize and understand errors” to improve on the predictive accuracy of the healthcare practitioners (p. 811), because, for the developers, the ideal scenario involved replacing the more error-prone practitioner. As such, the implementation of the system also involved the (5) reorganization of healthcare practice by “by identifying a more ‘right’ way of practicing healthcare and by designing AI systems in accordance with this way” (p. 811). These practices each involve complex communication such as information management, sensemaking, and meaning and relationship negotiation.

Implications of Communication Research for the Study of Automation

The research reviewed in this article makes clear the distinctive contributions that communication scholarship can make to the study of automation and the need for such research. Communication research can make visible the communication effects of automation in general and the effects of the automation of communication itself. Communication research can reveal the public deliberations and argumentation that shape the implementation and effects of automation. Communication research can explain the communicative work practices distinctive to automation. Those communication practices include work associated with automation as processes, but also the brokering work that communicators do with and for automation and the ways communicators deploy their own tools of automation. Because automation transforms work, communication research should seek to understand how to intervene in that transformation and how to facilitate conversations about the future of work.

Guided by this review, we next articulate three overarching recommendations for future communication research on automation. First, research should examine the interactions among the communication phenomena that are the substance, discourse, and practice of automation. Second, communication research on automation should take care to study data-intensive automation, the use of data generated by automation, and the changing nature of agency in the context of intelligent machines. At the same time, research should avoid confounding these phenomena with automation or ignoring automation that involves less sophisticated technologies. Third, the communicative study of automation should empower individual, organizational, and societal choices about automation through empirical, critical and design research.

Study Intersections among the Substance, Discourse, Practice of Automation

The connections among the three dimensions of the communicative nature of automation identified in the review hold much promise for future research. Automation and its effects occur in the context of public and private conversations about automation. For instance, automation in contexts like journalism involve not just technologies or specific work practices but "how practices are embedded within shifting discourses concerning the thorny issue of journalistic judgment" (M. Carlson, 2018, p. 1756). News selection algorithms are not just discrete bits of scripting but sociotechnical assemblages that "include institutional workings, but, more to the point…they also indicate justificatory rhetoric to legitimate their knowledge structures vis-à-vis existing knowledge structures" (p. 1761). That discourse circulates. For example, Hensmans (2020) documented the organizing involved in the automation of banking software, a case demonstrating that managers did not entirely understand the technology but projected onto it their own ideas for what it might do. Hensmans argued that the managerial allure of technological determinism is strong and that, despite an organizational commitment to shared power, a traditional form of market capitalism emerged in the bank because of a desire for efficiency. This case exemplifies the intersecting dynamics of communication as the substance, discourse, and practice of automation. The negotiation of ideas about automated technologies and market and managerial ideologies at a particular organization are intertwined and have their basis in both the public sphere and marketing materials and documentation of the organizations creating and selling them (Carter & Egliston, 2021; Kushner, 2013; McGuigan, 2019; Peña Gangadharan & Niklas, 2019; Yu & Couldry, 2022).

A key intersection exists in the study of the relationship between the social imagination and anticipation of automated technologies and corresponding understandings of the communication and practice of automation. The robots-are-coming discourse has important societal, organizational, and professional implications. The expectations, fears, and beliefs entwined with that discourse likely have outsized importance because the talk about intelligent machines is not necessarily aligned with the roles these technologies play in our lives (Horstmann & Krämer, 2019). The hype surrounding intelligent machines can overstate what communication can be automated. That hype figures in public and workplace discussions of automation and complicates implementation efforts. AI communicators may even play a role in shaping the impressions we form about particular instances of automation and the intelligent machines involved (Endacott & Leonardi, 2022).

The influence of the social imagination of what automaton might be also illustrates that the connections among substance, discourse, and practice cross levels of analysis. Societal conversations about robots show up in organizational efforts to implement them. That the implications of automation unfold across levels suggests the value of multilevel approaches, and future communication automation research needs to look across levels. For example, simpler forms of automation that follow straightforward rules like automated correspondence, scheduling, or social media posting may have effects that are more complex and more difficult to predict or explain in the aggregate (Endacott & Leonardi, 2022; Jensen et al., 2022; Woolley et al., 2018). Automation of communication may have straightforward effects on interaction between communicators and surprising effects across conversations (Laitinen et al., 2021).

Looking at communication across levels can bolster interdisciplinary conceptions of intelligent machines and automation. Bailey and Barley (2020) called for a multidisciplinary widening of the study of intelligent machines beyond the orthodox boundaries of design and use research. Studies of design need greater consideration of the ideologies of designers and the power-laden conversations involved in selling automation in organizations. Studies of use need greater consideration of the variation within and across industries, going beyond specific case studies in particular industries and with more nuance than economic studies of automation offer.

Communication should play a central role in the multidisciplinary project Bailey and Barley describe. Communication research can look for connections among designers' and users' conversations about AI-driven automation and the interplay of conversations about such technologies within and across organizational boundaries. Intersections among the substance, discourse, and practice of automation make clear that taking communication as the focus of research can facilitate the move beyond studies of design and use.

Study the Connections between Datafication, Machine Agency, and Automation without Confounding Them

The stakes of the deliberations about automation are high in part because the datafication of work and the concomitant rise of machine agency together heighten the transformative power of automation for communication (Brynjolfsson & Mitchell, 2017; Hancock et al., 2020; Sundar, 2020). To explicate datafication, Leonardi and Treem (2020) defined two related concepts, digitization and digitalization: "Digitization refers to the encoding of actions or representations of actions into a digital format (zeros and ones) that can be read, processed, transmitted, and stored by computational technologies" (pp. 1601-1602), and "Digitalization refers to the ways in which social life is organized through and around digital technologies" (p. 1602). They also defined datafication as "the practice of taking an activity, behavior, or process and turning it into meaningful data," (p. 1602), a practice that is not neutral.

Datafication also refers to the spread of the ideology that the world can and should be digitized (Flyverbom, 2019; Lycett, 2013; Sandberg et al., 2020; van Dijck, 2014). "Datafication" refers to the value seen in the volume, velocity, and variety of big data (H. Chen et al., 2012), efforts to harness those data (McAfee & Brynjolfsson, 2012), and the organizational frenzy for analytics (Barbour et al., 2018; Liberatore & Luo, 2010; Marchland & Peppard, 2013). Whereas digitization and digitalization are necessary in the technologies that produce digital traces people leave as they work, play, and live (Lupton, 2016; Neff & Nafus, 2016), datafication points idea that those digital traces can and should be harnessed (Zuboff, 2019). For example, digital learning platforms support teaching and learning at most campuses by digitizing the processes involved, but "the prevailing vision of datafication" in discourses about those platforms positions "software systems, not teachers, as central to education" (Yu & Couldry, 2022, p. 127).

Automation produces flows of data about work being done (Alaimo & Kallinikos, 2020; Applebaum & Albin, 1989; Zuboff, 1988) and the interactions that constitute day-to-day organizational life (Pentland et al., 2010). For example, manufacturing has long involved the translation of "three-dimensional production process into two-dimensional digital data," which are "typically made available on a video display terminal or computer printout, in the form of electronic symbols—numbers, letters, and graphics" (Zuboff, 1985, p. 8). Likewise, readers' engagement with algorithmically curated news articles provides digital traces that allow news organizations to learn about them (Flyverbom, 2019). Healthcare providers' acceptance, modification, and rejection of recommendations from automated clinical decision support systems produces information as do patient outcomes that can refine the production and delivery of the recommendations (Maiers, 2017). Automation can change how, when, and why work is visible to others (Leonardi & Treem, 2020; Treem et al., 2020).

Datafication magnifies the transformative potential of the automation. Zuboff (1988) argued that in order to realize most meaningful and lasting benefits of datafication, organizations should make use of the information generated by automation. For example, automation can enhance and create new opportunities for organizational decision-making by increasing "the available amount of information about products, procedures, and clients available to workers at every level within the organization" (Applebaum & Albin, 1989, p. 260). The information produced by automation can inform talk about automation and shape its design and use (Bailey & Barley, 2020; Leonardi, 2012).

Datafication is even apparent in the accomplishment of communication research itself (e.g., Schmitt et al., 2018). Computational social science has a principal focus on developing and deploying tools of automated data collection, transformation, and analysis (Lazer et al., 2009). Indeed, studies of automation may themselves rely on automation. For example, when Belair-Gagnon and colleagues (2020) studied journalists' use of chatbots in newswork, they automated archive scraping to identify mentions of chatbots and then manually coded the results. Furman and Teodoridis (2020) found that researchers who automated a data-gathering task shifted the trajectories of their research and had higher and more diverse research output because their technology adoption and, by extension, their ability to derive insights from relatively larger datasets, helped generate creative outcomes. However, although researchers may benefit from automated tools, they tend not to reflect on the implications for researchers doing the work or the work itself (boyd & Crawford, 2012; Lazer et al., 2020). They should.

Datafication creates new possibilities for the information generated by automation. As such, implementers' difficulties in making choices about automation are paralleled by and intertwined with the problems of deciding what data to collect and analyze, and, by implication, what processes and outcomes matter (Hanusch, 2017; Nafus & Sherman, 2014; Sholler et al., 2016). Datafication and automation raise important questions about who owns the data generated, how they should be used, and what the implications will be for the most intimate domains of life. Tools are increasingly accessible to individuals, for example, in the context of health, wellness, and personal productivity (Fortunati, 2018; Neff & Nafus, 2016). The informating functions of data-intensive automation underscore the importance of understanding its communicative dynamics in that harnessing the long-term benefits of automation depends on managing its implementation.

The expansion of what machines can do without human intervention amplifies the transformative potential of data-intensive automation (Brynjolfsson & Mitchell, 2017). Sundar (2020) used the term “machine agency” to refer to technology that users can deploy as a proxy of human agency. Sundar warned that technology is “becoming increasingly capable of exerting its own agency, thanks to advancements in machine learning and artificial intelligence (AI)” (p. 74). In previous waves of automation, the work being automated had to be codified. In the abstract, automators identified tasks, their order, and their influences on each other to recreate them in whole or in part. In practice, automation often involves as much invention as it did recreation because the process of codifying involves making sense of, representing, and translating work, which are complex political and rhetorical endeavors (Henderson, 1998). Furthermore, much work involved tacit knowledge, which can be difficult if not impossible to explicate (Collins, 2001; Treem & Leonardi, 2016) and thus difficult to automate.

Contemporary advances mean that human-generated representations of work are no longer necessarily a precondition for automation. “Where engineers are unable to program a machine to ‘simulate’ a nonroutine task by following a scripted procedure, they may nevertheless be able to program a machine to master the task autonomously by studying successful examples of the task being carried out by others” (Autor, 2015, p. 25). Brynjolfsson and McAfee (2016) summarized changes in automation along these lines: Computers once excelled at following rules but struggled with more complex pattern recognition; robots executed defined movements in controlled conditions but struggled to navigate and interact with uncertain environments; but advances in computational power, the spread of digitization, deep learning, machine vision, natural language processing, robotics, and so forth mean that these limitations apply less and less, and the combinatorial potential of these technologies is still unfolding (see also, Beane, 2019; Brynjolfsson & Mitchell, 2017).

The balance of human and machine agency and human oversight of machines raises key questions. We tend to "welcome…the convenience of machines" but hesitate to cede "decision-making control" (Sundar, 2020 p. 76), and the complexity and opacity of the tools means that human oversight may be superficial or fail to materialize at all. Indeed, the very prediction and control that motivates the adoption of automation can contribute to complexity and chaos in the aggregate over time (Hilbert & Darmon, 2020; Jensen et al., 2022). How to intervene should be the focus of inquiry as researchers shift focus from "who" is doing what to understanding the trade-offs and "strategies for negotiating agency between the human user and the intelligent machine" (Sundar, 2020, p. 78). Any intervention that assumes the intentions and actions of agents remain distinct and limited because machine and human agency change together as each negotiates the other (Orlikowski, 1992). Andrejevic and colleagues (2020) underscored this issue in the context of pre-emptive technologies that "know" where and when to act even before activities occur such as anticipatory shipping bots or social media monitoring systems that predict school violence. These technologies should draw researchers' focus toward the complex temporalities of machine agency and the broad array of communication tasks being automated. Though technologists often sell automation as saving time, automation and intelligent machines might be better understood as changing the temporalities of work. Likewise, although we tend to evaluate machine communicators as we would humans, the evolving reach of machine communicators demand we ask new questions about the communication to, from, and between machines and human actors (Reeves & Nass, 1996; Westerman et al., 2020; Wojcieszak et al., 2021)—communication increasingly common in automation. For example, the domestication of automation in workplaces and at home increases contact with these machines, which may shift the scripts we have for them and each other (C. Edwards et al., 2016; Fortunati, 2018; Taipale et al., 2015).

Indeed, human-machine communication research is important for but distinct from the study of automation. It is important because AI creators, conversers, curators, and co-authors do more than offer novel means of communication (Sundar & Lee, 2022). Communication researchers have already begun to grapple with the changing nature of agency in the development of these technologies (Hancock et al., 2020; Laapotti & Raappana, 2022; Sundar & Lee, 2022). They may influence communicators' goals and introduce new and unpredictable ones. They complicate communication situations (Gambino & Liu, 2022). The theoretical sophistication available for describing, predicting, criticizing, designing, and evaluating communication phenomena provides advantages for the study of automation across disciplines especially when it is communication that is being automated. Apt to the opacity of machine learning, communication researchers are practiced at making sense of communication phenomena and its effects even when the communicators' motivations are unclear or unexplainable.

The importance of datafication and machine agency notwithstanding, researchers should also take care not to conflate them with automation. Conflating them would obscure less sophisticated forms of automation that are nonetheless important and centralize the changing technologies and the hype surrounding them without sufficient attention to the work and workers involved. The interplay of substance, discourse, and practice make clear why this caution is important: First, even well-established forms of mechanization and computerization may take on different meaning as the diffusion of intelligent machines changes conversations about automation. Analytics and algorithmic decision making shine brighter in an era marked by intelligent machines even if the analytics are bunk or the algorithms unfair (Eubanks, 2017; Zuboff, 1988). Second, the hype surrounding intelligent machines can obscure the real humans laboring to make those machines work (Crawford, 2021; Murdock, 2018). For example, the importance of crowdsourced data collection and analysis for intelligent machines inspired Alorwu and colleagues (2022) to push for a research agenda for the design of crowdsourcing platforms and tools to broaden their availability and to "integrate the diverse needs of multiple stakeholders in the overall data labelling ecosystem" (p. 3). Benjamin (2019) argued for the need for an abolitionist movement that would disrupt and replace automated systems of oppression. Communication research can contribute to these endeavors by empowering individuals, organizations, and societal choices about automation by helping us have better conversations about automatic technologies, specific tasks, work, and occupations, and workers using or being subject to those technologies.

Conduct Empirical, Critical, and Design Research to Empower Choices about Automation

The research exemplars reviewed in this article indicate that the study of communication as the substance, discourse, and practice of automation also requires answering empirical, critical, and design questions (Jackson & Aakhus, 2014; Nelson & Stolterman, 2012). Empirical research reveals automation as it is. Critical research asks what automation should be. Design research asks what it might be and how (see Table 1). Whereas we have extensive empirical and critical research on automation as communication, we need research that unpacks the choices about communication embedded in these tools and in our conversations about them, the kinds of choices we might want to encourage, and how to do so.

That is, automation involves puzzles of collective communication design and focusing on these puzzles can bolster theorizing about how individuals and organizations communicate to solve problems (Aakhus, 2007; Jackson & Aakhus, 2014). Collective communication design refers to the mix of individual and collective processes and practices through which individuals problematize, test, evaluate, and craft what and how they communicate. In advocating for and trying out different communication choices, actors negotiate the fit, function, and fragmentation of differing communication techniques and employ differing communication design logics. For example, in the study of automation as communication practice, analytical attention may be given to the choices managers and workers make about communication, and thereby (a) generate concrete insight for intervening in communication, (b) identify specific theory- and practice-based communication strategies and evaluate their effectiveness, and (c) make explicit taken-for-granted assumptions about why a particular form of communication does or does not work *and* the interests and power imbalances inherent to such practices. At the same time, this scholarship could contribute to theory of the communicative negotiation of organizational and technological change by bridging macrolevel interests in occupational factors embodied in the beliefs of professionals, a mesolevel concern for workers' and managers' routine practices of work, and a microlevel focus on specific communication practices. A focus on design questions can unpack not only the effects of the automation of communication but how those effects vary based on where and when humans get involved (e.g., see the contrast between analytics and automation in Maiers, 2017).

Communication scholarship's contributions to the design of automation are essential. For example, Murdock (2018) argued of the study of journalism in particular that "Recent production studies have thrown valuable light on the continuing transformations of journalism and other media occupations, but have seldom asked questions about the manufacture and maintenance of the machines media workers use and the infrastructures they rely on" (p. 363). Communication scholars must "intervene in debates around communication technologies in the formative stages of conception and design, asking questions about the materials they are made of, the energy they will consume, the uses they allow and deny, and the social and environmental costs of their production and disposal" (p. 366). Benjamin (2019) argued that the study of human-centered design needed to include a consideration of “which humans are prioritized in the process” (p. 174) and encouraged a wariness of design that does not consider the “process and power dynamics of design across multiple axes of oppression” (p. 175). Benjamin called for the development of an auditing system, empowered by policy making and grassroots activism. Research involving automation and design must grapple with changing technology in the context of work and workers, and studies of discourse for patterns in talk about automation will be especially welcome.

At the same time, communication scholarship also needs to be positioned to guide the communication through which automation will unfold. Hancock et al. (2020) called for the study of design questions focused on “how people interact with and understand AI-MC” (p. 92). A focus on conversations among workers will likewise help address Bailey and Leonardi’s (2015) recommendations for the study of technology choices. They argued that future research should begin by “mapping occupations’ ideas, beliefs, norms, and values to technology choices” (p. 197). Automation complicates agency, and especially relevant for communication scholars, it complicates the communication goals relevant in any given communication situation. Understanding how workers, managers, and implementers make choices about how they interact to automate can reveal how they negotiate those “ideals, beliefs, norms, and values” and the logics operating in their practice.

A focus on understanding and empowering choices about communication emphasizes not just describing patterns in discourse about automation but also the rhetorical moves made by actors with their own agendas and ends. A focus on communication design draws attention to the choices about communication embedded into, for example, automated messaging and interaction systems and the underlying beliefs about communication those choices represent. As communication practice, automation involves making choices about how to embody interaction in automation but also about the process of automating itself. These choices are especially important in the early development of automated technologies (Leonardi, 2013). This practice must grapple with the issues of trust, transparency, visibility, efficiency, bias, and control and resistance documented in the research reviewed in this article, and studying automation as the substance, discourse, and practice of communication can speak to those issues.

In sum, communication research should seek to understand how automation will transform work, how to intervene in that transformation, and how to facilitate conversations about the future of work. Communication research can do so by asking, what are the connections among the choices made and the effects cultivated, what choices can we make in conversations about automation and how do we cultivate more effective deliberation, and how might communicators engage in more effective or fairer communication practices that may become automated? Understanding and intervening in the implementation of automation technology can be accomplished in part by studying the communication involved. Doing so can reveal how complex, competing, and at times, contradictory goals for action are reconciled, how actors negotiate the affordances and constraints of the technologies available to them, and how differing ideals and logics for action may be managed. Moreover, this approach can inform concrete recommendations for improving practice and wrestling with practical and moral problems of automation because it focuses on more and less adaptive choices about communication.

Conclusion

Returning to the robots-are-coming trope that opened the review, existing research demonstrates a few misconceptions in the public sphere. First, it is too late. The robots are here. Second, it is worse and better than we might fear and hope. Third, the robots-are-coming discourse focuses too much on specific technologies and not enough on work and workers.

Communication approaches have distinctive contributions to make in this space. Because it is communication that is being automated, automation research needs theoretical frameworks that can explain how communication works and is changing. The study of communication offers a means to understanding automation within and across organizational boundaries at multiple levels of analysis. Communication scholarship is well poised not just to understand the communication of and with intelligent machines but the design of communication about them: Communication scholarship can and should help orchestrate better professional, organizational, and societal conversations about automation. Rather than predicting what the next wave of automation will be, communication research can help navigate whatever course it takes.

References

Aakhus, M. (2007). Communication as design. *Communication Monographs*, *74*(1), 112–117. https://doi.org/10.1080/03637750701196383

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *The Journal of Political Economy*, *128*(6), 2188–2244. https://doi.org/10.1086/705716

Adamson, A. S., & Smith, A. (2018). Machine learning and health care disparities in dermatology. *JAMA Dermatology*, *154*(11), 1247–1248. https://doi.org/10.1001/jamadermatol.2018.2348

Alaimo, C., & Kallinikos, J. (2020). Managing by data: Algorithmic categories and organizing. *Organization Studies*, 0170840620934062. https://doi.org/10.1177/0170840620934062

Al-Khateeb, M. T. (2021). Toward a rhetorical account of refugee encounters: Biometric screening technologies and failed promises of mobility. *Rhetoric Society Quarterly*, *51*(1), 15–26. https://doi.org/10.1080/02773945.2020.1841276

Alorwu, A., Savage, S., van Berkel, N., Ustalov, D., Drutsa, A., Oppenlaender, J., Bates, O., Hettiachchi, D., Gadiraju, U., Goncalves, J., & Hosio, S. (2022). REGROW: Reimagining Global Crowdsourcing for Better Human-AI Collaboration. *Extended Abstracts of the 2022 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3491101.3503725

Andrejevic, M., Dencik, L., & Treré, E. (2020). From pre-emption to slowness: Assessing the contrasting temporalities of data-driven predictive policing. *New Media & Society*, *22*(9), 1528–1544. https://doi.org/10.1177/1461444820913565

Applebaum, E., & Albin, P. (1989). Computer rationalization and the transformation of work: Lessons from the insurance industry. In S. Wood (Ed.), *The transformation of work? Skill, flexibility, and the labour process* (pp. 247–265). Routledge.

Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *The Journal of Economic Perspectives*, *29*(3), 3–30.

Bader, V., & Kaiser, S. (2019). Algorithmic decision-making? The user interface and its role for human involvement in decisions supported by artificial intelligence. *Organization*, *26*(5), 655–672. https://doi.org/10.1177/1350508419855714

Bailey, D. E., & Barley, S. R. (2020). Beyond design and use: How scholars should study intelligent technologies. *Information and Organization*, *30*(2), 100286. https://doi.org/10.1016/j.infoandorg.2019.100286

Bailey, D. E., & Leonardi, P. M. (2015). *Technology choices: Why occupations differ in their embrace of new technology*. The MIT Press.

Bailey, D. E., Leonardi, P. M., & Chong, J. (2010). Minding the gaps: Understanding technology interdependence and coordination in knowledge work. *Organization Science*, *21*, 713–730. https://doi.org/10.1287/orsc.1090.0473

Bainbridge, L. (1983). Ironies of automation. *Automatica*, *19*, 775–779.

Barbour, J. B., Treem, J. W., & Kolar, B. (2018). Analytics and expert collaboration: How individuals navigate relationships when working with organizational data. *Human Relations*, *71*, 256–284. https://doi.org/10.1177/0018726717711237

Barcellos Almeida, M., & Farinelli, F. (2017). Ontologies for the representation of electronic medical records: The obstetric and neonatal ontology. *Journal of the Association for Information Science and Technology*, *68*(11), 2529–2542. https://doi.org/10.1002/asi.23900

Barge, J. K., Lee, M., Maddux, K., Nabring, R., & Townsend, B. (2008). Managing dualities in planned change initiatives. *Journal of Applied Communication Research*, *36*, 364–391. https://doi.org/10.1080/00909880802129996

Barrett, A. (2020). 'I can tell you right now, EHR does not improve communication. It does not improve healthcare': Understanding how providers make sense of advanced information technology workarounds. *Journal of Applied Communication Research*, *48*(5), 537–557. https://doi.org/10.1080/00909882.2020.1820551

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

Beam, M. A. (2014). Automating the news: How personalized news recommender system design choices impact news reception. *Communication Research*, *41*(8), 1019–1041. https://doi.org/10.1177/0093650213497979

Beane, M. (2019). Learning to work with intelligent machines. *Harvard Business Review*, *97*(5), 140–148.

Beattie, A., Edwards, A. P., & Edwards, C. (2020). A bot and a smile: Interpersonal impressions of chatbots and humans using emoji in computer-mediated communication. *Communication Studies*, *71*(3), 409–427. https://doi.org/10.1080/10510974.2020.1725082

Belair-Gagnon, V., Lewis, S. C., & Agur, C. (2020). Failure to launch: Competing institutional logics, intrapreneurship, and the case of chatbots. *Journal of Computer-Mediated Communication*, *25*(4), 291–306. https://doi.org/10.1093/jcmc/zmaa008

Benjamin, R. (2019). *Race after technology: Abolitionist tools for the new jim code*. Polity Press.

Berkelaar, B. L. (2017). Different ways new information technologies influence conventional organizational practices and employment relationships: The case of cybervetting for personnel selection. *Human Relations*, *70*(9), 1115–1140. https://doi.org/10.1177/0018726716686400

Bisel, R. S., & Barge, J. K. (2011). Discursive positioning and planning change in organizations. *Human Relations*, *64*, 257–583. https://doi.org/10.1177/0018726710375996

Blauner, R. (1964). *Alienation and freedom: The factory worker and his industry*. University of Chicago Press.

Bolsover, G., & Howard, P. (2019). Chinese computational propaganda: Automation, algorithms and the manipulation of information about Chinese politics on Twitter and Weibo. *Information, Communication & Society*, *22*(14), 2063–2080. https://doi.org/10.1080/1369118X.2018.1476576

boyd, d., & Crawford, K. (2012). Critical questions for big data. *Information, Communication & Society*, *15*, 662–679. https://doi.org/10.1080/1369118X.2012.678878

Brandtzaeg, P. B., Skjuve, M., & Følstad, A. (2022). My AI friend: How users of a social chatbot understand their human–AI friendship. *Human Communication Research*, hqac008. https://doi.org/10.1093/hcr/hqac008

Brynjolfsson, E., & McAfee, A. (2016). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W.W. Norton & Company.

Brynjolfsson, E., & Mitchell, T. (2017). What can machine learning do? Workforce implications. *Science*, *358*(6370), 1530–1534. https://doi.org/10.1126/science.aap8062

Carlson, M. (2018). Automating judgment? Algorithmic judgment, news knowledge, and journalistic professionalism. *New Media & Society*, *20*(5), 1755–1772. https://doi.org/10.1177/1461444817706684

Carlson, P. A. (2001). Information technology and organizational change. *Journal of Technical Writing and Communication*, *31*, 77–95. https://doi.org/10.1145/318372.318389

Carter, M., & Egliston, B. (2021). What are the risks of virtual reality data? Learning analytics, algorithmic bias and a fantasy of perfect data. *New Media & Society*, 14614448211012794. https://doi.org/10.1177/14614448211012794

Chapanis, A. (1965). On the allocation of functions between men and machines. *Occupational Psychology*, *39*, 1–11.

Chaplin, C. (Director). (1936). *Modern Times*. United Artists.

Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS Quarterly*, *36*, 1165–1188.

Chen, M. (2019, November 27). The robots are coming for our jobs. *The Nation*. https://www.thenation.com/article/archive/work-automation-jobs/

Chen, Y. K., & Wen, C.-H. R. (2021). Impacts of attitudes toward government and corporations on public trust in artificial intelligence. *Communication Studies*, *72*(1), 115–131. https://doi.org/10.1080/10510974.2020.1807380

Chui, M., Manyika, J., & Miremadi, M. (2015). Four fundamentals of workplace automation. *McKinsey Quarterly*, 1–9.

Collins, H. M. (2001). Tacit knowledge, trust and the Q of sapphire. *Social Studies of Science*, *31*(1), 71–85. https://doi.org/10.1177/030631201031001004

Crawford. (2021). *Atlas of AI: Power, politics, and the planetary costs of artificial intelligence*. Yale University Press.

Crowston, K., Erickson, I., & Nickerson, J. (2022). *The Work in the Age of Intelligent Machines Research Coordination Network*. https://waim.network/about

Curchod, C., Patriotta, G., Cohen, L., & Neysen, N. (2020). Working for an algorithm: Power asymmetries and agency in online work settings. *Administrative Science Quarterly*, *65*(3), 644–676.

Darr, A. (2018). Automatons, sales-floor control and the constitution of authority. *Human Relations*, *72*(5), 889–909. https://doi.org/10.1177/0018726718783818

Demo, A. T. (2017). Hacking agency: Apps, autism, and neurodiversity. *Quarterly Journal of Speech*, *103*(3), 277–300. https://doi.org/10.1080/00335630.2017.1321135

Diakopoulos, N. (2019). *Automating the news: How algorithms are rewriting the media*. Harvard University Press.

Dodel, M., & Mesch, G. S. (2020). Perceptions about the impact of automation in the workplace. *Information, Communication & Society*, *23*(5), 665–680. https://doi.org/10.1080/1369118X.2020.1716043

Dougherty, D., & Dunne, D. D. (2012). Digital science and knowledge boundaries in complex innovation. *Organization Science*, *23*(5), 1467–1484. Business Source Complete.

Duan, Z., Li, J., Lukito, J., Yang, K.-C., Chen, F., Shah, D. V., & Yang, S. (2022). Algorithmic agents in the hybrid media system: Social bots, selective amplification, and partisan news about COVID-19. *Human Communication Research*, *48*(3), 516–542. https://doi.org/10.1093/hcr/hqac012

Edwards, A., Edwards, C., & Gambino, A. (2020). The social pragmatics of communication with social robots: Effects of robot message design logic in a regulative context. *International Journal of Social Robotics*, *12*(4), 945–957. https://doi.org/10.1007/s12369-019-00538-7

Edwards, C., Edwards, A., Spence, P. R., & Westerman, D. (2016). Initial interaction expectations with robots: Testing the human-to-human interaction script. *Communication Studies*, *67*(2), 227–238. https://doi.org/10.1080/10510974.2015.1121899

Endacott, C. G. (2021, November). *How AI technologies enable and constrain the enactment of multiple identities*. Annual meetings of the National Communication Association, Seattle, WA.

Endacott, C. G., & Leonardi, P. M. (2022). Artificial intelligence and impression management: Consequences of autonomous conversational agents communicating on one's behalf. *Human Communication Research*, *48*(3), 462–490. https://doi.org/10.1093/hcr/hqac009

Eubanks, V. (2017). *Automating inequality: How high-tech tools profile, police, and punish the poor*. St. Martin's Press.

Faunce, W. (1965). Automation and the division of labor. *Social Problems*, *13*, 149–160.

Fleming, P. (2018). Robots and organization studies: Why robots might not want to steal your job. *Organization Studies*, *40*(1), 23–38. https://doi.org/10.1177/0170840618765568

Flyverbom, M. (2019). *The digital prism: Transparency and managed visibilities in a datafied world*. Cambridge University Press.

Flyverbom, M., & Murray, J. (2018). Datastructuring—Organizing and curating digital traces into action. *Big Data & Society*, *5*, 1–12. https://doi.org/10.1177/2053951718799114

Fortunati, L. (2018). Robotization and the domestic sphere. *New Media & Society*, *20*(8), 2673–2690. https://doi.org/10.1177/1461444817729366

Furman, J. L., & Teodoridis, F. (2020). Automation, research technology, and researchers' trajectories: Evidence from computer science and electrical engineering. *Organization Science*, *31*(2), 330–354.

Gambino, A., & Liu, B. (2022). Considering the context to build theory in HCI, HRI, and HMC: Explicating differences in processes of communication and socialization with social technologies. *Human-Machine Communication*, *4*, 111–130. https://doi.org/10.30658/hmc.4.6

Garson, B. (1988). *The electronic sweatshop: How computers are transforming the office of the future into the factory of the past*. Penguin Books.

Geiger, R. S. (2016). Bot-based collective blocklists in Twitter: The counterpublic moderation of harassment in a networked public space. *Information, Communication & Society*, *19*(6), 787–803.

Gibbs, J. L., Kirkwood, G. L., Fang, C., & Wilkenfeld, J. N. (2021). Negotiating agency and control: Theorizing human-machine communication from a structurational perspective. *Human-Machine Communication*, *2*, 153–171.

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, *14*(2), 627–660. https://doi.org/10.5465/annals.2018.0057

Graham, S. S. (2022). *The doctor and the algorithm: Promise, peril, and the future of health AI*. Oxford University Press.

Groleau, C., Demers, C., Lalancette, M., & Barros, M. (2012). From hand drawings to computer visuals: Confronting situated and institutionalized practices in an architecture firm. *Organization Science*, *23*(3), 651–671.

Gupta, A., Ip, I. K., Raja, A. S., Andruchow, J. E., Sodickson, A., & Khorasani, R. (2014). Effect of clinical decision support on documented guideline adherence for head CT in emergency department patients with mild traumatic brain injury. *Journal of the American Medical Informatics Association*, *21*, e347–e351. https://doi.org/10.1136/amiajnl-2013-002536

Guzman, A. L., & Lewis, S. C. (2020). Artificial intelligence and communication: A Human–Machine Communication research agenda. *New Media & Society*, *22*(1), 70–86. https://doi.org/10.1177/1461444819858691

Hancock, J. T., Naaman, M., & Levy, K. (2020). AI-mediated communication: Definition, research agenda, and ethical considerations. *Journal of Computer-Mediated Communication*, *25*(1), 89–100. https://doi.org/10.1093/jcmc/zmz022

Hanusch, F. (2017). Web analytics and the functional differentiation of journalism cultures: Individual, organizational and platform-specific influences on newswork. *Information, Communication & Society*, *20*, 1571–1586. https://doi.org/10.1080/1369118X.2016.1241294

Hasan, S., Ferguson, J.-P., & Koning, R. (2015). The lives and deaths of jobs: Technical interdependence and survival in a job structure. *Organization Science*, *26*(6), 1665–1681.

Hemon-Hildgen, A., Rowe, F., & Monnier-Senicourt, L. (2020). Orchestrating automation and sharing in DevOps teams: A revelatory case of job satisfaction factors, risk and work conditions. *European Journal of Information Systems*, *29*(5), 474–499. https://doi.org/10.1080/0960085X.2020.1782276

Henderson, K. (1998). The role of material objects in the design process: A comparison of two design cultures and how they contend with automation. *Science, Technology, & Human Values*, *23*, 139–174. https://doi.org/10.1177/016224399802300201

Henriksen, A., & Bechmann, A. (2020). Building truths in AI: Making predictive algorithms doable in healthcare. *Information, Communication & Society*, *23*(6), 802–816. https://doi.org/10.1080/1369118X.2020.1751866

Hensmans, M. (2020). How digital fantasy work induces organizational ideal reversal? Long-term conditioning and enactment of digital transformation fantasies at a large alternative bank (1963–2019). *Organization*, *28*(1), 132–163. https://doi.org/10.1177/1350508420968185

Herkert, J., Borenstein, J., & Miller, K. (2020). The Boeing 737 MAX: Lessons for engineering ethics. *Science and Engineering Ethics*, *26*(6), 2957–2974. https://doi.org/10.1007/s11948-020-00252-y

Hilbert, M., & Darmon, D. (2020). Large-scale communication is more complex and unpredictable with automated bots. *Journal of Communication*, *70*(5), 670–692. https://doi.org/10.1093/joc/jqaa021

Horstmann, A. C., & Krämer, N. C. (2019). Great expectations? Relation of previous experiences with social robots in real life or in the media and expectancies based on qualitative and quantitative assessment. *A*, *10*. https://www.frontiersin.org/articles/10.3389/fpsyg.2019.00939

Hsieh, S.-J. (2016, June 26). *Skill sets needed for industrial automation careers*. ASEE Annual Conference, New Orleans, LA.

Jackson, S., & Aakhus, M. (2014). Becoming more reflective about the role of design in communication. *Journal of Applied Communication Research*, *42*, 125–134. https://doi.org/10.1080/00909882.2014.882009

Jensen, J. T., Rolison, S. L., & Barbour, J. B. (2022). Temporal dominance: Controlling activity cycles when time is scarce, sudden, and squeezed. *Management Communication Quarterly*, *36*(1), 30–61. https://doi.org/10.1177/08933189211023471

Johnson, D. G., & Verdicchio, M. (2017). AI anxiety. *Journal of the Association for Information Science and Technology*, *68*(9), 2267–2270. https://doi.org/10.1002/asi.23867

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals*, *14*(1), 366–410.

Kelly, C. R. (2021). White pain. *Quarterly Journal of Speech*, *107*(2), 209–233. https://doi.org/10.1080/00335630.2021.1903537

Klatzky, S. R. (1970). Automation, size, and the locus of decision making: The cascade effect. *The Journal of Business*, *43*, 141–151.

Krumholz, H. M. (2014). Big data and new knowledge in medicine: The thinking, training, and tools needed for a learning health system. *Health Affairs*, *33*, 1163–1170. https://doi.org/10.1377/hlthaff.2014.0053

Kushner, S. (2013). The freelance translation machine: Algorithmic culture and the invisible industry. *New Media & Society*, *15*(8), 1241–1258. https://doi.org/10.1177/1461444812469597

Laapotti, T., & Raappana, M. (2022). Algorithms and organizing. *Human Communication Research*, hqac013. https://doi.org/10.1093/hcr/hqac013

Laitinen, K., Laaksonen, S.-M., & Koivula, M. (2021). Slacking with the bot: Programmable social bot in virtual team interaction. *Journal of Computer-Mediated Communication*, *zmab012*. https://doi.org/10.1093/jcmc/zmab012

Lammi, I. J. (2020). Automating to control: The unexpected consequences of modern automated work delivery in practice. *Organization*, *28*(1), 115–131. https://doi.org/10.1177/1350508420968179

Lange, A.-C., Lenglet, M., & Seyfert, R. (2018). On studying algorithms ethnographically: Making sense of objects of ignorance. *Organization*, *26*(4), 598–617. https://doi.org/10.1177/1350508418808230

Lazer, D. M. J., Pentland, A., Adamic, L., Aral, S., Barabasi, A.-L., Brewer, D., Christakis, N., Contractor, N., Fowler, J., Gutmann, M., Jebara, T., King, G., Macy, M., Roy, D., & Van Alstyne, M. (2009). Computational social science. *Science*, *323*(5915), 721–723.

Lazer, D. M. J., Pentland, A., Watts, D. J., Aral, S., Athey, S., Contractor, N., Freelon, D., Gonzalez-Bailon, S., King, G., Margetts, H., Nelson, A., Salganik, M. J., Strohmaier, M., Vespignani, A., & Wagner, C. (2020). Computational social science: Obstacles and opportunities. *Science*, *369*(6507), 1060–1062. https://doi.org/10.1126/science.aaz8170

Lee, J., & Berente, N. (2012). Digital innovation and the division of innovative labor: Digital controls in the automotive industry. *Organization Science*, *23*(5), 1428–1447. https://doi.org/10.1287/orsc.1110.0707

Lee, M. K., Kusbit, D., Metsky, E., & Dabbish, L. (2015). Working with machines: The impact of algorithmic and data-driven management on human workers. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 1603–1612. https://doi.org/10.1145/2702123.2702548

Lee, S., Nah, S., Chung, D. S., & Kim, J. (2020). Predicting AI News Credibility: Communicative or Social Capital or Both? *Communication Studies*, *71*(3), 428–447. https://doi.org/10.1080/10510974.2020.1779769

Leonardi, P. M. (2009a). Crossing the implementation line: The mutual constitution of technology and organizing across development and use activities. *Communication Theory*, *19*, 278–310. https://doi.org/10.1111/j.1468-2885.2009.01344.x

Leonardi, P. M. (2009b). Why do people reject new technologies and organizational changes of which they are in favor? Exploring misalignments between social interactions and materiality. *Human Communication Research*, *35*, 407–441. https://doi.org/10.1111/j.1468-2958.2009.01357.x

Leonardi, P. M. (2011). Innovation blindness: Culture, frames, and cross-boundary problem construction in the development of new technology concepts. *Organization Science*, *22*(2), 347–369. https://doi.org/10.1287/orsc.1100.0529

Leonardi, P. M. (2012). *Car crashes without cars: Lessons about simulation technology and organizational change from automotive design*. MIT Press.

Leonardi, P. M. (2013). When does technology use enable network change in organizations? A comparative study of feature use and shared affordances. *MIS Quarterly*, *37*(3), 749–775. https://doi.org/10.25300/MISQ/2013/37.3.04

Leonardi, P. M., & Contractor, N. (2018). Better people analytics: Measure who they know not just who they are. *Harvard Business Review*, *96*(6), 70–81.

Leonardi, P. M., & Treem, J. W. (2020). Behavioral visibility: A new paradigm for organization studies in the age of digitization, digitalization, and datafication. *Organization Studies*, *41*(12), 1601–1625. https://doi.org/10.1177/0170840620970728

Leonardi, P. M., Woo, D., & Barley, W. C. (2021). On the making of crystal balls: Five lessons about simulation modeling and the organization of work. *Information and Organization*, *31*(1), 100339. https://doi.org/10.1016/j.infoandorg.2021.100339

Lepore, J. (2019, March 4). The robot caravan. *The New Yorker*. https://www.newyorker.com/magazine/2019/03/04/are-robots-competing-for-your-job

Lewis, L. K. (2019). *Organizational change: Creating change through strategic communication* (2nd ed.). Wiley-Blackwell.

Lewis, L. K., & Russ, T. L. (2011). Soliciting and using input during organizational change initiatives: What are practitioners doing? *Management Communication Quarterly*, *26*, 267–294. https://doi.org/10.1177/0893318911431804

Liang, Y., & Lee, S. A. (2017). Fear of autonomous robots and artificial intelligence: Evidence from national representative data with probability sampling. *International Journal of Social Robotics*, *9*(3), 379–384. https://doi.org/10.1007/s12369-017-0401-3

Liberatore, M. J., & Luo, W. (2010). The analytics movement: Implications for operations research. *Interfaces*, *40*, 313–324. https://doi.org/10.1287/inte.1100.0502

Lin, W., Yueh, H.-P., Wu, H.-Y., & Fu, L.-C. (2014). Developing a service robot for a children's library: A design-based research approach. *Journal of the Association for Information Science and Technology*, *65*(2), 290–301. https://doi.org/10.1002/asi.22975

Liu, B. (2021). In AI we trust? Effects of agency locus and transparency on uncertainty reduction in human–AI interaction. *Journal of Computer-Mediated Communication*, *26*(6), 384–402. https://doi.org/10.1093/jcmc/zmab013

Lobera, J., Fernández Rodríguez, C. J., & Torres-Albero, C. (2020). Privacy, values and machines: Predicting opposition to artificial intelligence. *Communication Studies*, *71*(3), 448–465. https://doi.org/10.1080/10510974.2020.1736114

Lucas, G. M., Gratch, J., King, A., & Morency, L.-P. (2014). It's only a computer: Virtual humans increase willingness to disclose. *Computers in Human Behavior*, *37*, 94–100. https://doi.org/10.1016/j.chb.2014.04.043

Lucas, G. M., Rizzo, A., Gratch, J., Scherer, S., Stratou, G., Boberg, J., & Morency, L.-P. (2017). Reporting mental health symptoms: Breaking down barriers to care with virtual human interviewers. *Frontiers in Robotics and AI*, *4*, 51. https://doi.org/10.3389/frobt.2017.00051

Lupton, D. (2016). *The quantified self*. Polity Press.

Lycett, M. (2013). /`Datafication/': Making sense of (big) data in a complex world. *European Journal of Information Systems*, *22*, 381–386. https://doi.org/10.1057/ejis.2013.10

Maiers, C. (2017). Analytics in action: Users and predictive data in the neonatal intensive care unit. *Information, Communication & Society*, *20*(6), 915–929. https://doi.org/10.1080/1369118X.2017.1291701

Marchland, D. A., & Peppard, J. (2013). Why IT fumbles analytics: Tech projects should focus less on technology and more on information. *Harvard Business Review*, *91*, 104–112.

McAfee, A., & Brynjolfsson, E. (2012). Big data: The management revolution. *Harvard Business Review*, *90*, 60–68.

McGuigan, L. (2019). Automating the audience commodity: The unacknowledged ancestry of programmatic advertising. *New Media & Society*, *21*(11–12), 2366–2385. https://doi.org/10.1177/1461444819846449

Meng, J., & Dai, Y. (Nancy). (2021). Emotional support from AI chatbots: Should a supportive partner self-disclose or not? *Journal of Computer-Mediated Communication*, *zmab005*. https://doi.org/10.1093/jcmc/zmab005

Meyer, M. W. (1968). Automation and bureaucratic structure. *American Journal of Sociology*, *74*(3), 256–264.

Miller, C. R. (2007). What can automation tell us about agency? *Rhetoric Society Quarterly*, *37*(2), 137–157. JSTOR.

Morath, E. (2020, February 23). AI is the next workplace disrupter—And it's coming for high-skilled jobs. *Wall Street Journal*. https://www.wsj.com/articles/ai-is-the-next-workplace-disrupterand-its-coming-for-high-skilled-jobs-11582470000

Muller, J. Z. (2018). *The tyranny of metrics*. Princeton University Press.

Murdock, G. (2018). Media materialties: For a moral economy of machines. *Journal of Communication*, *68*(2), 359–368. https://doi.org/10.1093/joc/jqx023

Nafus, D., & Sherman, J. (2014). This one does not go up to 11: The Quantified Self movement as an alternative big data practice. *International Journal of Communication*, *8*, 1784–1794.

Neff, G., & Nafus, D. (2016). *Self-tracking*. MIT Press.

Nelson, H. G., & Stolterman, E. (2012). *The design way: Intentional change in an unpredictable world* (2nd ed.). MIT Press.

Newlands, G. (2020). Algorithmic surveillance in the gig economy: The organization of work through Lefebvrian conceived space. *Organization Studies*, 0170840620937900. https://doi.org/10.1177/0170840620937900

Noble, D. F. (2011). *Forces of production: A social history of industrial automation*. Taylor & Francis.

Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science*, *366*(6464), 447. https://doi.org/10.1126/science.aax2342

Ohl, J. J. (2015). Nothing to see or fear: Light war and the boring visual rhetoric of U.S. drone imagery. *Quarterly Journal of Speech*, *101*(4), 612–632. https://doi.org/10.1080/00335630.2015.1128115

Oliver, N., Calvard, T., & Potočnik, K. (2017). Cognition, technology, and organizational limits: Lessons from the Air France 447 disaster. *Organization Science*, *28*(4), 729–743.

O'Neill, C. (2016). *Weapons of math destruction*. Crown Books.

Orlikowski, W. J. (1992). The duality of technology: Rethinking the concept of technology in organizations. *Organization Science*, *3*, 398–427. https://doi.org/10.1287/orsc.3.3.398

Pääkkönen, J., Laaksonen, S.-M., & Jauho, M. (2020). Credibility by automation: Expectations of future knowledge production in social media analytics. *Convergence*, *26*(4), 790–807. https://doi.org/10.1177/1354856520901839

Pachidi, S., Berends, H., Faraj, S., & Huysman, M. (2020). Make way for the algorithms: Symbolic actions and change in a regime of knowing. *Organization Science*, *32*(1), 18–41. https://doi.org/10.1287/orsc.2020.1377

Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on Systems, Man, and*

Cybernetics - Part A: Systems and Humans, *30*(3), 286–297. https://doi.org/10.1109/3468.844354

Park, S., & Humphry, J. (2019). Exclusion by design: Intersections of social, digital and data exclusion. *Information, Communication & Society*, *22*(7), 934–953. https://doi.org/10.1080/1369118X.2019.1606266

Peña Gangadharan, S., & Niklas, J. (2019). Decentering technology in discourse on discrimination. *Information, Communication & Society*, *22*(7), 882–899. https://doi.org/10.1080/1369118X.2019.1593484

Pentland, B. T., Hærem, T., & Hillison, D. (2010). Comparing organizational routines as recurrent patterns of action. *Organization Studies*, *31*(7), 917–940. https://doi.org/10.1177/0170840610373200

Pentland, B. T., Haerem, T., & Hillison, D. (2011). The (n)ever-changing world: Stability and change in organizational routines. *Organization Science*, *22*(6), 1369–1383.

Pew Research Center. (2017). *Automation in everyday life*. https://www.pewresearch.org/internet/2017/10/04/automation-in-everyday-life/

Pezzullo, P. C., & Hunt, K. P. (2020). Agribusiness futurism and food atmospheres: Reimagining corn, pigs, and transnational negotiations on Khrushchev's 1959 U.S. tour. *Quarterly Journal of Speech*, *106*(4), 399–426. https://doi.org/10.1080/00335630.2020.1828605

Piercy, C. W., & Gist-Mackey, A. N. (2021). Automation anxieties: Perceptions about technological automation and the future of pharmacy work. *Human-Machine Communication*, *2*, 191–208. https://doi.org/10.30658/hmc.2.10

Poole, M. S., & Holmes, M. E. (1995). Decision development in computer-assisted group decision making. *Human Communication Research*, *22*, 90–127.

Popejoy, A. B., & Fullerton, S. M. (2016). Genomics is failing on diversity. *Nature News*, *538*, 161–164.

Rahman, H. A. (2021). The invisible cage: Workers' reactivity to opaque algorithmic evaluations. *Administrative Science Quarterly*, 00018392211010118. https://doi.org/10.1177/00018392211010118

Ratcliff, C. L., Kaphingst, K. A., & Jensen, J. D. (2018). When personal feels invasive: Foreseeing challenges in precision medicine communication. *Journal of Health Communication*, *23*(2), 144–152. https://doi.org/10.1080/10810730.2017.1417514

Rawley, E., & Simcoe, T. S. (2013). Information technology, productivity, and asset ownership: Evidence from taxicab fleets. *Organization Science*, *24*(3), 831–845.

Reeves, B., & Nass, C. (1996). *The media equation: How people treat computers, television, and new media like real people and places*. Cambridge University Press.

Ringel, S., & Davidson, R. (2020). Proactive ephemerality: How journalists use automated and manual tweet deletion to minimize risk and its consequences for social media as a public archive. *New Media & Society*, 1461444820972389. https://doi.org/10.1177/1461444820972389

Ringel, S., & Ribak, R. (2021). 'Place a book and walk away': Archival digitization as a socio-technical practice. *Information, Communication & Society*, *24*(15), 2293–2306. https://doi.org/10.1080/1369118X.2020.1766534

Rydenfelt, H. (2021). Transforming media agency? Approaches to automation in Finnish legacy media. *New Media & Society*, 1461444821998705. https://doi.org/10.1177/1461444821998705

Sandberg, J., Holmström, J., & Lyytinen, K. (2020). Digitization and phase transitions in platform organizing logics: Evidence from the process automation industry. *MIS Quarterly*, *44*(1), 129–153.

Santini, R. M., Salles, D., Tucci, G., Ferreira, F., & Grael, F. (2020). Making up audience: Media bots and the falsification of the public sphere. *Communication Studies*, *71*(3), 466–487. https://doi.org/10.1080/10510974.2020.1735466

Sardar, M. R., Badri, M., Prince, C. T., Seltzer, J., & Kowey, P. R. (2014). Underrepresentation of women, elderly patients, and racial Minorities in the randomized trials used for cardiovascular guidelines. *JAMA Internal Medicine*, *174*(11), 1868–1870. https://doi.org/10.1001/jamainternmed.2014.4758

Scherr, C. L., Dean, M., Clayton, M. F., Hesse, B. W., Silk, K., Street, R. L. J., & Krieger, J. (2017). A research agenda for communication scholars in the precision medicine era. *Journal of Health Communication*, *22*(10), 839–848. https://doi.org/10.1080/10810730.2017.1363324

Schmitt, J. B., Rieger, D., Rutkowski, O., & Ernst, J. (2018). Counter-messages as prevention or promotion of extremism?! The potential role of YouTube recommendation algorithms. *Journal of Communication*, *68*(4), 780–808. https://doi.org/10.1093/joc/jqy029

Seeber, I., Bittner, E., Briggs, R. O., de Vreede, T., de Vreede, G.-J., Elkins, A., Maier, R., Merz, A. B., Oeste-Reiß, S., Randrup, N., Schwabe, G., & Söllner, M. (2020). Machines as teammates: A research agenda on AI in team collaboration. *Information & Management*, *57*(2), 103174. https://doi.org/10.1016/j.im.2019.103174

Seering, J., Flores, J. P., Savage, S., & Hammer, J. (2018). The Social Roles of Bots: Evaluating Impact of Bots on Discussions in Online Communities. *Proc. ACM Hum.-Comput. Interact.*, *2*(CSCW). https://doi.org/10.1145/3274426

Sennett, R. (2009). *The craftsman*. Yale University Press.

Shestakofsky, B. (2017). Working algorithms: Software automation and the future of work. *Work and Occupations*, *44*(4), 376–423. https://doi.org/10.1177/0730888417726119

Sholler, D., Bailey, D. E., & Rennecker, J. (2016). Big data in medicine: Potential, reality, and implications. In C. R. Sugimoto, H. R. Ekbia, & M. Mattioli (Eds.), *Big data is not a monolith* (pp. 173–185). The MIT Press.

Shorey, S., & Howard, P. N. (2016). Automation, algorithms, and politics: A research review. *International Journal of Communication*, *10*, 5032–5055.

Soffer, O. (2021). Algorithmic personalization and the two-step flow of communication. *Communication Theory*, *31*(3), 297–315. https://doi.org/10.1093/ct/qtz008

Sproull, L., & Kiesler, S. (1991). Two-level perspective on electronic mail in organizations. *Journal of Organizational Computing*, *1*(2), 125–134. https://doi.org/10.1080/10919399109540154

Sundar, S. S. (2020). Rise of machine agency: A framework for studying the psychology of human–AI interaction (HAII). *Journal of Computer-Mediated Communication*, *25*(1), 74–88. https://doi.org/10.1093/jcmc/zmz026

Sundar, S. S., & Lee, E.-J. (2022). Rethinking communication in the era of artificial intelligence. *Human Communication Research*, *48*(3), 379–385. https://doi.org/10.1093/hcr/hqac014

Taipale, S., de Luca, F., Sarrica, M., & Fortunati, L. (2015). *Robot shift from industrial production to social reproduction* (pp. 11–24). Springer International Publishing. https://doi.org/10.1007/978-3-319-15672-9_2

Topol, E. J. (2019a). *Deep medicine: How artificial intelligence can make healthcare human again*. Basic Books.

Topol, E. J. (2019b). High-performance medicine: The convergence of human and artificial intelligence. *Nature Medicine*, *25*, 44–56. https://doi.org/10.1038/s41591-018-0300-7

Treem, J. W., & Leonardi, P. M. (2016). *Expertise, communication, and organizing*. Oxford University Press.

Treem, J. W., Leonardi, P. M., & van den Hooff, B. (2020). Computer-mediated communication in the age of communication visibility. *Journal of Computer-Mediated Communication*, *25*(1), 44–59. https://doi.org/10.1093/jcmc/zmz024

van Dijck, J. (2014). Datafication, dataism and dataveillance: Big data between scientific paradigm and ideology. *Surveillance & Society*, *12*, 197–208.

Velkova, J., & Kaun, A. (2021). Algorithmic resistance: Media practices and the politics of repair. *Information, Communication & Society*, *24*(4), 523–540. https://doi.org/10.1080/1369118X.2019.1657162

Vergeer, M. (2020). Artificial intelligence in the Dutch press: An analysis of topics and trends. *Communication Studies*, *71*(3), 373–392. https://doi.org/10.1080/10510974.2020.1733038

Wajcman, J. (2019). The digital architecture of time management. *Science, Technology, & Human Values*, *44*(2), 315–337. https://doi.org/10.1177/0162243918795041

Weber, M. S., Barley, W. C., & Kahn, E. (2021, May). *Artificial intelligence and the power of the past to predict the future of work*. International Communication Association.

Westerman, D., Edwards, A. P., Edwards, C., Luo, Z., & Spence, P. R. (2020). I-it, I-thou, I-robot: The perceived humanness of AI in human-machine communication. *Communication Studies*, *71*(3), 393–408. https://doi.org/10.1080/10510974.2020.1749683

Witteborn, S. (2022). Digitalization, digitization and datafication: The “three D” transformation of forced migration management. *Communication, Culture and Critique*, *15*(2), 157–175. https://doi.org/10.1093/ccc/tcac007

Wojcieszak, M., Thakur, A., Ferreira Gonçalves, J. F., Casas, A., Menchen-Trevino, E., & Boon, & M. (2021). Can AI enhance people’s support for online moderation and their openness to dissimilar political views? *Journal of Computer-Mediated Communication*, *zmab006*. https://doi.org/10.1093/jcmc/zmab006

Wolf, Z. (2019, September 3). The robots are coming for your job, too. *CNN*. https://www.cnn.com/2019/08/24/politics/economy-us-workforce-automation/index.html

Woolley, S., Shorey, S., & Howard, P. N. (2018). The bot proxy: Designing automated self-expression. In Z. Papacharissi (Ed.), *A networked self and platforms, stories, connections* (pp. 59–76). Routledge.

Wright, B. D. (2016, March 28). Robots are coming for your job. *Los Angeles Times*. https://www.latimes.com/opinion/op-ed/la-oe-wright-robots-jobs-data-mining-20160328-story.html

Yu, J., & Couldry, N. (2022). Education as a domain of natural data extraction: Analysing corporate discourse about educational tracking. *Information, Communication & Society*, *25*(1), 127–144. https://doi.org/10.1080/1369118X.2020.1764604

Zuboff, S. (1985). Automate/informate: The two faces of intelligent technology. *Organizational Dynamics*, *14*, 5–18. https://doi.org/10.1016/0090-2616(85)90033-6

Zuboff, S. (1988). *In the age of the smart machine: The future of work and power*. Basic Books.

Zuboff, S. (2019). *The age of surveillance capitalism: The fight for a human future at the new frontier of power*. Hachette Book Group.

Table 1

An Agenda for Communication Research about Automation

Foci	Conceptualization	Empirical	Critical	Design
Substance	Communication as the focus or locus of automation.	What are the effects of the automation of communication?	How are these effects distributed?	What are the connections among the choices made and the effects cultivated?
Discourse	Talk about automation at work, at play, at home, and in the public sphere.	What are the conversations? Who talks? Who decides?	Are these the right conversations among the right people? Who gets to have voice?	What choices can we make about these conversations and how do we cultivate more effective deliberation?
Practice	Communication as the space in which automation occurs.	What does the practice look like? How does it unfold?	Is this practice fair? Whom does it advantage and disadvantage?	How might communicators engage in more effective or fairer communication practice to automate?

Figure 1

Explicating Automation