ALGORITHMS AT WORK: THE NEW CONTESTED TERRAIN OF CONTROL

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ALGORITHMS AT WORK:
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ABSTRACT

The widespread implementation of algorithmic technologies in organizations prompts questions about how algorithms may reshape organizational control. We use Edwards' (1979) perspective of "*contested terrain,*" wherein managers implement production technologies to maximize the value of labor and workers resist, to synthesize the interdisciplinary research on algorithms at work. We find that algorithmic control in the workplace operates through six main mechanisms, which we call the "6 Rs"—employers can use algorithms to direct workers by *restricting* and *recommending*, evaluate workers through *recording* and *rating*, and discipline workers by *replacing* and *rewarding*. We also highlight several key insights regarding algorithmic control. First, labor process theory helps to highlight potential problems with the largely positive view of algorithms at work. Second, the technical capabilities of algorithmic systems facilitate a form of rational control that is distinct from the technical and bureaucratic control used by employers for the past century. Third, employers' use of algorithms is sparking the development of new algorithmic occupations. Finally, workers are individually and collectively resisting algorithmic control through a set of emerging tactics we call algoactivism. These insights sketch the contested terrain of algorithmic control and map critical areas for future research.

INTRODUCTION

Over the past decades, the use of algorithms has transformed how firms and markets operate. We focus in this paper on algorithmic technologies, defined in emerging social science usage 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 (e.g., Gillespie, 2014: 167). To date, most research in management and economics has emphasized the benefits of using algorithms to improve allocation and coordination in complex markets, facilitate efficient decision-making within firms, and improve organizational learning (e.g., Athey & Stern, 2000; Hall, Horton, & Knoepfle, 2019; Liu, Brynjolfsson, & Dowlatabadi, 2018a). These analyses primarily focus on the impact of algorithms in terms of economic value derived from greater efficiency, revenue, and innovation.

Here we provide a different perspective. Drawing on labor process theory (Braverman, 1974; Burawoy, 1979; Smith, 2015; Thompson & Smith, 2009) which describes organizational control as "contested terrain" (Edwards, 1979), we analyze algorithms as a major force in allowing employers to reconfigure employer-worker relations of production within and across organizations. In this view, managers implement new production technologies and control mechanisms that maximize the value created by workers' labor (e.g., Burawoy, 1979; Smith, 2006). Workers, in turn, resist and defend their autonomy in the face of tighter employer control, potentially reshaping the relations of production (e.g., Thompson & Vincent, 2010).

We argue that organizational scholarship has not kept pace with the ways that algorithmic technologies have the potential to transform organizational control in profound ways, with significant implications for workers. Even though organizational scholars have begun to explore the intersection between emerging technologies and the changing nature of work and control (e.g., Bailey, Leonardi, & Barley, 2012; Barley, 2015; Barley, Bechky, & Milliken, 2017; Barrett, Oborn, Orlikowski, & Yates, 2012; Leonardi & Vaast, 2017), most of the research about algorithms at work has been published outside of management journals (for important exceptions, see Curchod, Patriotta, Cohen, & Neysen, 2019; Faraj, Pachidi, & Sayegh, 2018; Orlikowski & Scott, 2014b).

Scholars across the disciplines of information science, human-computer interaction, sociology, communication, legal studies, and computer-supported cooperative work have discussed the societal implications of algorithms in terms of surveillance and discrimination (boyd & Crawford, 2012; Eubanks, 2018; Noble, 2018; O'Neil, 2016; Pasquale, 2015; Scholz, 2012; Zuboff, 2019), but have not focused on how algorithms can reshape the control relationship between managers and workers. In management, scholars have analyzed the implications of big data for organizational strategy and design (Loebbecke & Picot, 2015; Newell & Marabelli, 2015; Puranam, Alexy, & Reitzig, 2014), and for research methods (Agarwal & Dhar, 2014; George, Haas, & Pentland, 2014), but have not analyzed the effects of these technological developments on manager-worker dynamics.

Drawing on our review of the vast and interdisciplinary literature on algorithms, we offer a synthesized framework of the contested terrain of algorithmic control (**Figure 1**). To do so, we first describe the management and economics literature on the use of algorithms to facilitate improved decision-making, coordination, and organizational learning in organizations. We next delineate the two key previous forms of rational control—technical and bureaucratic control—and elaborate how the affordances of algorithmic technologies have provided employers with an opportunity to implement new control mechanisms to activate workers' efforts. Then, based on a detailed review of algorithms' studies, we argue that employers can use algorithms to control workers through six main mechanisms, which we call the "6 Rs:" employers can use algorithms help to direct workers by *restricting* and *recommending*, evaluate workers by *recording* and *rating*, and discipline workers by *replacing* and *rewarding*.

We conclude by providing an updated model of algorithmic control as the new contested terrain of control and offer a roadmap for future research along four main lines. First, we discuss how labor process theory raises important questions not addressed in the existing research on the positive economic value of algorithms. Second, we analyze algorithmic control as distinct from previous regimes of control, namely

technical and bureaucratic control. Third, we highlight the emergence of novel occupations—algorithmic curators, brokers, and articulators—that offer new avenues for control and resistance. Last, we discuss the development of different forms of worker resistance, which we label "algoactivism," that range from individual practical action to platform organizing, discursive framing, and legal mobilization.

ECONOMIC VALUE OF ALGORITHMS FOR EMPLOYERS

Before reviewing the literature on rational control and on how employers can use algorithms to reshape the relations of production between managers and workers, we begin by briefly reviewing the management and economics research to date on algorithms in organizations. Up to this point, this research has primarily focused on the economic and operational value of algorithms to organizations. In particular, scholars in organizational strategy, economics, information systems, and human-computer interaction have emphasized how employers can use algorithms to facilitate improved decision-making, coordination, and organizational learning.

First, existing studies have documented how algorithmic technologies can enable individuals to make more accurate decisions than they did before. Some of this improved decision making stems from the finely-grained data that organizations are now collecting on how customers engage with products and marketing materials (Glynn, 2018; Hollebeek et al., 2016); some stems from computational analyses, such as systems that can improve doctors' interpretation and decision-making about radiologic images (Hosny, Parmar, Quackenbush, Schwartz, & Aerts, 2018), or machine-learning algorithms that can predict customer preferences (Boyle, 2018; Gomez-Uribe & Hunt, 2016). In some cases, automated analyses remove humans almost entirely from the decision-making process, such as systems that maintain optimized stock portfolios that outperform human traders (Heaton, Polson, & Witte, 2017). Algorithmic systems can also change how people produce and use evidence for decision-making. For instance, companies can rely on sophisticated data infrastructures that allow them to run randomized control trials or statistical tests (also called A/B tests) on many of their decisions, meaning some decisions that were previously intuition-based are now subject to the statistical "gold standard" for establishing causality or modeling expected impact (Bradley, 2019).

Second, scholars have found that algorithmic technologies can automate coordination processes in ways that produce economic value for employers. Employers have used algorithms to "stitch" together or combine "microtasks" (Bernstein et al., 2015; Little, Chilton, Goldman, & Miller, 2010). For example, studies have described how a crowd of workers can each label a single image and then an algorithm can combine their responses into a dataset that provides considerable analytical value for developing computer vision (Russakovsky et al., 2015). Such automated coordination processes have been shown to provide economic efficiency (Puranam, 2018). For example, studies of the "web-based enterprise" have shown that an "API" (an interface that a line of code can call to do things), can take a customized customer query and automatically check stock, combine the requested products, inform the customer, and send customized products; each of these interdependencies (e.g., between "front-facing" services and inventory management), which previously had been coordinated by people, could now be automatically coordinated by code, thus lowering labor costs (Davis, 2015; Davis, 2016).

Third, existing studies document how employers can use algorithmic technologies to automate organizational learning in ways that produce economic value for them. These studies show how employers have used algorithmic systems to identify and learn from use patterns across individuals, and then responsively change system behavior in real time (Boyle, 2018; Liu, Mandel, Brunskill, & Popovic, 2014). For instance, some employers have used smartphone operating systems to analyze and compare user patterns over time to recognize information that was relevant to users across different apps, like phone numbers or addresses in emails or texts that users had copied to the map or phone apps (Cipriani & Dolcourt, 2019; Yin, Davis, & Muzyrya, 2014). Academic studies have noted that, as employers begin to use latent data collection systems related to the "internet of things," similar algorithmic systems will be able to track what information people search or create in different rooms or meetings, and automatically

offer personalized information or ideas for different individuals, meetings, teams, and projects (e.g., Landay, 2019). Scholars of organizational learning suggest that these systems are likely to lead to more efficient search and retrieval of information, as well as better analyses of ideas or decisions that impact financial or service performance for the organizations. They argue that these benefits to organizations will unfold in automated and tightly-coupled feedback loops between user and system behavior (e.g., Nikolaidis & Shah, 2012; Sachon & Boquet, 2017; Shah, Wiken, Williams, & Breazeal, 2011).

These studies emphasize the benefits to employers of algorithmic technologies in terms of economic value, based on improved efficiency in decision-making, coordination processes, and organizational learning. What they miss is an understanding of algorithmic systems as instruments of control that are contested between employers and workers.

THE HISTORICAL CONTESTED TERRAIN OF RATIONAL CONTROL

To set the stage for our review of algorithms and the changing nature of rational control, we briefly lay out the intellectual history of rational control in the post-industrial era as a "contested terrain" (Edwards, 1979) between employers and workers. As noted earlier, labor process theorists have highlighted how managers are compelled to establish control over workers to maximize the value created by workers' labor (e.g., Braverman, 1974; Burawoy, 1985; Thompson & Smith, 2009). In this view, control is a dialectical process in which employers continuously innovate mechanisms to maximize value captured from workers, and workers inevitably engage in resistance to maintain their autonomy, dignity, and identity (e.g., Edwards, 1979; Jaros, 2010; Thompson & Van den Broek, 2010).

For more than a century, organizational scholars have examined the activities of managers attempting to control the labor process using both normative and rational control (Barley & Kunda, 1992). While employers use normative control when they try to obtain desired behavior from workers by "winning their hearts and minds" (e.g., Kunda, 1992), they use rational control to obtain desired behavior from workers by appealing to workers' self-interest (e.g., Taylor, 1911). In this paper, we focus primarily on algorithmic control as a new form of rational control, considering normative control in our suggestions for future research.

We suggest that Edwards' (1979) foundational typology of control mechanisms is useful for reviewing and organizing both the expansive past literature on rational control, and the emerging interdisciplinary literature on algorithms in the workplace. Edwards asserts that employers obtain desired behavior from workers using three related control mechanisms: direction, evaluation, and discipline. *Direction* entails the specification of what needs to be done, in what order and time period and with what degree of accuracy. *Evaluation* entails the review of workers to correct mistakes, assess performance, and identify those who are not performing adequately. *Discipline* entails the punishment and reward of workers so as to elicit cooperation and enforce compliance with the employer's direction of the labor process. Edwards' approach also emphasizes the inevitable resistance tactics that workers develop to defend their autonomy in the face of tightening employer control. Rather than control systems unfolding as ever more systematic applications of total power, workers have the ability to resist and, in consequence, potentially reshape the relations of production.

Within systems of rational control, *technical control* has historically been located in the physical and technological aspects of production (Braverman, 1974; Burawoy, 1979), while *bureaucratic control* has relied on standardized rules and roles to guide worker behavior (Blau, 1955; Weber, 1947). These different systems of rational control should be viewed as ideal-types; in practice, models of control frequently overlap, and can be combined in hybrid forms (e.g., Barley & Kunda, 1992; Cardinal, Kreutzer, & Miller, 2017; Sitkin, Cardinal, & Bijlsma-Frankema, 2010).

Technical Control

Scholars have characterized technical control as control that is exercised through organizational

technologies that substitute for the presence of direct supervision. The development of assembly lines in the first half of the twentieth century allowed employers to set a machine-driven pace for workers, changing workers' perception of space in the process by making it harder for them to wander around and chat with co-workers; over time, "the worker became nearly as much locked in place as the machinery" (Edwards, 1979: 114). With technical control, employers accomplish the direction of workers via technologies that drive workers to do particular tasks at a particular rate (e.g., Nussbaum & DuRivage, 1986). These modes of automated production establish specific work directions through task sequencing, specialization, and deskilling (e.g., Braverman, 1974; Burawoy, 1979). Evaluation occurs via the recording of frequency and length of work tasks, and worker productivity, accuracy, response time, and time spent away from the assembly line or computer terminal (Aiello & Svec, 1993; Dworkin, 1990). Discipline is accomplished via the recruitment of a reserve army of secondary workers ready to take the jobs of any primary workers who do not cooperate and comply with employer directives (Edwards 1979).

Scholars have demonstrated that technical control can lead workers to experience alienation because they can be deprived of the right to conceive of themselves as the directors of their own actions (Blauner, 1964). It can also create feelings of constant surveillance that lead workers to police their own behavior to comply with organizational expectations (e.g., Sewell, Barker, & Nyberg, 2012). Workers have resisted technical control by sabotaging the machines and related equipment (Haraszti, 1978; Juravich, 1985; Ramsay, 1966), stealing supplies or time (Anteby, 2008; Stempien, 1984), developing alternative technical procedures (Bensman & Gerver, 1963), collectively withholding effort (Roy 1954, Gouldner 1954), and creating secret social spaces in bathrooms and corridors (Pollert, 1981).

Bureaucratic Control

While technical control is primarily embedded in the technical or physical aspects of the production process, bureaucratic control typically relies on impersonal and formal system of rules, procedures, and roles to guide worker behavior (e.g. Edwards, 1979). Bureaucratic control, which many scholars suggest emerged in the years following the Second World War, is manifested in the organizational structure of the firm, establishing the impersonal force of company policy as the basis for legitimacy (e.g., Blau, 1955; Selznick, 1943). Bureaucratic control achieves direction, evaluation, and discipline differently than does technical control. Here, direction is accomplished through job descriptions, rules (e.g. Weber, 1946; Gouldner, 1956), checklists (e.g., Grol & Grimshaw, 2003; Pronovost & Vohr, 2010), and employee scripts (Moreo 1980). Evaluation is accomplished via direct observation and subjective judgement of supervisors (Vancil, 1982) and through the use of metrics (Govindarajan, 1988). Discipline is accomplished primarily through incentives and penalties; workers who exhibit desired behavior are rewarded with promotions, higher pay, and jobs with greater responsibility, more benefits, better work stations or preferable tasks while those who do not are fired according to rules, policies, or schedules (e.g., Ezzamel & Willmott, 1998; McLoughlin, Badham, & Palmer, 2005).

Bureaucratic control can lead workers to feel as if they are in an iron cage—a technically ordered, rigid, and dehumanized workplace (Weber, 1968). They may experience a loss of individuality, autonomy, and a lack of individual freedom (e.g. Whyte, 1956). In response, workers may use some of the same resistance tactics they use in response to technical control, including work stoppages or strikes (McLoughlin et al., 2005). They may also resist by using humor, cynicism, direct criticism, workarounds, or pro forma compliance (e.g., Bolton, 2004; Gill, 2019; Hodgson, 2004; Lipsky, 2010).

Algorithmic Technologies: Comprehensive, Instantaneous, Interactive, and Opaque

Technological innovation plays an important role in facilitating employers' invention of novel control systems (e.g. Hall, 2010). Over the past decades, the development of algorithmic technologies has allowed employers to transform the exercise of rational control. Algorithms are often defined as computer-programmed procedures for transforming input data into a desired output (Gillespie, 2014: 167;

Barocas et al. 2014). As Dourish (2016) notes, however, "since algorithms arise in practice in relation to other computational forms, such as data structures, they need to be analyzed and understood within those systems of relation that give them meaning and animate them" (see also Christin, 2019; Seaver, 2017; Ziewitz, 2016). In particular, the connections between algorithmic systems and the data they draw upon has become more complex over time. Algorithmic procedures became salient as early as the 1950s, when mainframe computers and computerized systems were first implemented (Hicks, 2017). By the 1980s, they were widely used in workplaces through the development and commercialization of microcomputers and information technologies (Zuboff, 1988). Over recent decades, employers have begun to use algorithms—in particular data-mining and machine-learning algorithms —that are more likely to rely on "big data" characterized by volume (often measured in petabytes and involving tens of millions of observations), variety (the data has widely different formats and structures), and velocity (data can be added in real-time and over a long time frame) (e.g., Zuboff, 2019). Here we report four technological affordances, or potential for social action provided by technological forms (Leonardi & Vaast, 2017; Zammuto, Griffith, Majchrzak, Dougherty, & Faraj, 2007), that are relevant to how employers can use algorithms to interact with managers and workers. Specifically, we describe how algorithmic technologies can be more comprehensive, instantaneous, interactive, and opaque than prior workplace technologies (**Table 1**).

First, algorithms—and the data they process—are now often more *comprehensive* than any kind of technology mobilized for technical or bureaucratic control. Cameras, sensors, and audio devices can now record workers' bodily movements and speech to provide evidence of worker adherence to or departure from production routines (e.g., Austrin & West, 2005; Beane & Orlikowski, 2015; Landay, 2019; Xu, He, & Li, 2014). Accelerometers from smartphones can be analyzed to gauge worker movement (e.g., Clemes, O'Connell, & Edwardson, 2014; Thorp et al., 2012). Biometric and sensor data are being used to verify employee identities, screen for drug and alcohol use, and collect feedback on emotional and physiological indicators in real time (Ball & Margulis, 2011). Text data, video-based recognition techniques, and natural language processing algorithms can monitor email or chat in real-time to assess employee mood, productivity, and turnover intent (e.g., Angrave, Charlwood, Kirkpatrick, Lawrence, & Stuart, 2016; Goldberg, Srivastava, Manian, Monroe, & Potts, 2016; Leonardi & Contractor, 2018; Lix, Goldberg, Srivastava, & Valentine, 2019).

Second, algorithms now typically provide *instantaneous feedback*, which relates to the velocity aspect of Big Data (Jacobs, 2009; Katal, Wazid, & Goudar, 2013). Given the double ability of digital technologies to automate and produce information (Zuboff, 1988), platforms can instantaneously compute, save, and communicate real-time information with workers and managers—including client comments, completion rates, or number of page views (e.g., Etter, Kafsi, Kazemi, Grossglauser, & Thiran, 2013; Mayer-Schönberger & Cukier, 2013; Sachon & Boquet, 2017). As a result, feedback and assessment can be incorporated continuously into the production process (Crowston & Bolici, 2019).

Third, algorithms can promote *interactivity*, especially when used in conjunction with algorithmically-mediated platforms that provide data from multiple parties (Amershi, Cakmak, Knox, & Kulesza, 2014; Cambo & Gergle, 2018; Chalmers & MacColl, 2003). Employers can use algorithmically-powered chat bots to monitor chat channels and interactively prompt groups to pause and take a poll regarding next steps (Zhou, Valentine, & Bernstein, 2018b), or even adjust the team hierarchy and workflow depending on inputted information (Valentine et al., 2017). These interactive changes are made possible by the affordances of platforms, which have powerful computing power "behind the scenes" and interactive interfaces that can be accessed by different categories of people in diverse locations, through individual logins on personal devices (e.g., Holzinger & Jurisica, 2014; Kulesza, Burnett, Wong, & Stumpf, 2015).

Last, algorithms can be *opaque*, for three main reasons: intentional secrecy, required technical literacy, and machine-learning opacity (Burrell, 2016). The data and algorithms used to collect and analyze behavior data are usually proprietary and undisclosed (Orlikowski & Scott, 2014a). In addition, given the complexity of the technologies, most workers do not fully grasp what kind of data is being

collected about them, how it is being used, or how to contest it (Bolin & Andersson Schwarz, 2015). Finally, in the context of machine-learning (e.g., models that perform without using explicit instructions, relying on patterns and inference), algorithms are particularly difficult to decipher (Dietvorst, Simmons, & Massey, 2015; Weld & Bansal, 2018). According to Burrell, "When a computer learns and consequently builds its own representation of a classification decision, it does so without regard for human comprehension…The workings of machine learning algorithms can escape full understanding and interpretation by humans, even for those with specialized training, even for computer scientists" (Burrell, 2016: 10).

ALGORITHMIC CONTROL: THE NEW CONTESTED TERRAIN OF CONTROL

Having reviewed the literature on technical and bureaucratic control mechanisms, and explored the technological affordances of emerging algorithmic technologies, we now develop a model of algorithmic control as the new contested terrain between employers and workers. We draw on Edwards' (1979) typology of managers attempting control by *directing, evaluating*, and *disciplining* workers as a conceptual lens for reviewing the research on algorithms at work. Through this review, we find that employers are using algorithms to control workers through six main mechanisms, which we call the "6 Rs"—they are using algorithms to direct workers by *restricting* and *recommending*, evaluate workers by *recording* and *rating*, and discipline workers by *replacing* and *rewarding*. We identify related worker experiences for each of the "6 Rs."

Rational Control via Algorithmic Direction

Our review suggests that employers are using algorithmic control to direct workers— specify what needs to be done, in what order and time period, and with different degrees of accuracy— in different ways than they do when using technical and bureaucratic control. Under technical control, direction is primarily accomplished via technologies that drive employees to do particular tasks at a particular rate through task sequencing, specialization, and deskilling (e.g., Braverman, 1974; Burawoy, 1979). Under bureaucratic control, direction is accomplished through job descriptions, rules, checklists, and scripts (e.g. Weber, 1946; Blau, 1955). In contrast, under algorithmic control, employers use two key mechanisms to direct worker behavior: algorithmic recommending and algorithmic restricting (**Table 2**).

Algorithmic Recommending. Algorithmic recommending entails employers using algorithms to offer suggestions intended to prompt the targeted worker to make decisions preferred by the choice architect. As with earlier forms of rational control, employers can inscribe technology with prescriptions that prioritize specific decisions for workers to implement *(e.g., Kellogg, 2018)*. Unlike previous regimes of rational control, however, algorithmic recommending often guides worker decisions by automatically finding patterns in the data, often through machine-learning algorithms that operate without using explicit instructions, relying on patterns and inference to present workers with choices and opportunities pre-selected by the algorithm (e.g., Gabrilovich, Dumais, & Horvitz, 2004; Goldman, Little, & Miller, 2011; Karunakaran, 2016). For example, the non-profit organization "Crisis Text Line," which connects people in crisis with volunteer counselors, uses machine-learning algorithms to analyze text data and recommend which messages should be prioritized. Their algorithmic system identified that the term "ibuprofen" was 16 times more likely to predict the need for emergency aid than the word "suicide." Consequently, it automatically prioritized messages containing the word "ibuprofen**,**" which helped to shorten volunteer response time for high-risk texters from 120 seconds to 39 seconds (Gupta, 2018).

In addition, employers are now using algorithmic recommending to *bypass the heuristics workers typically use to make decisions*. For instance, a retail technology company that historically depended on fashion buyers' expertise to make decisions about future merchandising began to data mine the actual performance of past judgements to recommend more profitable future merchandising decisions (Valentine & Hinds, 2019). Similarly, Uber relied on personalized data, such as braking and acceleration speed, to analyze whether workers were driving erratically and algorithmically recommend when they might need

to rest (Rosenblat & Stark, 2016). In many cases, such recommendations came in the form of nudges (Thaler & Sunstein, 2009) that were built into algorithmic systems, and therefore were hard for workers to ignore. For instance, Uber engaged in individualized and real-time nudging to actively compel drivers to go home whenever three passengers in a row reported feeling unsafe (Scheiber, 2017).

While the hope is that algorithms will improve the accuracy and objectivity of managerial decisions (e.g., Brockman, 2019), these forms of algorithmic recommending may negatively affect workers' conditions and livelihoods in several ways. First, workers may be *frustrated when algorithmic recommendations are not intelligible to them.* Take the example of warehouse logistics. Under technical control, employers used recommendation systems that stocked warehouses so that similar items were located close to one another, which frustrated workers when employers' categories differed from the categories of the workers, but which were intelligible to the workers. Algorithmic recommendation systems may exacerbate such worker frustration by relying on more opaque categories. For example, Amazon's algorithmic recommendation system stocked its large warehouses using a 'chaotic storage algorithm' which assigned shelves based on space and availability (Bumbulsky, 2013; Danaher, 2016). Because the algorithmic logic was opaque, workers could not rely on their own cognition to find items for order fulfillment and had no way to find items when the algorithm broke down (Dahaner, 2016). In healthcare settings, this opacity has been shown to increase professionals' doubt and ambiguity regarding their diagnostic decisions (Lebovitz, Lifshitz-Assaf, & Levina, 2019).

Similarly, scholars of bureaucratic control have long shown that bureaucratic recommendation systems can frustrate workers in sales by requiring them to use employer-approved scripts rather than tailoring their sales messages to clients as they saw fit. Pachidi and her colleagues (2019) demonstrate how algorithmic recommendation systems can exacerbate such frustration when scripts become unintelligible to workers. In their study of algorithmic recommending in a telecommunications organization, salespeople were frustrated not only because they were expected to model their behavior based on recommendations provided by their employers, but also because the machine learning model built into the algorithmic system did not allow them to see what the recommendations were based on. Because their compensation depended on commissions, and because the recommendations often conflicted with the salespeople's own judgements about which customers were the best targets, workers only symbolically complied with the recommendations. This led to conflict between the salespeople and their employers; employers ultimately chose to fire many of the salespeople in response. Similarly, Christin (2017) shows that judges and prosecutors resented the opacity of predictive algorithms called risk-assessment tools, because they found them to be unintelligible.

Second, algorithmic recommending has the potential to *negatively affect the welfare of those being nudged.* For example, Rosenblat and Stark (2016) describe how Uber's algorithmic recommendation system did not let drivers see where a passenger was going before accepting the ride, making it hard to judge how profitable a trip would be. Similarly, scholars showed that surge pricing was billed by Uber as a means to ensure positive customer experience by attracting supply to an area of high demand, but that these surges and the attendant rates were often erratic and unreliable (Lee, Kusbit, Metsky, & Dabbish, 2015). In many cases, algorithmic nudges were not easily opted out of. For instance, Uber and Lyft both used an algorithm called "forward dispatch" that dispatched the next ride to a driver before the current one ended. While drivers could pause the services' automatic queuing feature, once they logged back in and accepted their next ride, the feature restarted. As a result, workers reported feeling powerless (Leicht-Deobald et al., 2019). Beunza (2019) suggests that, when workers are directed by an algorithm that they perceive as unfair, this may undermine their moral compass and increase their willingness to engage in unethical behavior.

Third, *social and racial inequalities may be reinforced* because algorithms may direct workers' attention to particular inferences and classes of people in ways that may be biased (Angwin, Larson, Mattu, & Kirchner, 2016; Harcourt, 2007). In the current literature, the lack of counterfactuals means that it is not clear if and when these new processes are worse or better than the older processes. Yet, some scholars have raised concerns that, when the algorithms' training data (e.g., the data used to allow the machine-learning algorithm to find patterns between inputs and outcomes) are biased, it can lead to

discriminatory models (Barocas & Selbst, 2016; O'Neil, 2016). Training data can be biased in two main ways. First, historical data can reflect existing patterns of inequality and discrimination. For example, Angwin et al. (2016) compared the recidivism rates predicted by the risk-assessment tools used in criminal justice with the rate that actually occurred over a two-year period. Because the algorithm had learned from cases in which structural discrimination had played a role, it flagged African-American defendants as higher risk, with higher rates of false positives, than comparable white defendants, even though the algorithm was correctly calibrated regarding true positives for African-American and white defendants (Corbett-Davies, Pierson, Feller, Goel, & Huq, 2017). Second, algorithms can draw inferences from a biased sample of the population. In such a case, any decision that rests on these inferences may systematically disadvantage those who are under- or over-represented in the dataset. For example, Brayne (2017) details how police organizations used 'predictive policing' algorithms to identify 'high risk' individuals and places, and used these to direct enforcement officials' inspection priorities. By devoting a large share of their attention to monitoring the activities of individuals belonging to protected classes, police officers observed potential issues for these individuals at systematically higher rates than for other individuals who did not face the same degree of scrutiny.

   Algorithmic Restricting. Algorithmic restricting is another mechanism that employers are using to direct the work of workers. It entails the use of algorithms to display only certain information and allow specific behaviors while preventing others. As with earlier forms of rational control, employers can inscribe algorithms with assumptions and prescriptions that restrict the activities of workers (e.g., Callaghan & Thompson, 2001).

   Unlike past forms of rational control, however, algorithmic control allows the restriction of information to be incorporated *instantaneously and covertly* into the work process. For example, platform organizations such as Uber used algorithms to narrow shift choices, ride choices, or delivery choices in order to smooth service offerings (Calo & Rosenblat, 2017; Lee et al., 2015). Similarly, a hospital employer used algorithms for real-time restriction of the loading requests of pharmacy assistants' robots (for replenishment of stock in its storage) in order to benefit clients waiting for prescription refills, despite the fact that this intensified the work of the pharmacy assistants (Barrett et al., 2012). Along these same lines, in order to discourage workers from working with clients off of the platform, Upwork used algorithmically-powered chat bot warnings reminding workers of their agreement to not work outside of the platform when certain words such as skype, phone, or email were typed into the chat between workers and clients; Upwork sent similar messages when workers shared email addresses or phone numbers with clients, or suggested using other cloud sharing platforms like Google Drive or Dropbox (Jarrahi, Sutherland, Nelson, & Sawyer, 2019).

   In addition, employers can use algorithms to *interactively restrict the behavior of crowds or online community members*. Algorithmic systems can be configured to constrain the activities of people who are not formally affiliated with the organization, but still provide work that is relevant to the organization. When firms use crowds through online platforms for innovation, they often limit the crowds' participation in order to facilitate the selection and integration of innovative solutions. For example, in crowdsourcing initiatives like TopCoder and Kaggle, managers used algorithmic restricting to limit and curate submissions for quality and relevance when they made open calls on the platforms (Afuah & Tucci, 2012; Lakhani, 2016). To mitigate organizational and professional barriers to adoption of crowdsourced solutions (Fayard, Gkeredakis, & Levina, 2016; Lifshitz-Assaf, 2018), employers have created algorithms to evaluate the crowd-based solutions (Kittur et al., 2019). Firms also utilize algorithmic restricting on online platforms used for participatory production, where customers produce and share content as they consume it (e.g., Faraj, Jarvenpaa, & Majchrzak, 2011; Karunakaran, 2018). For example, in journalism, managers have used algorithms in combination with social media platforms to invite the crowd to create content for news articles, but have restricted submissions in ways that increased compliance with existing standards (Muthukumaraswamy, 2010). Similarly, an advertising agency enlisted social media users to create and distribute content related to the brands that the agency represented, while at the same time strategically eliciting specific kinds of participation (Truelove, 2019). Organizations such as TripAdvisor, Wikipedia, and PatientsLikeMe, which have depended completely on external contributors for their

content, have faced particular challenges since they have needed to strike a balance between restricting the behavior of external contributors, on the one hand, while giving them enough freedom that they were willing to contribute content, on the other (Arazy, Daxenberger, Lifshitz-Assaf, Nov, & Gurevych, 2016; Barrett, Oborn, & Orlikowski, 2016; Kallinikos & Tempini, 2014; Orlikowski & Scott, 2014b; Tempini, 2015).

These forms of restriction come with important consequences for workers. As with technical control, workers often experience alienation with algorithmic restricting when they lose control over their own labor and are deprived of the right to conceive of themselves as directors of their own actions (Blauner, 1964). However, algorithmic restricting can *limit worker voice more extensively* than before. Askay (2015) shows how an online feedback system that interactively combined workers' experiences and ratings suppressed their expressions of negative feedback, which did not fit into the data collection interface. The ratings were known to be positively biased, which helped the company, but limited workers' feedback, which had to fit into the existing interface. Similar restrictions on communication are imposed in online labor markets. As Gray and Suri (2019) explain, "the API determines the dialogue and communication between the programmer and the worker. The API gives each individual requester and worker their own unique identifier, a string of seemingly random letters and numbers such as 'A16HE9ETNPNONN.'" Hidden behind such anonymized handles and restrictive interfaces, workers were prevented from communicating with each other on the platform, and from communicating with the requesters. These restrictions often prevented workers from ever speaking directly with a human manager (Martin, Hanrahan, O'Neill, & Gupta, 2014; Rosenblat & Stark, 2016; Salehi et al., 2015).

Algorithmic restricting can also increase *precarity for workers*. Algorithmically-mediated platforms can fragment workers' efforts in several, interconnected ways. First, on-demand workers are currently categorized as independent contractors, or "users" of the platforms, rather than employees (Rosenblat & Stark, 2016; Vallas, 2019; Vallas & Kovalainen, 2019). Second, jobs are frequently broken down into discrete or even "micro" tasks, which can be scheduled in finely-grained, opaque, and unpredictable ways. For example, food-delivery platforms restricted information about available shifts and delivery orders, so drivers were only able to choose from among the choices presented to them by the algorithmic interfaces, without fully grasping what kind of information was being restricted (Ivanova, Bronowicka, Kocher, & Degner, 2018). Workers on the Upwork platform who did not work for 30 days had their profile status changed to private so that clients could not find them (Jarrahi et al., 2019). And, on the Amazon Mechanical Turk platform, "requesters" (e.g., employers) could rate workers but workers could not rate requesters; this information asymmetry made it difficult for workers to sanction abusive clients, and prevented other workers from learning which clients to avoid (Martin et al., 2014).

Rational Control via Algorithmic Evaluation

Employers obtain desired behavior from workers not only through direction but also through *evaluation*— the review of workers' activities to correct mistakes, assess performance, and identify those who are not performing adequately. Our review of the literature on algorithms at work suggests that algorithmic control uses different mechanisms for evaluation than do technical and bureaucratic control. With technical control, evaluation occurs via the recording of frequency and length of work tasks, and worker productivity, accuracy, response time, and time spent away from the assembly line or computer terminal (Aiello & Svec, 1993; Dworkin, 1990). With bureaucratic control, evaluation is accomplished via direct observation and subjective judgement of supervisors (Vancil, 1982) and through the use of metrics (Govindarajan, 1988). With algorithmic control, employers use two primary mechanisms for evaluating workers: algorithmic recording and algorithmic rating (**Table 3**).

Algorithmic Recording. Algorithmic recording entails the use of computational procedures to monitor, aggregate, and report, often in real time, a wide range of finely-grained data from internal and external sources. As with earlier forms of rational control, employers typically use the data to quantify,

compare, and evaluate worker output regarding the frequency and length of work tasks, quality of worker output, and non-productive work time (e.g., Alvesson & Karreman, 2007; Vancil, 1982). Consequently, there is often an asymmetry between the information possessed by workers and managers (Zuboff, 1988).

Yet employers frequently use algorithmic recording to *track a wider range of worker behaviors* than in technical and bureaucratic systems. For example, some organizations have developed algorithms to monitor collective language and analyze sentiments in team chat interfaces (Lix et al., 2019). Klick Health, a large Canadian healthcare consulting firm, used a machine learning tool to calculate the average time it took workers to complete a variety of tasks and to alert managers when projects appeared to be going off-track (Schweyer, 2018). The organization tracked the activities of employees to flag and reduce distractions that may have impacted worker flow and productivity (Segal, Goldstein, Goldman, & Harfoush, 2014). Many companies have also used algorithmic recording to analyze how employees communicate with one other, using these data to "locate groups of employees who interact frequently, link employee communication groups to their business productivity, identify communication liaisons and isolates, and spot communication that may threaten the company" (Leonardi & Contractor, 2018; Watkins Allen, Coopman, Hart, & Walker, 2007: 173).

The development of comprehensive procedures of data-gathering has led to new modalities of surveillance. For instance, Uber relied on the data provided by its application—installed on drivers' and customers' smartphones—to monitor not only the behavior of individual drivers but also to manage its drivers and customer base as a whole (Rosenblat & Stark, 2016). In the trucking industry, employers have used fleet management systems to monitor a wide range of timekeeping and performance data about truck drivers, including a driver's fuel efficiency, idling time, speed, geolocation, lane departures, braking and acceleration patterns, cargo status, and vehicle maintenance information (Levy, 2015: 164). Similarly, UPS had a saying of "small amounts of time, large amounts of money" because they learned that, by using finely-grained data, they could reduce even "one keystroke per driver per day" which over a year saved the company $100,000; saving each driver one minute per day could save almost $15 million (Davidson, 2016).

In addition, as with bureaucratic control, managers are using algorithmic recording to provide feedback to workers. However, compared to bureaucratic control, which relies on subjective evaluations months after the directed behavior to reward or discipline workers (Alvesson & Karreman, 2007), algorithmic recording uses computational procedures to provide *real-time feedback* to workers and managers. In a large warehouse fulfillment services organization, employees and managers received real-time information throughout the day showing whether and how they were meeting their targets (McClelland, 2012). A handheld scanner program measured finely-grained worker behaviors like being late or searching through a bin where the correct item was not found, and calculated a worker score based on these data; if a worker's score was consistently lower than expected, this triggered an alert for a manager to redirect the worker (McClelland, 2012). Similarly, employer platforms like Upwork have used real-time metrics to monitor workers, including variables such as "up-to-date availability" and "100% complete worker profile," as well as data about the freelancers' activity on the platform in the past 90 days (Rahman, 2019). Uber used real-time geolocation information to optimize the matching of drivers and customers and to track the percentage of cancelled trips and unaccepted trip requests for each driver. Uber's system identified predicted areas of surge pricing, and alerted drivers through notifications (Rosenblat & Stark, 2016).

Regarding worker consequences, like with technical control via recording, algorithmic recording can shape the subjectivity of workers so that they come to see themselves in the ways they are defined through surveillance (Sewell, 1998). Feelings of constant surveillance, in turn, can lead workers to police their own behavior to comply with organizational expectations (Ahmed et al., 2016; Bailey, Erickson, Silbey, & Teasley, 2019). Making the output of algorithmic recording visible to other workers may also lead workers to change their behavior to match their peers (Lehdonvirta, Kässi, Hjorth, Barnard, & Graham, 2019). Unlike previous forms of recording under technical and bureaucratic control, however, since algorithmic recording greatly expands previous control mechanisms in scope and frequency, workers may experience a *loss of privacy* (Anteby & Chan, 2018; Fourcade & Healy, 2016; Rosenblat &

Stark, 2016; Tufekci, 2014). The data collected may relate to multiple aspects of the employee as a person—including their overall aptitude in various skills and settings, their physical and mental health, their reproductive plans, or even what they had for breakfast (Bock, 2015). This surveillance can extend control beyond work hours, as some employers have given workers wearable devices that rewarded lifestyle choices such as exercise and sleep (O'Connor, 2015).

Algorithmic recording may also raise worker *concerns about the accuracy of the data collected*. For example, in the context of drug testing, false positives can deprive workers of their jobs and tarnish their reputations for future opportunities. This is problematic given the fact that algorithmic recording can—like previous forms of recording—be inaccurate or biased (Angwin, 2014; boyd & Crawford, 2012; Miller, 2015; O'Neil 2016; Eubanks 2017). In larger data pools, however, bias and inaccuracies may be harder to check than before: it can be difficult to reverse engineer the data, or to cross-compare it with related indicia in order to ensure its accuracy (Bodie et al., 2017). Because workers may not be aware of the data being collected about their behavior and performance, they may not be able to appeal judgments against them or correct missing or mistaken information.

Algorithmic Rating. Algorithmic rating is another mechanism for guiding worker behavior through evaluation. Managers are now often using computational technologies to gather ratings and rankings to calculate some measure of workers' performance, as well as predictive analytics to predict measures of their future performance. As with earlier forms of rational control, managers draw on a mix of quantitative and qualitative data collected inside the organization to measure productivity and evaluate workers against those measures (e.g. Alvesson & Karreman, 2004). Yet algorithmic rating can also provide *ongoing aggregation of quantitative and qualitative feedback* about worker performance *from both internal and external sources*. For instance, most online marketplaces and online labor markets such as Amazon, Craigslist, Upwork (Rahman, 2018), Ebay (Curchod et al., 2019), Uber, and Lyft, (Rosenblat, 2018), AirBnb (Jharver et al., 2018), and TripAdvisor (Orlikowski & Scott, 2014) and most online health communities (Barrett, Oborn, & Orlikowski, 2016), have used user-generated rating systems. One company assigned contractors a single "kharma" rating based on manager, peer, and client ratings of their work, skills, and personality and on their objective compliance with budgets and deadlines; workers who had higher scores got better access to additional projects (Lix & Valentine, 2019). In web journalism, many newsrooms used data including ratings produced by content management systems and analytics software programs to track the preferences of online readers in order to manage their staffers' workflow (Christin, 2018). In the restaurant and hospitality industry, crowdsourced platforms such as Yelp and TripAdvisor provided managers with an ongoing flow of crowdsourced data about worker behavior. Customers could review restaurants and hotels through ratings in a range of categories (value, service, room quality, etc.); they could also post comments and pictures on the aggregator's website. This ongoing flow of ratings was routinely used by managers to monitor the performance of their staff (Orlikowski & Scott, 2014a). All of these developments contribute to the institutionalization of "refractive surveillance" (Levy & Barocas, 2018), in which data such as ratings that are recorded about external users (e.g., customers) can be repurposed to assess internal sources (e.g., workers).

In addition, and in contrast to past forms of technical and bureaucratic control, employers can use algorithms to *predict how workers are likely to perform in the future*. For example, one consulting firm used algorithmic rating to predict turnover intention, identifying "high-flight risk" individuals who were likely to leave the company (King, 2016). Another company deployed algorithms to predict the expertise of their employees using data from both their enterprise systems (resumes, explicit assessments of employee expertise, job position histories, and footprints of employees' work activities such as sales pipeline, software documentation, and publications) and from their corporate social networking site (Horesh, Varshney, & Yi, 2016; Varshney et al., 2014). Studies have used algorithmic rating models to predict the need for employee upskilling based on a mismatch between employee skills and their current job demands (Ramamurthy et al., 2015), and to predict the potential for employees to achieve performance targets based on historical data about the employees' achievement orientation, adaptability, analytical thinking, communication, and information seeking (Mallafi & Widyantoro, 2016).

Algorithmic rating comes with several important consequences for workers. First, similar to algorithmic recommending, algorithmic rating raises important concerns about *discriminatory outcomes*. Algorithmic rating can be subject to gender and race stereotyping (Greenwood, Adjerid, & Angst, 2017; Levy & Barocas, 2017; Rosenblat, Levy, Barocas, & Hwang, 2017). For example, in the case of credit scoring, low credit scores were more likely to lead to negative hiring and salary-related outcomes for female (versus male) and black (versus white) job applicants (O'Brien & Kiviat, 2018). With algorithmic rating, however, online customers (instead of managers) also often act as raters, with implications for evaluations. Customers have been shown to discriminate in online labor markets (Chan & Wang, 2018; Edelman, Luca, & Svirsky, 2017). But they may not be held accountable for their ratings in the way a manager in an ongoing employment relation would be. Workers also have fewer mechanisms for contesting unfair evaluations (Rosenblat et al., 2017; Rosenblat & Stark, 2016). Overall, the legal status of algorithmic rating in connection to discrimination remains unclear. While companies are currently prohibited from making employment-related decisions based on workers' protected characteristics under Title VII of the Civil Rights Act of 1964, consumer ratings may escape legal action because they fall under the "business necessity" argument (Rosenblat et al., 2017; Rosenblat & Stark, 2016).

In addition, in comparison to bureaucratic rating, *algorithmic rating carries extreme weight in hiring decisions*. Some online labor platforms have used algorithms to restrict access to jobs for contractors with low ratings (Wood, Graham, Lehdonvirta, & Hjorth, 2019). In addition, algorithmic ratings are often much more public than past forms of rating (e.g. Curchod et al., 2019). They also can be volatile because they can dynamically draw from multiple data sources, update frequently, and automatically deny access even based on small variations in rating. They also may be accidental or erroneous (Wood & Lehdonvirta, 2019). Both in online marketplaces (e.g., AirBnB, Amazon, Craigslist, and Ebay) and online labor markets (e.g., UpWork, Uber, Lyft, Care.com), employers and customers have been shown to select workers primarily based on prior ratings and to communicate with workers primarily via online tools that do not allow in-person assessments of workers rather than via face-to-face interviews (Chan & Wang, 2018; Rahman & Valentine, 2017). Consequently, algorithmic ratings have become an essential reputational asset for workers. In the words of a freelancer on UpWork, ratings are "our billboard, it is our PR megaphone, it is the front door to our shop" (Rahman 2019: 21). From ride-sharing to care work platforms, good algorithmic ratings ensure the visibility of online workers, which in turn shapes their ability to find work. For instance, on Care.com, algorithmic ratings have been used to create different categories of workers: the label "CarePros" indicated that workers maintained a high star rating and responded to 75% of messages within 24 hours (Ticona & Mateescu, 2018: 4395). "CarePros" workers' profiles were more prominently displayed on the platform, which increased their likelihood of future employment.

Rational Control via Algorithmic Discipline

Finally, employers obtain desired behavior from workers through *discipline*—the punishment and reward of workers in order to elicit cooperation and enforce compliance. Our review of the literature on algorithms at work suggests that employers using algorithmic control use different mechanisms for discipline than they do when using technical and bureaucratic control. With technical control, discipline is accomplished via the recruitment of a reserve army of secondary workers ready to take the jobs of any primary workers who do not cooperate and comply with employer directives (Edwards, 1979). With bureaucratic control, discipline is accomplished primarily through incentives and penalties; workers who exhibit desired behavior are rewarded with promotions, higher pay, and jobs with greater responsibility, more benefits, better work stations or preferable tasks while those who do not are fired according to rules, policies, or schedules (Ezzamel & Willmott, 1998; McLoughlin et al., 2005). With algorithmic control, employers use two main mechanisms for disciplining workers: algorithmic replacing and rewarding (**Table 4**).

__Algorithmic Replacing.__ Algorithmic replacing entails rapidly or even automatically firing underperforming workers from the organization, and replacing them with substitute workers. While others have addressed the macro-economic changes associated with replacement of jobs by algorithms (Arntz, Gregory, & Zierahn, 2016; Autor, 2015a; Autor, 2015b; Brynjolfsson & McAfee, 2014; Davenport & Kirby, 2016; Ekbia & Nardi, 2017; Elliott, 2014; Frey & Osborne, 2017; Mindell, 2015; Mokyr, Vickers, & Ziebarth, 2015; Sachs & Kotlikoff, 2012; Shestakofsky, 2017), we examine algorithmic replacement at the workplace level with a focus on how it can be used by employers as a mechanism of control.

As with past forms of replacing, algorithmic replacing is accomplished by accessing a reserve army of workers ready to take the jobs of those who do not comply with managerial directives. That said, algorithmic replacing differs from past forms of control in two main ways. First, *market-making platforms can automatically kick workers off the platform if their ratings drop below a certain level* (Rosenblat & Stark, 2016). On platforms such as Amazon Mechanical Turk (Irani, 2015), Uber (Rosenblat & Stark, 2016) and Caviar (Shapiro, 2018), workers who did not comply with directives were either banned from the platform or punished by making their profiles extremely difficult to find. For example, Upwork workers who were regularly submitting proposals but not winning projects had their freelance accounts closed (Jarrahi et al., 2019). Uber drivers were instantly penalized for rejecting orders or not following detailed guidelines provided by complex feedback systems (Cherry & Aloisi, 2018; De Stefano, 2015). Drivers with a low average passenger rating and acceptance rate were subject to immediate deactivation on ridesharing platforms (Lee et al., 2015; Rosenblat & Stark, 2016).

Second, in contrast to past forms of technical and bureaucratic control, *organizations can recruit workers on a greater scale and in a fraction of the time recruiting used to take* (Kittur et al., 2013; Sundararajan, 2016; Valentine et al., 2017). In terms of the scope at which workers can be replaced, algorithmic replacement can be more far-reaching, especially on on-demand platforms, which allow for the recruiting of workers globally as well as up and down the occupational hierarchy (Aneesh, 2009; Kittur, Smus, Khamkar, & Kraut, 2011; Retelny et al., 2014; Valentine et al., 2017). Rather than relying on managers to recruit workers, predictive analytics can also be built into hiring tools so that replacement is accomplished more quickly than in the past (Valentine et al., 2017). For example, employers have used hiring platforms such as Equifax, Kronos, SnagaJob, and Recruit that require workers to submit their work history, identification information, and schedule availability; workers needed to agree to do background checks and participate in lengthy personality and skill assessments so that the algorithmic software could automatically process and sort applicants according to employer criteria (Ajunwa & Greene, 2018). Algorithms can also be used to replace highly skilled workers (Beunza & Millo, 2015; Borch & Lange, 2016; Lange, Lenglet, & Seyfert, 2016; Lenglet, 2011; Lenglet & Mol, 2016; MacKenzie, 2018). For instance, recruiters using LinkedIn could enter search criteria including one or several examples of ideal candidates for the position (e.g. existing members of the team), instead of needing to construct complicated queries describing hiring criteria; LinkedIn automatically built a query from the ideal candidates and then retrieved and ranked results for recruiters (Ha-Thuc et al., 2016). Finally, algorithms can be used to recruit workers in thin labor markets (Jackson, 2019). For instance, platforms dedicated to the recruitment of under-represented candidates (e.g. women and racial minorities) can help companies find high quality, high skill workers faster and more efficiently than the traditional recruiting model.

In comparison to technical replacement, algorithmic replacement can result in greater *precarity for less skilled workers* (Aneesh, 2009; Kittur et al., 2011; Retelny et al., 2014; Valentine et al., 2017). Workers currently employed by organizations using platforms like Upwork and AMT could have their work outsourced at any time (Barley et al., 2017). Even traditional organizations have been shown to use platforms such as these to source on-demand work directly from freelancers, creating the threat of immediate replacement for existing workers (Corporaal & Lehdonvirta, 2017; Howe, 2006; Schenk & Guittard, 2011). Workers have limited options for dissent because the global supply of workers is high and because there are currently three times as many contractors as clients on many labor market platforms (Bergvall-Kåreborn & Howcroft, 2014; Graham, Hjorth, & Lehdonvirta, 2017; Irani & Silberman, 2013). Many platforms treat workers interchangeably, and platforms can often sustain losing those who do

not accept the system's terms (Kleemann, Voß, & Rieder, 2008; Postigo, 2016). However, Wood and colleagues (2018) note that worker outcomes on these platforms are divergent according to type of worker—workers with specialized skills may gain even more opportunities, while workers with fewer skills become even more powerless.

Algorithmic Rewarding. Algorithmic rewarding is another mechanism used by managers to discipline worker behavior. It entails using algorithms to interactively and dynamically reward high performing workers with more opportunities, higher pay, and promotions. As with past forms of technical and bureaucratic control, algorithmic rewarding uses professional and material incentives to guide worker behavior.

Algorithmic rewarding systems can also *provide rewards and penalties in real time,* for behaviors that comply with predefined correct behaviors. For example, Beunza (2019) described how an algorithmic system encoded with a set of formal rules rewarded specialists who followed its rules with additional stock listings. Algorithmic tools are also being used to differentiate the performance of workers by department, who then receive differential rewards (Kim, 2018; Liu, Huang, & Zhang, 2018b; Payne, 2018). In platform labor markets such as Amazon Mechanical Turk (Irani, 2015), Uber (Rosenblat & Stark, 2016), Caviar (Shapiro, 2018), and others (Rahman, 2019), workers who complied with algorithmic assignments were immediately rewarded with more work, higher pay, and increased flexibility. In particular, managers have often used algorithmic rewarding to enhance one of the gig economy's main selling points—work-shift flexibility and worker self-determination in scheduling (Ivanova et al., 2018). For instance, Amazon Mechanical Turk's reward structure utilized finely-grained contingent payment: while the great majority of tasks provided modest rewards—amounting to $1–2/hour on average—a small fraction of tasks provided much more, sometimes as much as $10-$20/hour. These 'jackpot' tasks appeared only occasionally and tended to be quickly taken. Workers could thus gamble with their time, foregoing modest but certain rewards for a chance to earn bigger rewards (Lehdonvirta, 2018).

Like previous forms of control, managers may allow workers to game algorithmic rewards as a way to "manufacture consent" (Burawoy, 1979; Roy 1959). Yet, in contrast to past systems of control, algorithmic control can explicitly rely on the managerially-imposed *gamification of rewards* to make the affective experience of work more positive and "fun" for employees (Deterding, Khaled, Nacke, & Dixon, 2011; Edery & Mollick, 2009; Mollick & Rothbard, 2014a; Petre, 2018; Walz & Deterding, 2014). Nike, Google, Microsoft, Deloitte, Amazon, Samsung, Target, Disney, and many other large corporations have embedded the methods of game design in their day-to-day business processes (Kim, 2018). They have relied on smartphone-based apps, scoreboards, and video/app game elements such as digital points and badges to promote the structure, look, and feel of a designed game with the intent of advancing employer goals (Liu et al., 2018b; Stanculescu, Bozzon, Sips, & Houben, 2016). For example, one employer used a basketball-themed game to algorithmically reward its salespeople for closing deals with customers: warm leads counted as "layups" while cold calls were "jump shots," and large display screens throughout the office floor showed basketball-based animations tracking the game status (Mollick & Rothbard, 2014).

Gamification can also be used to encourage unremunerated work by both external and internal workers (Edery & Mollick, 2009). For example, Google used the ESP game, which matches two players to compete against one another, to motivate external workers to label online images for free (Von Ahn, Maurer, McMillen, Abraham, & Blum, 2008). Similarly, Lloyds TSB bank employed virtual stock market games to encourage bankers to develop and submit innovation proposals (Mollick & Werbach, 2015), and IBM added points- and levels-based virtual reward systems to motivate employees to contribute to its internal knowledge management system (Farzan et al., 2008). U.S. hospitals have also used gamification to motivate surgical trainees to spend more practice hours on a simulator in order to improve their skill level in minimally invasive surgeries (Kerfoot & Kissane, 2014).

In comparison to bureaucratic rewarding, algorithmic rewarding through gamification may *compromise workers' capacity to deliberatively set moral and practical limits for their labor*.

Ranganathan and Benson (2017) demonstrate that RFID monitoring technologies that quantify output in real time can elicit "accidental gamification" for workers. Gamification may also manufacture consent by subtly transforming games from employee-generated spontaneous play into managerially-imposed, 'mandatory fun' (Mollick & Rothbard, 2014b). These dynamics have led Bogost (2015) to argue that gamification is an exploitative digital work motivation control system.

Algorithmic rewarding can also create *greater experiences of frustration and stress* for workers, for two main reasons: the intentional secrecy of the rewarding system and the rapid responsiveness of the rewards. Workers on labor market platforms often expressed suspicion and frustration about opaque and unclear guidelines regarding accessing and being paid for work (Martin et al., 2014; Rahman, 2019). Many online platforms have been shown to keep their rating and rewarding algorithms secret in order to discourage manipulation and ratings inflation. For instance, a prominent high-skilled online labor market switched its rating from a transparent star system to an opaque system: suddenly, workers had little to no insight about what they were being rated on, how exactly the ratings were used, why they were guaranteed pay at some times and not others, and why their designs were sometimes rejected (Dourish, 2016; Rahman, 2019; Raval & Dourish, 2016). In addition, when employer payment algorithms changed wages rapidly (Lee et al., 2015; Shapiro, 2018), workers often did not know why they were experiencing the pay changes and had limited recourse to find out (Rahman, 2017; Raval & Dourish, 2016; Schwartz, 2018b). Algorithms may also prevent contact with human managers. When an algorithm, instead of a person, is on the other side of a managerial relationship, it can create an additional obstacle for workers to question or challenge the directions they are given or have a say in the labor process (Graham et al., 2017; Irani & Silberman, 2013).

ALGORITHMIC CONTROL AS THE NEW CONTESTED TERRAIN OF CONTROL: INSIGHTS AND RESEARCH AGENDA

Our review above identified specific ways that employers have used algorithms to control worker behavior. Most generally, we see that algorithmic control plays out familiar themes from labor process theory around managers using technological systems to pursue economic value and increase their control over workers. In this section, we elaborate four key insights about how algorithmic control is a *new contested terrain of rational control* (see **Figure 2**). We discuss 1) how labor process theory helps to problematize the predominant research focus to date on the economic value of algorithms; 2) how algorithmic technologies facilitate employers' constant reconfiguring of control systems, ushering in a novel form of rational control that is distinct from the technical and bureaucratic control used by employers for the past century; 3) how algorithmic occupations represent an emerging landscape for the control-resistance dialectic; and 4) how what we call "algoactivism" tactics allow for individual and collective resistance of algorithmic control. Taken together, these themes reveal the contested terrain of algorithmic control and chart an agenda for future research.

Problematizing the Predominant Research Focus on the Economic Value of Algorithms

Our first insight related to algorithmic control is a problematization of the existing research focus on the economic value of algorithmic systems. To date, most of the research on algorithms in organizational strategy, economics, information systems, and human-computer interaction has emphasized how algorithms can facilitate and improve decision-making, coordination, and learning. In this view, algorithmic systems allow actors to optimize organizational and economic goals. Our application of a labor process perspective makes three distinct contributions.

Algorithmic Systems as Contested Instruments of Control. Applying a labor process perspective to the dominant understanding of algorithms draws attention to the structurally antagonistic character of employer-worker relations. It allows us to understand algorithmic systems not as neutral tools that facilitate efficiency and improve communication exchanges, but as contested instruments of control that

carry specific ideological preferences (Winner, 1980). In this view, algorithmic systems are not merely encoded with technical information embedded through rules and routines; instead, algorithms are often created and implemented based on the interests of powerful actors. As such, algorithmic systems tend to give employers disproportionate access to key resources in the workplace.

Mechanism for Action: Obscuring and Securing Surplus Value. Our application of Edwards' framework of direction, evaluation, and discipline reveals how employers may use algorithms to secure a share of capital from workers' exertions while obscuring their methods for doing so; this may, in turn, help to prevent or stall worker contestation. According to labor process theory, due to the relative autonomy of the labor process, a key challenge for employers is the activation of labor effort. Employers often want to keep the share of capital that labor receives low, yet also seeks to secure this surplus value with minimal conflict (e.g. Burawoy, 1979). Employers can use algorithms to obscure how they extract surplus value from workers and divert workers' attention from the actual distribution of gains to less contentious objects (e.g., Chai and Scully, 2019).

In this view, information asymmetries are not random: instead, they are deliberately created by employers to constrain workers' choices and control workers' ability to contest the distribution of surplus value (e.g., Felstiner, 2011; Howcroft and Bergvall-Kåreborn, 2019). The opaque nature of algorithmic control can allow employers to track what workers are doing, but limit workers' understanding of employers' strategies. When employers perpetuate the narrative that algorithmic control systems are fully automated, they may be deliberately underplaying their role in calibrating and intervening in the systems' architecture, nudges, and sanctions; this invisibility may make it harder for workers to find a relevant target for contestation (e.g., Lee et al., 2015; Rosenblat, 2018; Veen et al., 2019).

Important Outcomes: Worker Experiences and Livelihoods. A labor process perspective on algorithms at work also draws attention to employees' working conditions and livelihoods. Scholars of organizational strategy, economics, information systems, and human-computer interaction have primarily focused on the efficiency and organizational goal attainment made possible by the use of algorithmic systems, but have largely ignored the topic of how employers' use of algorithms may negatively affect workers. In fact, when studies in these literatures have addressed worker experiences, they have frequently emphasized primarily the positive worker outcomes associated with the use algorithmic systems, highlighting how this use may enable geographically dispersed people to come together (Brabham, 2013), give workers high levels of flexibility and autonomy (McAfee and Brynjolfsson, 2017), create better matching between the supply and demand of worker skills (Kittur, et al., 2013), and heighten inclusivity by offering better opportunities to workers whose availability or mobility prevents them from working regular hours (Valenduc and Vendramin, 2016).

Our use of labor process theory leads us to highlight some of the negative effects that algorithmic control may have on workers (see also Chai & Scully, 2018; Griesbach, Reich, Elliott-Negri, & Milkman, 2019; Vallas, 2019; Vallas & Kovalainen, 2019). For example, platform workers may become hypervigilant, spending many hours sorting through tasks and being on call day and night, because most microtask platforms only allow workers to pick up jobs on a first-come first-served basis (Gray and Suri, 2019). In addition, workers on these platforms can lose their jobs and wages, with no explanation and no opportunity to appeal the cancellation of their accounts (Martin et al., 2016; Rahman, 2018). Labor precarity for low-skilled workers can increase when recruitment is global and instantaneous (Brooks, 2012; Cherry, 2015). Finally, while platforms may afford workers high levels of flexibility, autonomy, and task variety, these benefits are often coupled with low pay, social isolation, irregular work hours, and exhaustion (Wood et al., 2019).

Variation Across Organizations and Individuals. Yet, while a labor process perspective draws attention to how algorithmic control can result in negative outcomes for workers, studies have also shown that there is variation in worker outcomes across organizations and individuals (Christin, 2017; Griesbach et al., 2019; Lehdonvirta, 2018). Organizations can facilitate more positive outcomes for workers both through informal managerial practices and through formal structuring of the work process. For example, regarding informal managerial practices, Kessinger and Kellogg (2019) demonstrate how managers in a digital marketing agency softened the edges of algorithmic evaluation by engaging in relational work with

employees who were subject to algorithmic recording; this reduced employee stress and encouraged employee learning.

Regarding formal structuring of the work process, Lehdonvirta (2018) shows how three microwork platforms deployed different algorithmic control regimes despite offering similar types of work. While MTurk was fashioned as a task marketplace where unbridled competition between workers resulted in workers having to be constantly on call, CloudFactory was designed after a more orderly 'assembly line' image, applying technical controls on workers' task throughput. This reduced competition between workers and allowed them to choose their working hours more freely. In another example of deliberate structuring of the work process, Windwehr, Corporaal, and Lehdonvirta (2019) demonstrate that employers can use algorithmic technologies to create a predictable and explicit means for workers to engage in internal dispute resolution; they detail how employers using relationship-driven dispute resolution and prevention practices can actually demonstrate less adherence to due process criteria than do employers using algorithmic technologies. Gray and colleagues highlight several other ways that employers can structure the work process to facilitate more beneficial outcomes for workers. First, employers can create two distinct streams of crowdwork: one explicitly available for group collaboration (e.g. sales lead verification) and the other requiring individual work (e.g. survey responses where independent results are required for validity); this can allow workers to collaborate when collaboration does not run counter to requesters' desired outcomes (Gray et al., 2016). Second, companies can "taskify" management by turning affirmation and training into paid tasks. For example, the LeadGenius platform included real-time chat tools that allowed groups to speak directly with other crowdworkers assigned to the same tasks. Workers were able to ask one another for help, keep each other company, and contact junior managers to answer questions during their scheduled work shifts. Team leaders and junior managers were paid for the time that they spent checking the quality of crowdworkers' tasks and answering crowdworkers' questions (Gray and Suri, 2019).

In addition to variation across organizations, scholars have shown variation across individuals regarding how they experience algorithmic control. For example, Cameron (2018) finds that some Uber drivers felt that these systems afforded them autonomy by allowing them to make choices at each stage in the work process so that they could maximize earnings and create a continuous stream of work from discontinuous tasks. Other scholars, too, have highlighted that some workers appreciate the high levels of flexibility, autonomy, task variety, and task complexity that algorithmic control can afford (Griesbach et al., 2019; Wood et al., 2019). Workers may also vary in how they come to understand their new work environment in the absence of traditional socializing agents such as managers or coworkers, with some seeing their employers as allies rather than adversaries (Cameron, 2019). Finally, worker experiences may vary according to country. Lehdonvirta et al. (2019) demonstrate that while clients on crowdwork platforms initially often discriminated against workers from lower-income countries, employer provision of data on worker quality allowed workers to eventually prove their quality to prospective clients and thus overcome discrimination based on country stereotypes.

Future Research on the Economic Value of Algorithms. This variation in worker outcomes across organizations and individuals raises questions for future research around what employers can do to mitigate negative worker outcomes associated with algorithmic direction, evaluation, and discipline. Since these studies demonstrate that neither the technologies themselves nor the type of work dictates the ways that employers use algorithmic control systems, what factors do shape this? Can employers using algorithmic technologies implement novel informal manager practices and formal work structures that result in more beneficial outcomes for workers across industries and geographies? And, can employers design these systems with an understanding of how different types of workers may have different needs?

In addition, firms implementing new technologies have been shown to benefit when they incorporate worker voice during technology deployment (e.g., Gittell, 2016; Kellogg, 2018; Litwin, 2011; Valentine, 2017), invest in working training to integrate the technologies into their workflow (Adler, Goldoftas, & Levine, 1999; Kellogg, Myers, Gainer, & Singer, 2020; Kochan et al., 2008), and partner with post-secondary education providers to teach workers the necessary skills to use the technologies (Lowe, Goldstein, & Donegan, 2011; Osterman, 2011). In the context of algorithmic technologies, how

can employers promote worker voice during technology design and implementation to shape worker experiences and livelihoods in more positive ways? How can they provide training to give workers the skills they need to work with these technologies? And how can employers partner with community colleges, apprenticeship programs, and sectoral training programs to recruit and retain a workforce that can skillfully use these technologies while also helping workers to increase their long-term employment and earnings prospects?

Algorithmic Control in Historical Perspective

Our second insight related to algorithmic control as a new contested terrain is our elaboration of the key similarities and differences between algorithmic control and the two primary forms of rational control—technical control and bureaucratic control—that have been used by employers over the course of modern industrial history. To synthetize these differences, we draw on the four affordances of algorithms introduced earlier (comprehensiveness, instantaneity, interactivity, and opacity), to which we add another key difference: facilitation of the disintermediation of managers. While we briefly address these five differences, we call for more research on additional affordances of algorithms, as well as on the relationship between the rational and normative aspects of algorithmic control.

Algorithmic comprehensiveness. Worker activities can be more constrained under algorithmic control than under previous regimes of rational control because algorithmic control can be more comprehensive in terms of how it directs, evaluates, and disciplines workers. As in technical and bureaucratic control, workers can be monitored, but as we saw, worker behaviors that were previously not directed can now be subject to algorithmic recommendation. Consider for instance how work collaboration can be heavily guided using algorithms. Under technical and bureaucratic control, social interactions and peer collaboration between workers have been hard to direct (e.g., Beane, 2019; Bernstein, 2012). On factory floors, interactions between workers have often served as spaces of resistance in which workers have contested managerial goals and methods (e.g., Morrill, Zald, & Rao, 2003). And, in professional workplaces, managers have historically relied on subjective evaluations to reward or sanction professional workers. For instance, Alvesson and Karreman (2004) describe how a bureaucratic control system for management consultants that directed workers to collaborate with team members was only loosely coupled with evaluation and discipline because collaboration was hard to measure.

Under algorithmic control, however, even collaboration is an activity that can be specifically evaluated, directed, and disciplined, as illustrated by the DreamTeam systems (Zhou, Valentine, & Bernstein, 2018a), the GroupGroup interface (Lix et al., 2019), or the Chorus.ai system (Bock, 2015). On these platforms, algorithms and bots have measured group affect and the interpretive diversity of ideas being expressed. The bots have then directly advised the teams to pause and have a democratic decision-making process, or to be aware that their language use was becoming increasingly divergent. As these examples indicate, algorithmic control can encroach on domains that were previously used by workers for resistance and pushback, ushering in a new contested terrain of control. Indeed, when U.S. Transportation Security Administration (TSA) workers engaged in invisibility practices to attempt to go unseen, managers responded by heightening their surveillance, thus creating a self-fulfilling cycle of coercive surveillance (Anteby and Chan, 2018).

Algorithmic instantaneity. We also find that algorithmic control can be more instantaneous and individualized than previous regimes of control. As we saw throughout the "6Rs," algorithms can provide real-time and personalized nudges, rewards, and penalties. These affordances may transform some of the structural mechanisms through which control operates. Under previous regimes of technical and bureaucratic control, employers relied on slower paced, one-size-fits-all systems to make their workers more productive. Under technical control, employers used machines and assembly lines set the pace, together with piece-rate rewards that evolved every couple of months (Roy, 1952). Under bureaucratic

control, firms primarily relied on institutionalized systems of rules, wage tables, and advancement guidelines, which remained largely stable over time (Gouldner, 1954).

Algorithmic control, where real-time and individualized nudges and penalties have become increasingly common, represents a large shift. For instance, automotive production plants now often rely on collaborative robots ("cobots"), which record data from every person in a similar role interacting with the same robotic interface across dozens of factories, automatically update their interactions depending on patterns identified by data mining algorithms (Sachon & Boquet, 2017), and pair these data with constraints and rewards that tend to be more immediate, dynamic, and personalized than the static, one-size-fits-all rewards used under technical and bureaucratic control. This, in turn, can transform the modalities of worker resistance. Whereas previous systems of control allowed collectives of workers to organize and share resistance tactics over time, especially regarding shared rewards and penalties, algorithmic control can make such initiatives and contestations harder to achieve.

Algorithmic interactivity. Compared to technical and bureaucratic control, algorithmic control can tighten the power of managers over workers by facilitating interactive and crowd-sourced data and procedures. As we saw in the "6Rs," organizations can capture data from external as well as internal sources; this, in turn, can affect worker experiences in negative ways. Take the example of the hospitality industry. Historically, under bureaucratic control, hotel managers looked at worker productivity, budget compliance, and adherence to operational efficiency targets to measure efficiency, but they lacked closed-loop analyses for controlling specific factors that caused poor performance (Moreo, 1980). Compare this to hotel managers who monitored online comments and ratings on TripAdvisor and related platforms to evaluate the performance of their employees (Orlikowski & Scott 2014), or AirBnB hosts who spent 30-minutes a day changing the name of their profiles with the hope of showing up in more searches by customers (Jharver et al., 2018): under algorithmic control, managers can get interactive and crowdsourced data that they can use to address variation in worker performance.

The interactive affordances of algorithms, and their ability to gather both internal and external evaluation data can further constrain the activities of workers in two main ways. First, because raters can be both internal and external to the organization, there are often inconsistent criteria for ratings. Thus, workers have been shown to multiply efforts in order to satisfy both external and internal criteria that often diverge (Orlikowski & Scott 2014). Second, because external ratings often depend on when customers next open the website or app, there can be erratic time intervals between service delivery and ratings, which can make it difficult for workers to understand or contest their performance assessment (e.g. Rosenblat, 2018).

Algorithmic opacity. Last, compared to previous regimes of control, algorithmic control is often more opaque in terms of how it directs, evaluates, and disciplines workers. As we saw in the "6Rs," workers often do not fully grasp how algorithms are being used to direct, evaluate, and discipline them (e.g. Burrell, 2016). Managers often rely on algorithmic direction through nudges that are unobtrusively incorporated in interfaces, and so may not be easily noticed by workers, even as they have powerful effects. Similarly, managers can engage in algorithmic evaluation by capturing data not only on workers' workplace behaviors but also on their personal lives; workers are often not informed about the existence and purpose of such data collection. In terms of disciplining, platform employers can use algorithmic replacing to automatically kick workers off the platform if their ratings drop below a certain level, without always making it clear to workers why they have been removed. Finally, employers using algorithmic rewarding often keep their algorithms secret in order to discourage manipulation and ratings inflation, which gives workers limited transparency into why work is rejected or why they are guaranteed pay at some times and not others.

Because of these multiple layers of opacity, algorithmic control may encroach on procedural due process, that is, "the constitutional requirement that any government deprivation of a liberty or property right must be preceded—at a minimum—by notice and the opportunity for a hearing on the matter before an impartial adjudicator" (Crawford & Schultz, 2014: 111). Under the assumption of due process, workers should be warned about changes that could impact their liberty or property rights; they should also have a chance to contest such decisions. With algorithmic control, however, there is frequently no

procedure in place for workers to get access to, contest, or challenge algorithmic decisions (Wexler, 2018). This is different from previous instantiations of bureaucratic control, in the sense that the mere existence of standardized rules and publicly available guidelines typically increases the transparency, reliability, and predictability of organizational systems; of course, whether such standardized rules and guidelines actually increase workers' rights is another question (Blau, 1955).

Disintermediation of managers. In addition to these four affordances, our review revealed another key difference between algorithmic control and prior forms of rational control—algorithmic systems enable the disintermediation of managers around the direction, evaluation, and disciplining of workers. Traditionally, scholars have pointed to how impersonal rules can make bureaucratic control feel inhumane and even imprisoning (Weber, 1947). Interestingly, however, many of the studies in our review highlight that technical and bureaucratic regimes of control also included human decisions that could be made with varying degrees of discretion. 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. In many ways, algorithmic control at its most extreme is a polar opposite to some firms' attempts to leverage communication technologies to make managers more accountable to and in greater dialogue with workers (Turco, 2016). When managerial decisions are fully automated, there are fewer opportunities for workers to appeal to the empathy of human decision-makers, and often fewer rule exceptions granted (Schildt, 2017; Aneesh, 2009; Lee et al., 2015).

Gray and Suri (2019) introduce the label "algorithmic cruelty" to describe fully-automated decision-making that can materially impact workers' payment or future opportunities. Such algorithmic cruelty comes with additional constraints on workers' activities. In particular, when managers are disintermediated, workers cannot question their punishments and rewards; they have limited recourse to find out why they are experiencing pay changes or have been automatically replaced (Rahman, 2019; Raval & Dourish, 2016; Schwartz, 2018b). Workers on these platforms also often have no one to help them understand a problem they are trying to solve, or give them any feedback on what worked and did not work (Gray, Suri, Ali, & Kulkarni, 2016; Martin, Hanrahan, O'Neill, & Gupta, 2014; Schwartz, 2018). As we saw in the "6Rs," this is often a source of worker frustration, anxiety, and stress.

Future research on algorithms and control. Expanding on recent work mentioning the development of an "algorithmic cage" (Rahman, 2019; Faraj, Pachidi, & Sayegh 2018), our review demonstrates that algorithmic control can be more encompassing, instantaneous, interactive, opaque, and disintermediating than the historical regimes of control that employers have used over the past two centuries. What are the consequences of removing managers (and human supervision in general) from the scene of work? Who is accountable and responsible when things go wrong, and what are some potential mechanisms for holding actors accountable? Future research should also examine the consequences of such developments for workers' well-being and privacy (Fox, Howell, Wong, & Spektor, 2019). For instance, it is unclear how algorithmic opacity affects workers' identities and performance. Does it necessarily create a climate of fear, passivity, and frustration? Is the effect moderated by the level of support that workers perceive to be receiving from their supervisors (Bernstein & Li, 2017)? Or can algorithmic control lead to the emergence of novel "algorithmic imaginaries" (Bucher & Fieseler, 2017) —new values, institutions, and symbols related to algorithms through which people define their work-related identities and collectives—that change workplace dynamics in unexpected ways?

This in turn opens up an important avenue of research about the connections between the rational and normative aspects of algorithmic control. Whereas this review focuses on algorithmic control as a rational form of control, many aspects also carry normative implications. For instance, gamification, symbolic rewards, and real-time "surge" dynamics impact the affective experiences of workers, seeking to win their hearts and minds through feelings of "fun" and excitement (e.g., Gerber & Krzywdzinski, 2019; Griesbach et al., 2019). Future research should explore how such rational and normative features play out to reinforce algorithmic control.

Mapping the Emerging Landscape of Algorithmic Occupations

A third insight related to algorithmic control as a new contested terrain relates to what we refer to as "algorithmic occupations." When employers develop algorithms to automate various kinds of work, some jobs and tasks are eliminated (Benzell, Kotlikoff, LaGarda, & Sachs, 2015; Brynjolfsson & McAfee, 2014; Sachs & Kotlikoff, 2012). But existing studies consistently show that employers' use of algorithms can also create or reconfigure forms of work (Anteby, Chan, & DiBenigno, 2016; Autor, 2015a; Autor, 2015b; Davenport & Kirby, 2016). Some of the new work emerges because most computational tools are not "off the shelf" or "plug and play," technologies, despite the dominant rhetoric—they require considerable work to develop, fine-tune, implement, maintain, and change over time (e.g., Sachs, 2019; Shestakofsky, 2017). Our review draws attention to how these occupational developments may affect the control-resistance dialectic. Employers may develop and fund new or reconfigured occupational work to strengthen algorithmic control, but this work may also become an active area for worker agency. Here we highlight three kinds of occupational work emerging as part of the dialectic of algorithmic control and resistance: algorithmic curation, algorithmic brokerage, and algorithmic articulation.

Algorithmic curation. As organizations pursue the collection, analysis, and deployment of additional varieties of data about customers' and workers' activity, they also create a novel type of work, which is the curation of this data in order for it to be useful to managers. Curation work, per se, is not a new phenomenon: from internal librarians to laboratory technicians, workers have long engaged in cleaning data and interpreting quantitative results for their employers (Bechky, 2019; Nelson & Irwin, 2014). Yet, the kind of curation work that is emerging under algorithmic control is distinct from previous forms of curation in at least two ways.

First, many employers use rhetoric around artificial intelligence that suggests that it is fully automated, meaning that it is a technical system with no "humans in the loop" (Danaher, 2016), even though human curation remains essential to make most algorithmic technologies function correctly (e.g., Pine, Wolf, & Mazmanian, 2016). Employers tend to externalize curation work, which is typically staffed by contingent workers, who have been characterized as "ghost workers" or "crowdworkers" (Gray & Suri, 2019; Kittur et al., 2013). Some employers treat these algorithmic curators as interchangeable by setting up systems that make the workers as replaceable as possible, so that their particular skills or social connections are not relevant. Relatedly, major social media platforms tend to outsource the curation of social media posts to sub-contracting companies where workers with low pay and no benefits manually delete offensive content (e.g., Common, 2019; Gillespie, 2018; Lintott & Reed, 2013). However, in the new contested terrain of control, just as employers may use curation work to strengthen their control of workers, so workers in these contingent, low-paid jobs may push back. For instance, on one mainstream social media platform, algorithmic curators exchanged and publicized guidelines and priorities that the platform had attempted to obscure (Gray, Suri, Ali, & Kulkarni, 2016; Martin et al., 2014; Schwartz, 2018a).

In addition, algorithmic curation is more interactive than previous forms of curation work. Truelove (2019) showed this in her study of an advertising firm that engaged external audiences in the creation and distribution of content using social media technologies; members of the advertising firm tracked audience-generated content in real time and continuously curated it in ways that steered the audience to create content that was desired by the client. Even as employers implement such interactive algorithmic curation in an effort to bring internal and external worker decision-making into line with organizational goals, so workers may introduce considerable discretion and agency as they curate algorithmic data.

Algorithmic brokerage. The adoption and development of large data-driven and algorithmic systems often leads to the creation of another type of work that we call algorithmic brokerage. Algorithmic brokers typically seek to communicate the logic and value of the algorithmic systems to various groups in the organization. Such brokerage roles are shaping the development of occupations that specialize in interpreting algorithmic outputs (e.g., Henke, Levine, & McInerney, 2018). Similar to traditional brokerage work, algorithmic brokerage involves two main sets of practices—connecting practices and

buffering practices—to bridge different groups with disparate expertise, meanings, and status (Barley, 1996; Burt, 1992; Kellogg, 2014; Lingo & O'Mahony, 2010; Obstfeld, 2005).

However, algorithmic brokerage differs from prior forms of brokerage in several ways. First, the success of employers' algorithmic control attempts is determined by the degree to which workers change their workflows to consume algorithmic outputs. Employers, thus, may hire algorithmic "trainers, explainers, and sustainers" and "data translators" to translate, train, and sell other workers on the merits of the algorithms (Henke et al., 2018; Wilson, Daugherty, & Morini-Bianzino, 2017). This algorithmic brokerage work differs from prior forms of brokerage, because it involves brokers trying to sell workers on accepting algorithmic outputs that are often putting workers under more comprehensive control. For example, Karunakaran (2016) demonstrates how lower-status occupations such as crime analysts in a police department performed important brokering roles in implementing a predictive policing technology across the organization and, in the process, gained additional jurisdiction through their ability to do the "data janitorial work" of acquiring, cleaning, and integrating the different sources of training data.

Because algorithmic brokerage work involves social meanings and interactions, it provides a new terrain for worker agency. For example, in their ethnographic study of a police organization, Waardenburg, Sergeeva, and Huysman (2018) find that the introduction of predictive policing was followed by the emergence of the occupational role of "intelligence officer." While the employer intended for intelligence officers to shape the work of police officers to comply with the algorithmic outputs, the intelligence officers began to steer police action based on their own—largely subjective—interpretations.

Algorithmic articulation. Employers' development of algorithmic systems has shaped the emergence of a third kind of occupational work, which we label algorithmic articulation. Scholars have long shown that articulation work (Star, 1995; Strauss, 1985)—not the work of designing a system or producing a product, but the surrounding work that makes it possible—involves a lot of planning and coordinating about who will be doing what, when, where, and how, as well as handling missed responsibilities, unfinished jobs, and all the steps necessary so that projects do not break down. For example, Bailey, Leonardi, and Chong (2010) demonstrate how articulation work was needed to connect technologies as well as people, describing it as "minding the gaps" of technological interdependence via navigating, bridging, crossing, expanding, and bypassing the gaps that emerge in all sociotechnical systems. Under algorithmic control, new occupations related to the articulation of computational technologies have emerged. For example, many "data-driven" organizations have developed novel divisions of labor between algorithms developers, platform engineers, non-algorithm engineers, user-interface designers, user testing engineers, product developers, and information technology support staff (Colner, 2018). Members of each of these occupations have done extensive articulation work to integrate their own specialized work with other groups' jurisdictional work. Similarly, digital consultants and project managers engaged in such integrative articulation work as they developed and maintained algorithmic systems and workflows (Shaughnessy, 2018).

Another type of articulation work involves addressing the failure of algorithmic technologies. Previous technologies used to fail in relatively predictable ways, but machine-learning algorithms often fail in ways that are difficult or impossible to forecast (Shestakofsky, 2017). Thus, a new form of articulation work involves handling the unpredictable failures of algorithmic technology interdependence by applying flexibility, situational adaptability, creativity, interpersonal interaction, or persuasion. For example, Gray and Suri (2019) describe how Uber relied on articulation work to authenticate their drivers. Drivers had to upload photos of themselves each day; Uber's real-time ID check algorithm confirmed if the uploaded photo matched the photo ID on record. But sometimes the algorithms could not discern if a driver who had shaved his beard was, in fact, the same driver. In such cases, microworkers "repaired" (Jackson, 2014) algorithmic failure by reviewing the content of the recorded data to adjudicate whether the photos matched the driver's identity.

For employers, articulation work is necessary to integrate and streamline algorithmic workflows in order to produce economic value in the organization. But, these novel forms of articulation work also provide opportunities for workers to contest algorithmic control. Payoff for employers usually only occurs after a substantial portion of the employers' sites have switched to the new infrastructure. For

example, a cloud computing system designed to aggregate global customer demand only generated analytics useful to the employer once stores in different countries all collected the same type of data regularly; this integration required smoothing differences in existing employer processes across different regions (e.g., Tabrizi, Lam, Girard, & Irvin, 2019). In such situations, algorithmic articulators have the opportunity to claim new jurisdictions and push back on employer control.

   Future research on algorithmic occupations. The emergence of these new forms of algorithmic occupational work raises several key questions for future research. Regarding algorithmic curation, how can workers engaged in the "ghost work" of data curation creatively adapt or reshape algorithmic production technologies as they do their work? Are there policy changes required to support their economic security and mobility given such temporary, part-time, and potentially invisible jobs? Regarding algorithmic brokerage, future research should explore the specific work practices involved in brokering algorithmic knowledge across groups. For example, because of the opacity of most algorithmic systems, even brokers with specialized training in computer science may not be able to fully interpret how the systems work. More needs to be understood about how such brokers make sense of these systems and communicate their functioning across constituencies. Regarding algorithmic articulation, future research should investigate the shape that this work takes across organizations and fields. For instance, how can algorithmic failure be addressed proactively through articulation work? Do industries learn from their mistakes? One potential case study could be high-frequency trading (HFT) and the reconfiguration of articulation work after different "flash crashes" (Borch, 2017; Karppi & Crawford, 2016). Finally, since many of these new occupation members may occupy lower-power "peripheral expert" roles in organizations (DiBenigno, 2018), future studies should examine how these experts can influence others as they engage in such articulation work.

   More broadly, future research should explore the reskilling involved as organizations and educational institutions create programs to train members of these algorithmic occupations. A report by McKinsey Global Institute estimates that, by 2026, in the US alone, the demand for algorithmic "translators" will reach two to four million. Training workers to be technically literate would require the redesign of educational system at all levels and the expansion of on-the-job training in computational thinking (Wing, 2006). For example, Myers and Kellogg (2019) detail how state actors and workforce intermediaries in four U.S. states built more coordinated workforce development systems statewide by spreading career pathways that spanned from secondary to postsecondary education and involved intermediary organizations and employers. Kaynak (2019) describes the emergence in the US of coding bootcamps that have taught web application development to individuals with no background in programming. Similarly, a number of universities have created research facilitator roles for cybersecurity experts to guide the work of an ever-increasing set of researchers using cyberinfrastructure (CI) resources; CI experts engaged in "care and feeding" of these users of CI capabilities (Berente et al., 2017; Berente, Howison, King, Cutcher-Gershenfeld, & Pennington, 2014). More research is needed to understand the structure, professionalization, and career paths of these emerging occupations.

Algoactivism: Individual and Collective Resistance of Algorithmic Control

   A final insight related to algorithmic control is our identification of emerging tactics of resistance, within and beyond the workplace. Studies of technical and bureaucratic control have demonstrated that workers can resist control in a variety of ways, from individual strategies of resistance to collective organizing through discursive framing and legal mobilization (e.g., Morrill et al., 2003). Here we advance the concept of "algoactivism" to both describe emerging tactics along each of these lines, and distinguish them from prior resistance tactics. We also suggest areas for future research related to each kind of resistance.

   Individual Resistance Via Practical Action. We find three main individual practical strategies of resistance: non-cooperation, leveraging algorithms, and personal negotiation with clients. Regarding noncooperation, workers have long engaged in non-cooperation under regimes of technical and bureaucratic control by carving out psychological, social, temporal, or physical niches in their

workplace (e.g., Roy, 1952; Edwards, 1979). Under algorithmic control, workers continue to engage in non-cooperation, but can now do so in different ways because of the instantaneous and interactive character of algorithms. One way they do so is by ignoring algorithmic recommending or rewarding. For instance, Valentine and Hinds (2019) describe how fashion buyers resisted the algorithmic recommendations stemming from employer-established recommendation systems, adapting them to be more consistent with their own professional experience. Mollick and Rothbard (2014) show that workers at a sales company resisted the interactive gamification designed by their employer by refusing to learn the rules of the game, suggesting that the games were unfair, and not playing the games in their daily work. And, Christin (2017) demonstrates that web journalists and legal professionals engaged in foot-dragging (ignoring risk scores and analytics systems in their daily work), gaming (manipulating the variables they entered in algorithmic systems in order to obtain the score that they desired), and open critique (contesting the data and methods used to build algorithmic systems as "crude"' and "problematic"). Another way that workers engage in noncooperation is by disrupting algorithmic recording. For example, in a study comparing criminal courts and police departments, scholars find that legal professionals and police officers developed a set of resistance strategies, which they analyzed as "data obfuscation"—making things obscure either by blocking data collection or by producing more data (Brayne & Christin, 2019; see also Levy, 2015). Similarly, Lee et al. (2015) show how Uber drivers resisted control by turning off their driver mode when in bad neighborhoods, staying in residential areas to avoid bar patrons, and frequently logging off to avoid long trips. And Lehdonvirta et al. (2019) find that workers on online labour platforms assessed clients' past feedback-giving behavior before accepting contracts, and if bad feedback ratings did pile up, started afresh with different accounts.

Workers have also been shown to leverage algorithms to resist control. They may reverse engineer the algorithm that produced the rating in order to be able to prioritize the activities that seem to impact the score (Jharver et al., 2018; Rahman, 2017; Lix & Valentine, 2019). For example, some AirBnB hosts participated in online forums, read the company's technical documentation, and monitored competitors' profiles and ratings in order to figure out what characteristics or behaviors seemed to influence their ratings. Other hosts preferred long-term guests, but figured out that they could be penalized for directly declining short-term guests, so they set filters on their profiles to screen out short-term guests in ways that the algorithm would not penalize (Jhaver, Karpfen, & Antin, 2018). Along similar lines, MTurk workers deployed their own algorithms to try to gain an upper hand against the platform's control regime. For instance, workers utilized scripts that monitored the marketplace and alerted the worker when suitable tasks became available. Workers also applied hacks to remove distracting information from the user interface (Lehdonvirta, 2018).

Finally, workers have been shown to resist algorithmic control by personally negotiating with clients in order to bypass or alter algorithmic ratings. In one online marketplace, sellers contacted buyers who had left a negative evaluation and tried to convince them to withdraw it (Curchod et al., 2019). In an online labor market, contractors preemptively asked clients for guarantees of high ratings as part of the terms of the contracts, rather than allowing clients to simply rate the work at the end of the projects; when problems arose, the contractors often offered to work for free in exchange for good ratings (Rahman, 2017). In addition to negotiating reciprocal five-star ratings with clients and sometimes foregoing payment to avoid bad ratings, contractors also complained to platform customer support about unduly low ratings (Lehdonvirta et al., 2019). In another study of "gig" project teams, kharma ratings were negotiated and used as ultimatums. In one case, a product manager told his team to "just finish this milestone and I'll immediately push the button on your kharma score!" (Lix & Valentine, 2019). Such personally negotiated interactions around algorithmic ratings partly explain why online labor markets often have ratings inflation (Filippas, Horton, & Golden, 2018; Horton & Golden, 2015; Rahman, 2017).

Platform organizing. In addition to individual strategies, workers can resist through collective action. Workers under regimes of technical and bureaucratic control have long organized to protect their rights (e.g., Cutcher-Gershenfeld & Kochan, 2004; Kellogg, 2011; Roscigno & Hodson, 2004). Yet compared to the dense networks of informal social ties that existed on production floors, workers under algorithmic control often do not have the same connections: limited, arms-length, virtual connections

often prevail (Darr, 2018; Massa & O'Mahony, 2015). In this context, workers have limited power to shape face-to-face interactions and shopfloor games because of the control system's features (Lehdonvirta, 2016). Instead, they have begun to organize via online forums and platforms and via platform cooperativism.

A first form of organizing involves the development of online forums and platforms dedicated to workers' empowerment and knowledge sharing. In such work-oriented online communities, workers have been shown to help each other learn new systems and practices, anticipate or avoid disciplinary processes, regain access when locked out of platforms, identify desirable clients or jobs, or learn how to smooth their earnings (Martin et al., 2014; Wood et al., 2019). The blog "The Rideshare Guy," for instance, provided guidance and instructions to drivers around how to maximize their income in diverse car sharing marketplaces (Campbell, 2018). Academics and organizers have also designed dedicated platforms to allow workers to rate and flag requesters who have treated them badly. These platforms include Turkopticon (an activist system for workers to publicize and evaluate their relationships with employers on Amazon Mechanical Turk) and Dynamo (a platform for workers to gather, gain critical mass, and mobilize) (Gray et al., 2016; Martin et al., 2014; Schwartz, 2018a). Along similar lines, "Peers.org" offered a system for pooling multiple accounts; "Guild" was an insurance group that negotiated between major insurance companies and on-demand platforms; and "Zen99" designed an all-in-one dashboard that helped 1099 workers organize finances, taxes, and insurance policies (Aloisi, 2015).

Such forums and platforms can help workers address the lack of voice and information asymmetries that are often associated with algorithmic control in a variety of ways. In some cases, workers have collectively engaged in tasks that are somewhat in line with managerial goals, such as on-boarding, sharing information on customers, and discussing tricks of the trade for performing work effectively (Schwartz, 2018). In other cases, workers have used online forums to share resources and identify desirable clients or jobs; they have provided guidance to one another about how to anticipate or avoid discipline, how to regain access when locked out of platforms, how to organize finances, taxes, and insurance policies, and how to smooth earnings and maximize their income by switching between diverse platforms. Finally, workers have used online forums to engage in collective mobilization against platforms, for instance with the "#slaveroo" movement against food-delivery platforms in Europe, as well as through various strikes and mobilizing of drivers against Uber in the United States and elsewhere.

Workers have also used platforms to engage in "reverse surveillance" or "sousveillance," in which employees recorded and uploaded everything that happened in their workplaces in order to make managers accountable through "full documentary evidence" in case employers acted against them (Ali & Mann, 2013; Sewell et al., 2012). Employers have been shown to push back against worker sousveillance. For instance, at a warehouse fulfillment service, employees were not allowed to bring personal devices onto the warehouse floor (McClelland, 2012). And, it is an open question whether sousveillance can restore workers' power, since employees do not usually have access to the employers' large data sets and proprietary algorithms (Danaher, 2016).

Second, activists have organized via platform cooperativism. For instance, the "Platform Co-op" consortium brought together a wide range of organizations who adhered to the project of having platforms being owned by their members, with surplus revenues being transferred to the members (Scholz, 2012; Scholz & Schneider, 2017). The consortium featured a directory of 281 organizations across the world that engaged in some version of platform cooperativism. Scholars have suggested that increasing the number of platform cooperatives could help promote algorithmic transparency by addressing some of the concerns relating to opacity, bias, and profit extraction emerging through algorithmic control (Scholz, 2016). Similarly, studies of Wikipedia, Linux, and other peer production communities have demonstrated how these communities relied heavily on algorithmic control to manage their work processes, but that these controls reflected shared community values and were therefore experienced differently than by workers on corporate platforms that mostly reflected employer interests (Benkler, 2017; Fayard et al., 2016; Geiger, 2017; Karunakaran, 2018; O'Mahony & Ferraro, 2007).

Discursive Framing about Algorithmic Fairness, Accountability, and Transparency. Workers subject to technical and bureaucratic control have historically mobilized others by crafting frames

(Kaplan, 2008), to spark outrage and hope by depicting existing conditions as unjust and amenable to change via collective action (e.g. Creed, Scully, and Austin, 2002). Social movement organizers have begun to use social media to circulate these kinds of frames broadly in order to mobilize participants in online movements (e.g., Castells, 2015; Tufekci, 2017). In the context of algorithmic control, workers and advocates have engaged in discursive framing by developing novel forms of public discourse about algorithmic fairness, accountability, and transparency (e.g., Karunakaran, 2019).

First, workers have collectively resisted algorithmic control by engaging in public critique of algorithmic systems, criticizing how algorithms could lead to the reproduction or reinforcement of social and racial inequalities because of biased training data (Harcourt, 2007; O'Neil, 2016). For instance, in 2016, Angwin and her colleagues at the non-profit news organization ProPublica analyzed more than 10,000 criminal defendant files in Broward County, Florida, and published a critique of the predictive risk-assessment tool called COMPAS. ProPublica made the data set public and accessible to researchers. Following this publication, a vibrant debate emerged between Equivant (the company that owned COMPAS), the ProPublica journalists, and several academics and computer scientists who analyzed the data. The different parties offered distinct measurements of algorithmic fairness and conflicting justifications for using them (Feller, Pierson, Corbett-Davies, & Goel, 2016). In the aftermath of these discussions, activists convened a wide range of stakeholders to discuss the construction methods of their risk-assessment tools, making some of their data and models public to relevant experts as well as local communities affected by the tools (Hannah-Moffat, 2018). In this case, as in many others, activists used novel forms of public critique and interdisciplinary dialogue to address algorithmic bias.

Second, activists and computer scientists have begun to develop new professional codes of ethics and documentation for computational systems (Diakopoulos & Friedler, 2016). As noted earlier, scholars have drawn attention to opacity as a central concern in algorithmic control. To address such concerns, the Association for Computing Machinery (ACM) developed a "Code of Ethics and Professional Conduct." It also sponsored an annual ACM FAT* (Fairness, Accountability, and Transparency) Conference, in which academics and industry members developed novel designs for algorithmic fairness. For instance, at the 2019 ACM FAT*, engineers and computer scientists from Google, Microsoft, and other places noted that, in spite of the potential negative effects of reported biases associated with trained machine learning and artificial intelligence models, documentation accompanying these models, even when supplied, still provided little information regarding model performance characteristics, intended use cases, potential pitfalls, or other benchmarks to help users evaluate the suitability of these systems to their context. These activists argued in favor of providing "model cards," short (one to two page) documents for trained machine learning models that would include core metrics about bias, fairness, and inclusion (Gebru et al., 2017; Mitchell et al., 2019). Mitchell and colleagues (2019) give the example of a model card for a machine learning model designed to detect smiling in images—a model that could be used by employers to engage in algorithmic recording by using video surveillance to monitor the emotions of their employees. The model card detailed the authors of the smiling algorithm, the type of model built, the intended use for the model, the main factors and metrics incorporated, and some limitations and recommendations for future developments.

Legal Mobilization Around Employee Privacy, Managerial Surveillance, Discrimination, and Data Ownership. Workers and advocates have previously created political opportunities for contesting technical and bureaucratic control by using a climate of a supportive administration and vulnerable rivals to alter laws in line with their own interests, skillfully frame their projects in terms likely to be attractive to governments and elites, and battle with rivals to generate political support from the State for favorable legislation (e.g. McCann, 1996). Along these same lines, activists have mobilized to create political opportunities around employee privacy, managerial surveillance, discrimination, and data ownership. In doing so, they have transferred disputes from an arena where the resolution of conflicts depends on the relative power of the workers and employers to an arena where disputes are resolved by reference to legal norms and rules and are enforced by the power of the state and international institutions.

First, workers and labor organizers have advocated for workplace and legal policies to protect employee privacy, limit managerial surveillance, prevent discrimination, and reclassify independent

contractors as employees. Regarding workplace policy, they have resisted the lack of privacy associated with algorithmic recording by negotiating union agreements with employers around how and when employers can both track employees and use the tracking data to discipline employees (e.g., Davidson, 2016), and by engaging in arbitration around employees' social media posts (Lucero, Allen, & Elzweig, 2013). For instance, one arbitration case considered whether employees' social media posts were protected under laws that protect employees' rights to "engage in other concerted activities for the purpose of collective bargaining or for other mutual aid or protection" (Lucero et al., 2013). Similarly, through their union, UPS drivers developed an agreement with UPS that the company needed to make tracking explicit in drivers' contracts, could not discipline drivers only using data, and could not track drivers without telling them (Davidson & Kestenbaum, 2014). Workers have also protested against the discrimination that can arise through algorithmic rating by raising questions about whether consumer ratings are subject to legal action based on the Civil Rights Act of 1964, which prohibits employers from making employment-related decisions based on the protected characteristics of workers. Of particular interest are legal regulations in the European context. The Data Protection Impact Assessment (DPIA) clause of the European Union's General Data Protection Regulation (GDPR) requires preemptive assessments of the potential impact of high-risk algorithmic systems on "the rights and freedoms of natural persons" (GDPR, Art. 35). Yet the actual implementation of the DPIA and GDPR frameworks remains uncertain, pending ongoing case law, especially in the United States. More broadly, legal scholars have called for a reconceptualization of workers' privacy rights along the lines of "contextual" or "relational" privacy, which requires an articulation of a set of context-specific norms that constrain employers regarding the information they can collect via websites, with whom they can share it, and under what conditions it can be shared (Bannerman, 2018; Nissenbaum, 2009).

A second important development relates to the current employment status of workers under algorithmic control. Most platforms have relied almost exclusively on independent workers as their primary workforce (Rosenblat, 2018; Vallas and Schor, 2020). Workers have increasingly challenged this legal classification, arguing that they should be considered as employees instead of independent contractors. Through collective organizing, they have lobbied to implement legislative change, and in some cases have also started to sue companies—the ridesharing platforms Uber and Lyft and the cleaning platform Handy, for instance—for classifying them as contractors, but replacing them when they do not perform the work in the strict manner required by the platform (Aloisi, 2015). Interesting legislative efforts took place in California following the Dynamex decision and the California Assembly Bill 5 (AB 5), which in 2019 restricted the use of independent contractors by imposing the so-called "ABC test." Under the ABC test, a worker is presumed to be an employees unless the company proves that (A) the worker is free from the control and direction of the hiring entity in connection with the performance of the work, both practically and contractually; (B) the worker performs work that is outside the usual course of the company's business; and (C) the worker is customarily engaged in an independently established trade, occupation, or business of the same nature as the work performed for the company.

Third, activists have begun to engage in a set of regulatory initiatives related to *pressing for worker data ownership*. As noted earlier, many employers are engaging in comprehensive algorithmic recording and finely-grained algorithmic rating. Part of why they may be doing this is that the data are valuable, independent of the control of the workers— indeed, many platforms have monetized their workers' data through online advertising (Zuboff, 2018). Activists have argued in favor of giving people ownership of their digital data, and in favor of treating data as a form of labor that needs to be compensated (Arrieta-Ibarra, Goff, Jiménez-Hernández, Lanier, & Weyl, 2018; Scholz, 2012). One version of this proposal suggested that individuals should be allowed to rent or sell their data to technology companies through digital intermediaries, called "MIDs" (Mediators of Individual Data), that would "negotiate data royalties or wages, to bring the power of collective bargaining to the people who are the sources of valuable data. It would also promote standards and build a brand based on the unique quality and identity of the data producers they represent" (Lanier & Weyl, 2018).

Future research on algoactivism. The existence of multiple kinds of algoactivism raise fascinating questions for future research. Throughout this review, we have discussed the potential of employers to use

algorithmic technologies to implement a more comprehensive, instantaneous, interactive and opaque form of control. Yet the mere existence of such a wide range of strategies of resistance suggest that workers continue to have agency within organizational settings.

At a broad level, how do these reactions by workers modulate the impact of algorithmic direction, evaluation, and discipline on the ground? Regarding individual resistance via practical action, for instance, one study showed that warehouse workers received minute-by-minute scores from their handheld scanners that also directed their minute-by-minute paths through the warehouse; gaming or resisting such systems of algorithmic control was extremely difficult (McClelland, 2012). Future research should examine how employer algorithmic control and worker resistance co-produce new work dynamics across organizations and fields. In addition, in line with recent research on stock exchanges (Beunza & Millo, 2015; MacKenzie, 2018, 2019; Pardo-Guerra, 2019), further research should explore how such practical strategies of resistance are evolving in almost fully automated workplaces.

It could also investigate the opportunities and challenges that arise from platform cooperativism. For instance, future research could explore how cooperatives could implement iterative consultations of their members and users when developing algorithmic control systems. They could make the variables, weights, and models used to design their algorithms transparent and available to their members and users. Under these conditions, algorithmic data could be used to anchor collective discussions and promote reflexivity among members and users. Future research could also investigate how traditional unions could get involved with platform organizing (Kochan, Kimball, Yang, & Kelly, 2018; Wood, Lehdonvirta, & Graham, 2018).

Regarding novel kinds of public discourse about algorithms, scholars could explore the range of stakeholders that can best engage in algorithmic framing, the issues that are most amenable to discussion, the ways that different stakeholders can work across boundaries to mobilize for collective action, and how algorithmic technologies might facilitate such mobilization (Ananny & Crawford, 2018). Regarding codes of ethics and documentation, scholars could explore the processes through which organizations can make their data and code more public while protecting intellectual property, how new professional codes of ethics can be taught to engineers and computer scientists, and how documentation can best be employed by managers engaging in algorithmic control.

Last but not least, the emerging legal mobilization around algorithmic control provides intriguing ideas for future research. Scholars should explore the interplay between law, managerial control, and algorithmic technologies. How does the existing case law about privacy rights and third-party tracking influence algorithmic control within workplaces? How do the General Data Protection Regulation (GDPR) and Data Protection Impact Assessments (DPIA) frameworks developed by the European Union affect the modalities of algorithmic control within European and U.S.-based companies? Regarding employment classifications and the move from independent contracting to the employer-employee legal contract, what will be the ramifications of California AB 5 for on-demand platform labor and the relationship between platforms and their workers? Regarding worker data ownership, future research should explore the role of economic incentives in driving some of the modalities of algorithmic control. For instance, how is algorithmic recording and rating implemented differently by employers that sell these data versus by employers that do not? And, in pilot studies of worker data ownership systems, does this framework increase existing inequalities in terms of privacy rights, allowing a two-tiered landscape where affluent workers can hold on to their personal data and protect their privacy, whereas low-income workers cannot?

CONCLUSION

This article reviews the interdisciplinary research about algorithms at work to explore how employers are using algorithms for organizational control and how it affects workers. We find that employers may use algorithmic control via six main mechanisms, which we call the "6 Rs"—they may use algorithms to direct workers by *restricting* and *recommending*, evaluate workers by *recording* and *rating*, and discipline workers by *replacing* and *rewarding*. Our model suggests four important implications for organization

studies. First, our application of labor process theory to the research on algorithms at work problematizes the predominant focus to date on the economic value of algorithms; we draw attention to algorithmic systems as contested instruments of control that allow employers to secure a share of capital from workers' exertions while obscuring their methods for doing so, and to the important outcomes of worker experiences and livelihoods. Second, we demonstrate that algorithmic control can be more comprehensive, instantaneous, interactive, and opaque than prior forms of rational control, and that it can allow for further disintermediation of managers. While technical control leverages technology to limit the need for direct supervision, and bureaucratic control relies on standardized rules and roles for the same purpose, algorithmic control can remove managers (and human supervision in general) even further from the scene of work. Third, employers' use of algorithms in the workplace is sparking the emergence of new forms of work and occupations—algorithmic curation, algorithmic brokerage, and algorithmic articulation—that may help employers to implement algorithmic control, but also have the potential to become active areas for worker agency. Finally, workers are engaging in four main forms of algoactivism to resist algorithmic control—individual action, collective platform organizing, discursive framing around algorithmic fairness, accountability, and transparency, and legal mobilization around employee privacy, discrimination, worker classification, and data ownership. Our mapping of the contested terrain of algorithmic control will enable researchers to further explore some of the unique implications of this type of control, and to engage in future research around what employers and workers can do to mitigate negative worker outcomes associated with algorithmic direction, evaluation, and discipline.

ROLES OF AUTHORS ON THE RESEARCH TEAM

Kate Kellogg (MIT), Melissa Valentine (Stanford), and Angèle Christin (Stanford) are professors who study the intersection of culture, work, and organizing technologies.

APPENDIX: METHODS

We based our analysis on a review of more than 1,100 papers that reported an empirical study of algorithmic, crowd, or platform technologies. We identified the papers through multiple stages. First, we ran a search on the Web of Science database and Google Scholar for the following keywords: "algorithm*," "automation," "crowd*," or "platform*". We selected 2005 as the loose starting point, a period that represented an inflection point in algorithmic capabilities. Consistent with the motivation of our review, the search included peer-reviewed conference proceedings or journals in any social science field, including interdisciplinary social science fields such as human-computer interaction; science, technology, and society; and critical algorithms studies. We next skimmed the abstracts of all of these articles to identify studies that reported empirical studies of work contexts. We included empirical papers (e.g., including some kind of data, including observation, archival or trace data, survey). Not included at this point were studies of leisure or home contexts, or theoretical pieces, or review articles, though we reviewed the citations of the review articles to find additional articles to include. In our final review, we realized that some technologies were developing more quickly than reflected in peer-reviewed articles, so we also included case studies or practitioner journals as motivating examples. Finally, we circulated the paper to two experts in each of the interdisciplinary fields to solicit additional citations.

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Table 1: New Technological Affordances of Algorithms

Affordances of Algorithmic Systems	Key Insights	Example Studies
Comprehensive	• Wide range of devices and sensors • Collecting a variety of data about workers, from biometrics to accelerometers, text messages, and online footprints	Ball & Margulis (2011); Xu et al. (2014); Beane & Orlikowski (2015); Levy (2015); Angrave et al. (2016); Goldberg et al. (2016); Harari, Müller, Aung, & Renfrow (2017); Leonardi & Contractor (2018); Lix, Goldberg, Srivastava, & Valentine (2019); Landay (2019)
Instantaneous	• High velocity of algorithmic computation • Performance assessments incorporated in real-time into the system	Jacobs (2009); Katal et al. (2013); Etter, Kafsi, Kazemi, Grossglauser, & Thiran (2013); Mayer-Schönberger & Cukier, (2013); Sachon & Boquet (2017); Crowston & Bolici, (2019)
Interactive	• Algorithmically-mediated platforms allow for participation from multiple parties • Interactive interfaces channel user behavior in real-time	Chalmers & MacColl, (2003); Holzinger & Jurisica (2014); Amershi et al. (2014); Kulesza et al. (2015); Cambo & Gergle (2018); Valentine et al. (2017); Zhou, et al. (2018)
Opaque	• Intellectual property and corporate secrecy • Technical literacy • Machine-learning opacity	Pasquale (2010); Orlikowski & Scott (2014b); Bolin & Andersson Schwarz (2015); Dietvorst et al. (2015); Diakopoulus (2015); Burrell (2016); Danaher (2016); Weld & Bansal (2018)

Table 2: Algorithmic Direction

	Algorithmic Direction	Key Insights	Example Studies
Algorithmic Recommending	Prompting the worker to make decisions preferred by the choice architect Recommending specific courses of action	Can augment workers' decisions by automatically finding patterns in the data and prescribing actions based on this Can bypass the heuristics workers typically use to make decisions	Gabrilovich et al. (2004); Goldman et al. (2011); Pachidi et al. (2014); Danaher (2016); Rosenblat & Stark (2016); Schreiber (2017); Gupta (2018); Veale et al. (2018); Karunakaran (2019); Valentine (2019)
Algorithmic Restricting	Restricting access to information Restricting behavior	Can continuously and covertly restrict information available to workers Can interactively restrict the behavior of crowdworkers and online community members	O'Mahony & Bechky (2008); West & O'Mahony (2008); Muthukumaraswamy (2010); Shaikh & Cornford, (2010); Faraj, Jarvenpaa, and Majchrzak (2011); Afuah & Tucci (2012); Treem and Leonardi (2012); Majchrzak et al. (2013); Aneesh et al. (2014); Kallinikos & Tempini (2014); Orlikowski & Scott (2014a); Orlikowski & Scott, (2014b); Lee et al. (2015); Tempini (2015); Arazy et al. (2016); Barrett et al. (2016); Fayard, Gkeredakis, & Levina (2016); Lakhani (2016); Leonardi and Vaast (2016); Calo & Rosenblat (2017); Lifshitz-Assaf (2018); Kittur et al. (2019); Truelove (2019)
Potential Worker Experiences	Frustration Bias Overriding workers' conceptions of well-being Reduced voice Precarity	Recommendations may not be intelligible to workers, resulting in frustration Recommendations can reinforce social and racial inequalities Recommendations may negatively affect the welfare of those being nudged Restrictions can prevent workers from communicating with managers and with one another Restrictions can break jobs down into "micro" tasks, which can be scheduled in finely-grained, opaque, and unpredictable ways	Angwin et al. (2007); Martin et al. (2014); Pachidi et al. (2014); Askay (2015); Lee et al. (2015); Salehi et al. (2015); Barocas & Selbst (2016); Danaher (2016); O'Neil (2016); Rosenblat & Stark (2016); Brayne (2017); Christin (2017); Yeung (2017); Vallas (2018); Gray & Suri (2019); Vallas & Schor (2020)

Table 3: Algorithmic Evaluation

	Algorithmic Evaluation	Key Insights	Example Studies
Algorithmic Recording	Recording and aggregate finely-grained behavior and statistics from internal and external sources	Can track a wide range of behaviors	Alvesson & Karreman (2007); Watkins, Allen, Coopman, Hart, & Walker (2007); McClelland (2012); Segal et al. (2014); Karunakaran (2016); Levy (2016); Rosenblat & Stark (2016); Leonardi & Contractor (2018); Schweyer (2018); Bailey, Erickson, Silbey, & Teasley (2019); Kittur et al. (2019); Lehdonvirta et al. (2019); Lix et al. (2019); Rahman (2019)
	Providing real-time feedback	Can enable real-time adjustments of worker performance	
Algorithmic Rating	Using online rating and ranking	Can aggregate quantitative and qualitative data to measure work productivity and to evaluate workers within an organization based on external and internal sources	Orlikowski & Scott (2014b); Varshney et al. (2014); Ramamurthy et al. (2015); Barrett, Oborn, & Orlikowski (2016); Horesh et al. (2016); King (2016); Mallafi & Widyantoro (2016); Christin (2018); Jharver et al. (2018); Levy & Barocas (2018); Rosenblat (2018); Curchod et al. (2019); Rahman (2019); Lix & Valentine (2019)
	Using predictive analytics	Can predict future worker performance- achievement, skillset, potential, retention, etc	
Potential Worker Experiences	Loss of privacy	Workers may be concerned that the data collected may include their overall aptitude in various skills in work and home settings, and their physical and mental health	Angwin (2014); Tufekci (2014); Bock (2015); Miller (2015); O'Connor (2015); Ahmed et al. (2016); Fourcade & Healy (2016); Rosenblat & Stark (2016); Bodie, Cherry, McCormick, & Tang (2017); Greenwood, Adjerid, & Angst (2017); Levy & Barocas (2017); Rosenblat, Levy, Barocas, & Hwang (2017); Rahman & Valentine (2017); Anteby & Chan (2018); Chan & Wang (2018); Jhaver, Karpfen, & Antin (2018); Lix &Valentine (2019); Ticona & Mateescu (2018); Rahman (2019); Valentine & Bernstein (2019); Wood et al. (2019); Wood and Lehdonvirta (2019)
	Data accuracy	Workers may not be aware of the data being collected, so they may not be able to appeal judgements against them or correct misinformation.	
	Discrimination	Algorithmic recording and ratings can be subject to gender and race stereotyping; workers may have fewer mechanisms for contesting mechanisms they feel are unfair; consumer rating may escape legal action	
	Weight of ratings in hiring decisions	Workers may be concerned that employers may select workers primarily based on prior ratings and may communicate with workers primarily via online tools that do not allow in-person assessments of workers	

Table 4: Algorithmic Discipline

	Algorithmic Discipline	Key Insights	Example Studies
Algorithmic Replacing	Automatically replacing or removing

Immediately replacing or removing | Can be used to fire underperforming workers and replace them with others that will follow managerial directives

Can recruit on a greater scale and at the fraction of the time because people are interchangeable and labor is mainly digital | Aneesh (2009); Kittur, Smus, Khamkar, & Kraut (2011); Lenglet (2011); Kittur et al. (2013); Retelny et al. (2014); Beunza & Millo (2015); De Stefano (2015); Irani (2015); Lee et al. (2015); Borch & Lange (2016); Ha-Thuc et al. (2016); Lange, Lenglet, & Seyfert (2016); Lenglet & Mol (2016); Rosenblat &Stark (2016); Sundararajan (2016); Valentine et al. (2017); Rahman (2019); Ajunwa & Greene (2018); Cherry & Aloisi (2018); MacKenzie (2018); Shapiro (2018); Jackson (2019); Jarrahi et al. (2019) |
| **Algorithmic Rewarding** | Interactively and dynamically rewarding

Gamifying rewards | Can provide rewards in real time for behaviors that comply with predefined correct behaviors

Can use the principles of game design to make the affective experience of work more positive and "fun" for employees | Edery & Mollick (2009); Deterding, Khaled, Nacke, & Dixon (2011); Kerfoot & Kissane (2014); Mollick & Rothbard (2014); Walz & Deterding (2014); Bogost (2015); Irani (2015); Rosenblat & Stark (2016); Stanculescu, Bozzon, Sips, & Houben (2016); Rahman (2017); Ivanova et al. (2018); Kim (2018); Lehdonvirta (2018); Liu, Huang, & Zhang (2018); Petre (2018); Shapiro (2018); |
| **Potential Worker Experiences** | Precarity

Frustration and stress | Precarity can be greater for low-skilled workers, especially if they work for organizations that use platforms that allow for automatic replacement

Intentional secrecy of rewarding system and rapid responsiveness of the rewards may lead to worker frustration and stress | Kleemann, Voß, & Rieder (2008); Aneesh (2009); Kittur et al. (2011); Schenk & Guittard (2011); Irani & McClelland (2012); Silberman (2013); Bergvall-Kåreborn & Howcroft (2014); Martin et al. (2014); Retelny et al. (2014); Dourish (2016); Gray, Suri, Ali, & Kulkarni (2016); Postigo (2016); Raval & Dourish (2016); Barley et al. (2017); Corporaal & Lehdonvirta (2017); Graham, Hjorth, & Lehdonvirta (2017); Valentine et al. (2017); Schwartz (2018); Rahman (2019) |

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Figure 1. Review of Algorithmic Control as Contested Terrain

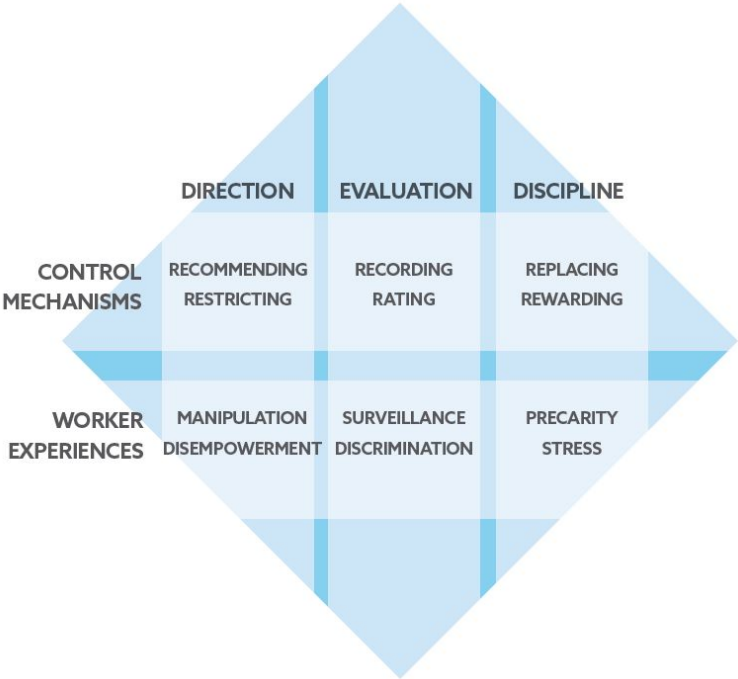|	DIRECTION	EVALUATION	DISCIPLINE
CONTROL MECHANISMS	RECOMMENDING RESTRICTING	RECORDING RATING	REPLACING REWARDING
WORKER EXPERIENCES	MANIPULATION DISEMPOWERMENT	SURVEILLANCE DISCRIMINATION	PRECARITY STRESS

Figure 2. New Insights and Future Directions

Problematizing the Predominant Focus on the Economic Value of Algorithms	Algorithmic Control in Historical Perspective	Mapping the Emerging Landscape of Algorithmic Work and Occupations	Algoactivism: Individual and Collective Resistance of Algorithmic Control
• New View of Algorithmic Systems: Contested Instruments of Control • New Mechanism for Action: Obscuring and Securing Surplus Value • New Important Outcomes: Worker Experiences and Livelihoods • Variation Across Organizations and Individuals	• Algorithmic Comprehensiveness • Algorithmic Instantaneity • Algorithmic Interactivity • Algorithmic Opacity • Disintermediation of Managers	• Algorithmic Curation • Algorithmic Brokerage • Algorithmic Articulation	• Individual Resistance Via Practical Action • Platform Organizing • Discursive Framing about Algorithmic Fairness, Accountability, and Transparency • Legal Mobilization around Employee Privacy, Managerial Surveillance, Discrimination, and Data Ownership