Effects of Algorithmic Control on Power Asymmetry and Inequality within Organizations

Mehdi Barati, BA[1], Bahareh Ansari PhD MA[2]

[1] Department of Information Science, University at Albany-State University of New York, Albany, NY, USA

[2] Center for Policy Research, Rockefeller College of Public Affairs and Policy, University at Albany, Albany, NY, USA

Corresponding Author:

Mehdi Barati, BA, University at Albany-SUNY, Department of Information Science, Draper Hall Room 015, 135 Western Ave, Albany, NY 12203, USA.

Email: mbarati@albany.edu

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Abstract

With the advancement of programming algorithms, continuous increase in hardware computing power, larger amounts of available fine-grained data, and an increasing number of organizations exercising remote work, algorithmic control are expanding in various domains. Scholars and practitioners in human resources management posit that organizations' adopting algorithms to substitute or supplement traditional rational control mechanisms to direct, discipline, and evaluate employees might increase the objectivity and transparency of employee-related decision-making processes and, therefore, reduce the power asymmetry and inequality within organizations. This discussion commentary argues that underlying assumptions of higher objectivity and transparency of algorithmic control in organizational control are very strong, and current literature does not support them. Further, there is evidence of large variation in organizations' adoption of algorithmic control due to their current technical, structural, and human capital resources, which further blurs the predicted outcomes. There is also evidence of over-relying on algorithmic suggestions by managers to circumvent accountability. Therefore, adopting algorithmic behavior must be conducted with serious precautions. This article proposes that incomplete adoption, overestimation of the objectivity, lack of technical and managerial knowledge of underlying mechanisms of learning algorithms, and complete abandoning of human intuitive judgment and reasoning could worsen the power asymmetry and inequality within organizations by increasing opacity of decisions, systematic biases, and discriminatory classification.

Keywords: Decision Making; Organizational Inequality; Decision Support System; Performance Monitoring; Machine Learning; Algorithmic Management

Introduction

With the increasing availability of vast amounts of granular data, cheap compute power, ubiquitous technologies, and innovative software developments, Artificial Intelligence (AI) has become involved in many aspects of today's world, including organizational management processes. Algorithms, mostly developed by third-party vendors, have been employed in organizations to improve, complement, or substitute managerial functions traditionally implemented through direct human involvement (Chowdhury et al., 2021). Among these managerial functions are organizational controls which refer to the processes that aim to align employees to the organization's objectives through influencing their behavior (Schafheitle et al., 2020).

The transfer of organizational control functions to machine learning-based technologies is referred to as algorithmic control (AC) in the organizational control literature (Kellogg et al., 2020). AC is built on the assumption that by collecting fine-grained data on employees' behavior, physiology, and emotions (Alec Cram & Wiener, 2020), organizational behavior can be modeled, predicted, and modified in a subjective, accurate, and transparent way. Adopting AC aims to improve, substitute, or supplement traditional means of organizational control, including technical and bureaucratic mechanisms. Although consensus appears to exist about the revolutionizing impact of AC on organizations, the nature of that impact is still a question in need of scholarly inquiry. One important question that merits thorough investigation is how AC will change the power relations between employer and employee.

Prior research on the effects of AC on employees has mainly focused on platform-based firms (gig companies) such as Uber and eBay (Alec Cram & Wiener, 2020; Curchod et al., 2020; Kellogg et al., 2020; Wiener et al., 2021). The control settings in these studies have some common characteristics. First, there had not existed any traditional control configuration before the introduction of AC. For example, there was no traditional human-to-human control mechanism in both Uber and eBay contexts. A designer with algorithmic capabilities in mind sets up the whole control configuration. Second, the control is enforced predominantly with automated algorithms with little intervention from the manager/supervisor or a shallow human-in-the-loop compliance procedure (Chowdhury et al., 2021; Kroger et al., 2021). Third, in many studied settings, the evaluation of the employee (freelancer in the majority of platforms) is performed based on customer ratings and feedback, aggregated and processed by an algorithm to generate a score for the employee.

Limiting the study of AC to the specific context of the gig economy makes the results barely generalizable to other organizational contexts. As an example, note that workers in these settings have independent contractor legal status, and therefore, most employment laws and liabilities do not apply to them, potentially increasing their vulnerability to unfair, coercive, privacy-invasive, and non-transparent treatment by the algorithm. Finally, the interests of these studies have usually been either the employee's perception of legitimacy and fairness of the algorithm or the detrimental effects of those perceptions on employee behaviors such as employee turnover, non-compliance, efficiency drop, and workaround, which affect organizational outcomes. To contribute to this literature, this discussion focuses on organizational settings that are witnessing a transformation of an organizational control from traditional bureaucratic forms into AC.

Building on Kellogg et al.'s (2020) framework of the contested terrain of AC, this study explores the organizational control mechanisms empowered by AC and discusses each mechanism's power asymmetry and inequality implications through the lens of their objectivity, fairness, accountability, and transparency. This study takes an integrative view of the AC phenomenon as a combination of human controller configuring of the algorithm, the algorithm enacting of the control functions, and traditional control mechanisms supported by the algorithm (Wiener et al., 2021). AC is different from algorithmic decision-making, intelligent decision support, and people analytics because AC involves direct interaction of employees with algorithms through a technology interface, such as the Uber driver app (Wiener et al., 2021), while decision support systems and algorithmic decision-making concern optimizing organizational decision-making in general. Some previous research (e.g., Möhlmann et al., 2020) distinguishes between AC and algorithmic management, arguing that algorithmic management includes all the functions of algorithmic control in addition to hiring and matching functions. However, the model used in the current study (Kellogg et al., 2020) integrates these concepts because, in this model, hiring and matching are considered complementary tools to other functions of controlling employees, such as rating and rewarding.

The selected framework for this study (Kellogg et al., 2020) has merits for the discussion because of its emphasis on AC’s excessive data collection and processing and its automatic and personalized recommendation systems. Furthermore, Kellogg et al.'s (2020) attention to the effects of AC on workers' experience and well-being is more compatible with the core interest of this study compared to other frameworks focused on organizational outcomes. The structure of this paper is as follows. The first section provides a brief review of the existing literature and background. In the second section, we discuss the power asymmetry and inequality implications of AC by examining six organizational mechanisms, including directing (recommending and restricting), evaluation (recording and rating), and discipline (replacing and rewarding). Finally, we discuss some broader concerns and remedies and conclude in the third section.

1. Literature review

This section comprises a brief review of the literature on power asymmetry and inequality, and transparency and objectivity in organizations and puts them in the context of AC, thus, providing a foundation for further discussions in section 2.

1.1 Power and Inequality in the context of AC

Power is the most central concept in analyzing social phenomena, specifically in the study of organizational behavior (Clegg et al., 2006). Scholars have a consensus about the central role of power construct in social sciences as many scholars confirm Russell's 1938 analogy between the concept of power in social sciences and the concept of energy in physics (Keltner et al., 2003). The other important sociological concept in the organizational context is inequality. An extensive body of knowledge shows that organizations' decision-making plays a key role in generating and perpetuating inequality in employment outcomes, including wage, promotion, work hours, autonomy, and dignity. Inequality created in organizations has further implications beyond the organization’s environment because it tends to be transferred and reinforced in society outside the organization. For example, inequal payments to women and men in Google has spillover effects on society by widening the existing gender gap in income. This section explores the historical developments of the concept of power and examines the antecedents and consequences of attaining and losing power for individuals and groups in organizations.

The social psychology and social cognition literature have studied the effects of power on the individual in social and organizational contexts for decades. The studied effects are reported in two ways: the behavioral and cognitive effects of having and gaining power on power holders and that of lacking and losing on the powerless. Drawing on the literature, Guinote (2017) proposes a framework for understanding the social-cognitive effects of power on individuals. She shows that power energizes thoughts, speech, and action, orient individuals toward goals, and enhances self-expression, confidence, self-regulation, and prioritization. The evidence on the effect of power on performance has been mixed depending on the context. However, strong evidence shows that power leads individuals to focus on goal-relevant aspects of the situation, ignore (or underestimate) impediments to goal achievement, and minimize the size of the constraints (Anderson & Brion, 2014).

Intuitively, there is an extensive overlap between power and inequality. Acker (2006) defines inequality as "systematic disparities between participants in power and control over goals, resources, and outcomes" (p 443). Research on organizational inequality has mainly focused on class, gender, and race. In this context, class refers to systematic disparities in access to and control over resources for provisioning and survival, gender is a socially constructed concept that supports the inequality between men and women, and race refers to a socially constructed concept that differentiates based on physical characteristics, culture, and historical domination and oppression, justified by entrenched beliefs (Acker, 2006).

Promoting a meritocracy culture in organizations has been shown to produce outcomes/evaluations in favor of men comparing equally performing women (Castilla & Benard, 2010). Ray (2019) defines organizations as racial structures that create and reproduce racial inequalities by changing and filtering state policy and individual attitudes on racial issues. According to Petersen & Saporta (2004), three processes create and reinforce inequality in organizations. They identified three processes: allocative discrimination, within-job wage discrimination, and evaluative discrimination. These processes are put in place by powerful groups with minimized input from the powerless.

The traditional way of exercising power in organizations is often performed through formal and informal monitoring and evaluation of employees by managers in a dyadic relationship. The introduction of algorithmic control to organizations has changed this relationship into a multiparty one with algorithm designers, data scientists, and online service receivers as new parties. The effects of this change in power asymmetry and inequality in organizations have rarely been studied in organizational studies except for some specific cases, such as Curchod et al. (2020) study of the effects of online evaluation of sellers by buyers on power asymmetries at the transactional (between sellers and buyers) and governance (between sellers and the platform) levels, on eBay platform. Therefore, there is a need for an in-depth examination of the effects of the phenomenon on power asymmetry and inequality in the organization and its implications for organizations, individuals, and the whole society. Specifically, the difference in effects for organizations with already established power relations and the organizations that started their manager-employee configuration with AC in the first place needs to be investigated. However, this study does not distinguish between the two cases and takes an overarching view on the matter.

1.2 Transparency and Objectivity in the context of AC

Transparency has often been offered as the first stage to building accountability in algorithmic systems through public attention, litigation, market pressure, and the like (Moss et al., 2020). More broadly, algorithmic transparency is discussed in the literature as a right to an explanation or providing meaningful information about the logic of processing (Edwards & Veale, 2017). In the AC context, however, transparency refers to the level of employees' awareness and being informed of organizational control mechanisms, including what is controlled, what are the performance measures, and how they are calculated. When organizational control is performed with algorithms involved, the transparency elements are extended to what data are collected about employees, what are the parameters of control algorithms, how the algorithm affects the employee's compensation, and how the employees can participate in the algorithm's performance. Objectivity in the organizational control context refers to the objectivity of performance measures, evaluation criteria, awards and punishments measures, assigning tasks to employees, and other decisions made by managers regarding the employees.

Recent literature emphasizes the involvement of affected individuals in designing accountability mechanisms to ensure the transparency of the algorithmic system is meaningful to them and thus enables them to act (Kameswaran et al., 2022). In this discussion, we argue that given the complexities involved in the context of AC, providing meaningful transparency is hard. Second, even if the transparency of AC is provided, activating accountability mechanisms still need awareness of the controlee. Employees must have enough technical knowledge to understand the provided information on how the control algorithms work. Further, enabled and aware employees must have enough power to use that awareness and create pressure and force the controller to modify the AC harms such as bias, unfairness, and discrimination. Therefore, the existing legacy power asymmetry inhibits the proposed transparency to act as an accountability mechanism to prevent the harms generated through the use of AC.

When employee decisions are transformed into algorithms with predefined objective functions and parameters, the resultant decision is perceived as objective because it is reached through rigorous mathematical calculations. There is no human heuristics and feel involved in the decision, and the result is expected to be the same given the inputs and parameters are similar. These arguments are made to conclude that algorithms can manage human resources more effectively, accurately, objectively, and transparently (Giermindl et al., 2021). This conception might be rooted in the perception that algorithms are superior to humans in the ability to process and compute large amounts of data, and they are not bounded by human cognitive and emotional biases. The common perception in the literature is that employing algorithms could eliminate human biases and provide unbiased and evidence-based decisions (Jabagi et al., 2020). Using live data, giving constant feedback, repeating the decision process, and evaluating the processes based on objective outcome metrics make algorithms constantly improve transparency and objectivity (Newman et al., 2020).

Although some of the above-mentioned benefits of transparency and objectivity are inevitable, there are some bold implicit assumptions for realizing all the above positive outcomes. First, organizations need to have large, accurate, and relevant data on their employees' characteristics, behavior, and performance from internal and external sources. Data from different departments, including human resources, sales, production, customer services, and external private and public sources, must be collected, merged, cleaned, and preprocessed to be fit for the algorithm input (Boudreau & Cascio, 2017). This predecessor might be missing in many small or medium-size organizations due to the small number of employees. Second, data do not speak for themselves, even if large, diverse, and granular. The issues of measurement, construct validity, reliability, and interdependencies among variables exist, and given the large amount of diverse data finding spurious correlations among variables with high confidence is highly common (Ravid et al., 2020). Even if the organization owns rich, accurate, and live data on their employees and work processes, there is still a need for developing concrete algorithms that perform efficiently and transparently. General-purpose algorithms might not fit all organizations, given the idiosyncrasies in work processes and social relationships among the members. All organizations might not have the human resources and technical abilities to devise well-performing algorithms for human resource management.

Furthermore, algorithms learn without considering whether a human can understand their underlying assumptions, logic, and processes. The more advanced an algorithm becomes, the less ability the users and even the builders of the algorithm have to understand how exactly it works and why it makes its decisions (Faraj et al., 2018). When neither employer nor employee does not understand the reasons and logic behind the decisions made by the algorithm, the transparency argument fails, and employees perceive the decisions as arbitrary and unreasonable. Further, when managers cannot explain the rationale behind their decisions, accountability erodes, resulting in more arbitrary decisions even in other contexts the algorithms do not involve. This problem might be less prevalent in organizations with knowledgeable individuals who can explain at least partially the mechanisms behind the algorithms. However, many organizations lack employees with this knowledge.

Overall, at best, there will be a large variation in transparency and objectivity of AC, depending on the size, human resources, and technical capabilities available to the organizations. Assuming that the organizations have any incentive to improve transparency and objectivity in their decision-making and work motivation to decrease power asymmetry and inequality, the effect of this variation on power asymmetry and inequality in organizations is unknown and difficult to predict. A bad algorithm with low quality and inaccurate input data could have unpredictable effects on the welfare of employees and the power dynamics of the workplace.

2. Assessment of algorithmic control based on Kellogg (2020)'s model

In contrast to the mainstream treatment of control as coordination of jobs, some theorists (Edwards, 1979) focus on managerial control as resolving or managing the conflict of interest between employer and employee. This conflict is created naturally between the two parties, each of which seeks its own interests. The employer wants to organize work conditions in a way that maximizes their profit from labor. Employees pursue their own interests and therefore create their own mechanisms to control job conditions and outputs. The resistance from employees and the pressure of competition in the market makes employers employ control mechanisms with the purpose of transforming labor capacity into profit. This is the essence of labor process theory based on which Edwards (1979) extracted contested terrains framework with three elements of control in organizations: direction and specification of tasks;

evaluation, monitoring, and assessment of performance; and discipline and rewarding to elicit cooperation and compliance.

Kellogg et al. (2020) revived Edwards's (1979) typology of control mechanisms in the context of AC and extensive electronic surveillance. They argue that new technologies, including artificial intelligence, enable employers to invent new control mechanisms and transform the traditional ones into more effective versions. Kellogg et al. (2020) identified four characteristics of algorithmic technologies that make these inventions possible. First, algorithms are more comprehensive than previous means of technical and bureaucratic control in the sense that they are able to collect more data with more volume, velocity, and variety. Second, algorithms are more instantaneous in that they can provide instant feedback. Third, they provide interactivity. Fourth, algorithms are opaque. Faraj et al. (2018) suggested learning algorithms by keeping opacity (black-boxed performance) and comprehensive digitization and adding two more characteristics of anticipatory quantification and hidden politics. These characteristics together make algorithm control capable of changing the nature of control in organizations.

Incorporating the characteristics of algorithmic technologies into Edwards's (1979) contested terrains of control, Kellogg et al. (2020) provides a model of AC in which employers use six mechanisms to control workers. They direct workers by restricting and recommending, evaluate workers by recording and rating, and discipline workers by replacing and rewarding. The following section explores each of these mechanisms and examines how they affect power asymmetry and inequality within the organizations.

2.1 Algorithmic recommending

Employers use algorithmic recommendations to make automated suggestions to prompt workers to make decisions within the boundary that employers prefer (Kellogg et al., 2020). This control mechanism differs from traditional means of rational control by recommendation in several important ways. First, algorithmic recommending relies on a large amount of fine-grained behavioral data from different sources to find patterns and make inferences about the best way to do a specific task. In most cases, these inferences are made by algorithms in a black box without either employer or employees knowing the logic behind them. In many cases, these recommendations are made to the employees through nudges (Kellogg et al., 2020) and gamified messaging (Küpper et al., 2021) to influence motivation and retention. In other words, employees are manipulated constantly without being aware of that. More emphasis on coordinating and directing the employees, rather than monitoring their behavior, has been identified as a distinguishing aspect of AC compared to traditional technology-mediated controls (Alec Cram & Wiener, 2020).

Recommending and restricting, which are identified as two processes of directing by Kellogg et al. (2020), affect power dynamics and inequality in organizations in various ways. The large information asymmetry between the algorithm and the workers makes it easy for the algorithm to nudge workers to make decisions in the employer's best interest. This information asymmetry is created due to the diverse sources of data that are available to the companies. Algorithms are provided with large emotional, behavioral, and external data, mostly unknown to the employee. This phenomenon has been documented by scholars in the case of the platform economy. For example, Pregenzer et al. (2020) showed that Uber uses Soft controls that guide behavior without explicit measurement, evaluation, rewards & sanctions. Most of the examples of nudging in algorithmic recommending are concerned with the gig economy, and it is unclear whether it can be applied to other types of corporations. However, because gig workers comprise a large part of the working-age population (Pregenzer et al., 2020), the power asymmetry and inequality implications of nudging are worth considering.

Algorithmic recommending, in this context, occurs in a black box. The lack of transparency and objectivity could originate from at least two sources. First, the quality of data as the raw material of the algorithm must be audited transparently. Given the proprietary nature of most organizational data, this quality is hard to achieve. Second, the objective function and limitations of the algorithm must be known to the parties. The objective could be maximizing the sale quantity, ride time, number of new customers, profit, employee welfare, or a combination. When the objective function is unknown to the employees, they will rely on their heuristics to decide whether to accept algorithmic recommendations. The other concern about algorithmic recommendations in the context of the gig economy is that the employees lack the knowledge or time to research and learn about how the algorithm works. Lack of understanding of the inner working of algorithmic recommendations reduces worker deliberation where they accept the recommendations without being able to assess their impact on their well-being resulting in decreased autonomy. Accepting algorithmic recommendations on how and when to do the assigned tasks can also have implications for other functions of AC, impacting power and inequality. For example, consider an employee performing a task according to the algorithm recommendation resulting in a high level of performance. Because learning algorithms commonly use historical data as their input, the target performance level of the task for future sessions is set to a high level without considering contextual irregularities. In other words, the algorithm expects the same performance in future sessions forcing the employee to increase their efforts, leading to higher physical and cognitive demands. The higher acceptance level forces the employee to increase their workload because otherwise, they will be punished by algorithmic rating, replacement, and no rewards.

2.2 Algorithmic restricting

Algorithmic restricting refers to the use of algorithms by employers to control the amount and type of information the employee can access and restrict the behaviors of the employee in certain ways based on the patterns extracted from past data (Kellogg et al., 2020). Restricting employees' behavior in the workplace might be the core element of rational control in organizations. Power as control over valued resources (Emerson, 1962) is seen as the source of control in organizations. Simultaneously, power is gained by restricting the employee's access to certain resources, including money, information, benefits, promotions, other people, places, or decision-making positions. Algorithms transform traditional restricting mechanisms by facilitating the manipulation of information available to the employees instantaneously and covertly (Kellogg et al., 2020) and by limiting the amount and type of information the employees can access and share. Increasingly, organizational social apps and chatbots are deliberately designed and controlled to foster select behaviors and prohibit others based on the interests of employers and managers. For instance, Amazon's social media is reported to restrict the thoughts and sentiments the employee can share by monitoring their posts and algorithmically banning particular words that are not in the company's interests. Such words included union, grievance, pay raise, compensation, ethics, and unfairness (Ken, 2022).

Algorithmic restricting can increase power asymmetry in different ways. In a traditional control setting, the employee can balance power relations through personal communication with managers, important individuals, and other employees or by acquiring information about the manager and organizational processes and leveraging that information to gain relative power. Both these coping mechanisms are undermined in AC by minimizing the interpersonal interaction among the employees and managers, leading to what Kellogg et al. (2020) have referred to as reduced voice.

The other path through which the power relations are affected by restricting AC is when the job is broken down into micro-tasks that are scheduled in "finely grained, opaque, and unpredictable ways" (Kellogg et al., 2020, p 373). Micro-tasking jobs impede the formation of social networks and personal competence as two main predictors of rank and power within groups and organizations (Anderson & Brion, 2014). In other words, by restricting the information flow among the employees and weakening the formation of social networks, AG absorbs and concentrates potential individual powers into the designers and controllers of the algorithm. In organizations with already established power relations, the adoption of AC distorts and reorganizes the power relations in unpredictable ways. Some sources of power, such as bridging structural holes by connecting two otherwise disconnected individuals and making deals between the parties with negotiation skills, can be removed or wakened when the traditional flow of information gives place to AC.

2.3 Algorithmic recording

Algorithmic recording refers to the use of algorithms along with ubiquitous technologies to monitor, aggregate, process, and report a wide range of employee behaviors (Kellogg et al., 2020). The distinction from traditional supervision is that employers can track and record "individual employees continuously, randomly, or intermittently; discreetly or intrusively; and with or without warning or consent" (Ravid et al., 2020). Furthermore, internal states and private behaviors of employees are recorded and fed to other processes of control such as rating, replacing, and rewarding. For instance, email monitoring, keystrokes, logs of organizational software, internet usage, video and audio recordings of behavior and conversations, social media activities, and even heart rates and body heat emissions can be recorded without the employee's meaningful consent (Ravid et al., 2020). As constant tracking and recording become cheaper and perceived efficiency gains of big data are boosted, companies are increasingly relying on granular, timely, and high-dimensional behavioral data as a means of worker control. Amazon provides an illustrative example by tracking and recording every minute of an arbitrary measure called "time off task" (TOT) with RFID scanners (Kaori Gurley, 2022). Workers with time off task greater than a threshold (30 minutes) are labeled as unproductive and will be punished or fired. Time off-task includes instances such as going to the bathroom, talking to colleagues, going to the wrong floor, and unaccounted times when the worker does not remember what they had been doing. Vrontis et al. (2022) posit in their review that some forms of electronic performance monitoring technologies are already widely used by companies to monitor and analyze their employee behavior through recording call and internet usage, medication administration records, and the like. Other technologies such as microchip wrist implants and body heat sensor desk hardware are argued to be employed by companies in the near future.

Algorithmic recording guides employee behavior through multiple mechanisms. The chilling effect of constantly being surveilled makes employees vigilant leading to more and more effort and overexploitation. Even though Amazon might forgive TOT for going to the bathroom, workers fear being punished or fired for skipped water and bathroom breaks (Kaori Gurley, 2022). In other words, recording is used as a tool to guide employee behavior through fear of constantly being observed and arbitrarily being disciplined, even if the actual punishment occurs rarely. This phenomenon perfectly creates a panopticon in the workplace. The consequence of the chilling effect is not limited to increased productivity. For instance, in the Amazon case, behavioral recording and TOT enforcement were allegedly used for union-busting purposes (Kaori Gurley, 2022).

The level of granularity of recorded data has been increasing in recent years. Fuller and Schafheitle et al. (2020) document the recording of employees' email traffic, response time, and time spent in meetings to provide an insightful overview of their work routines and optimize their time resources. In another example, Deloitte Canada had its employees wearing sociometric badges to assess which elements of the workplace increase productivity. The devices could collect voice, location, and movement data with analytical capabilities such as finding correlations between factors such as who is in meetings, how much time people spend together, or who is pushing back in their chair and productivity levels (Bersin et al., 2016). The organization could use these rich granular data in combination with other data sources for other decision-making purposes, such as identifying high-performance employees. However, these data usually lack the completeness and objectivity that seem to be a fundamental assumption for arguments proposing the extensive use of the algorithmic recording. If not used mindfully, incomplete and potentially misleading data could have detrimental consequences for organizations and employees. For example, suppose organizations overestimate the objectivity of these data. In that case, they might ignore qualitative aspects of employee performance such as cooperation, innovative thinking, and performance context, relying solely on incomplete and misleading quantitative data for deciding who gets promotions and who gets laid off (Gal et al., 2020). Rewarding and sanctioning wrong employees might negatively affect power asymmetry, and inequality within organizations as more powerful members are more likely to have the voice and influence to counter unfair decisions than the powerless.

Further, intrusive data collection immediately brings up the issue of privacy loss. With advancing machine learning and data collection technologies, the extent of invasive data collection is becoming more concerning. The boundary between work life and social and emotional lives is getting blurred, and the issue of surveillance in the workplace has becomes real (Zuboff, 2019). Some studies found that this feeling of constant surveillance endangers employees' autonomy and creates counterproductive behaviors (Hamilton, 2019; Jabagi et al., 2020).

2.4 Algorithmic rating

The output of algorithmic recording feeds into algorithms designed to find a pattern in recorded data relating to employee performance measures, although those records may not relate to employee performance. Kellogg et al. (2020) coin the term algorithmic rating for guiding employee behavior through evaluation techniques based on patterns found by learning algorithms. Data collected through algorithmic recording combined with data from other internal and external sources create input for algorithmic rating. Other data sources for rating purposes come from user-generated ratings on platforms, customer ratings, and peer ratings. All these data sources still may not create data with specific predefined standards. For example, data gathered from customers about the behavior of the employees could be noisy and subjective comparing the rating data gathered from supervisors, which are based on organizational procedures. Input data for algorithmic ratings are still full of human biases and discriminatory judgments. More importantly, online customers or clients can also rate employees. In case of discriminatory or unfair ratings, there is little the targeted employee can do to protest (Kellogg et al., 2020).

The impact of algorithmic rating on power and inequality can be addressed through the examination of recorded input data, inferred measures, algorithms that turn input data into outcome indicators, and the mapping between outcomes and rewards-punishments. Input data such as video recordings, personal networks, facial expressions, and social media activities may feed into rating algorithms while irrelevant to performance. Algorithms that turn data into outcome measures and predictions and algorithms that map those measures into reward-punishment may usually be opaque (e.g., Deep Neural Networks). Predicted measures of performance based on irrelevant data and opaque predictive algorithms have strong consequences for those employees with low predicted scores. Being predicted as a low performer leads to restricted training and role promotion opportunities, which in turn causes lower performance scores in the future, exacerbating the skill gap within organizations.

2.5 Algorithmic replacing

Algorithmic replacing is conceptualized by Kellogg et al. (2020) as rapidly and automatically firing the employees with low performance and replacing them with new employees from a pool of potentially eligible candidates by a learning algorithm. Replacing non-compliant or less efficient workers with new workers is a classic means of organizational control mechanism. With AC, however, this mechanism becomes more aggressive as it could be implemented faster, cheaper, and presumably more efficient (Kellogg et al., 2020). The other elements affecting the efficiency of algorithmic replacement originate from the affordances provided by other algorithmic control modules, including recommending, restricting, recording, rating, and rewarding. These affordances allow organizations to outsource and monitor their work and that most work can be done remotely. Accordingly, this interchangeability of the workforce would change the power relations between managers and subordinates. Employees could be fired for any reason, including the personal preferences of supervisors.

People analytics literature has shown extensive use of algorithmic prediction for decision-making about recruitment and lay off (Giermindl et al., 2021). Relying solely on algorithms' prediction of future absence from work for pregnancy or mental illness, employers might make decisions to layoff employees without understanding the probabilistic nature of these predictions (Giermindl et al., 2021). Easy and lower-cost replacement of employees creates job insecurity, especially for those with low-skill jobs who are already under economic pressure. An excessive supply of workers diminishes the negotiation power of employees and makes their relative power even less.

Algorithmic hiring has gained relatively more attention in the academic and public discourse due to its potential to cause large-scale discrimination. Discriminatory effects of algorithmic hiring on women, people of color, and marginalized populations have been reported widely (Engler, 2021). Algorithmic auditing has been proposed to remedy the concerns and avoid strict regulations (Brown et al., 2021). However, the effectiveness of algorithmic auditing depends on many factors, including whether an audit is conducted by an internal party or a third party, what are the metrics and procedures for auditing and who defines them, and how the organizations could be incentivized to accept the audits and improve their algorithms upon the audit results.

2.6 Algorithmic rewarding

Employing learning algorithms to "interactively and dynamically" determine and distribute professional and material rewards among the employees with the aim of contorting their behavior is referred to as algorithmic rewarding by Kellogg et al. (2020). Algorithmic rewarding could be more efficient than traditional technical and bureaucratic rewarding mechanisms for control purposes. First, it takes input from functions referred to above, specifically rating, and determines financial and non-financial rewards with the aim of maximizing those performance measures in future runs. Therefore, all the mechanisms of AC generating power asymmetry and inequality are reinforced through rewards. Second, the algorithmic assignment of rewards or punishments can be run on a large scale and at a low cost. There is no need for supervisors to make a decision on who gets and who does not get rewards. This may increase the error rate, but in turn, the error rate can be mitigated by increasing the frequency of rewards with smaller values. However, algorithmically determining the compensations of workers, based on contingent data and statistical models, decreases the wage reliability and has detrimental effects on worker well-being.

Further, taking algorithms' prediction of employees' future performance at face value has the drawback that they might fall into a self-fulfilling prophecy trap. Employers might invest in training programs for employees identified by the algorithm as promising and do not allocate resources to other employees. Trained employees will likely improve and perform better than untrained. This successful prediction reinforces the employer's perception of accurate algorithmic decision-making and leads to more future likely inefficient resource allocation (Giermindl et al., 2021).

3. Discussion

Data-driven AI solutions to Human Resources (HR) are advertised by the industry and HR scholars as a means of managing the workforce objectively and avoiding human supervisor subjectivity in employee-related decision-making (Chornous & Gura, 2020; Chowdhury et al., 2021; Tambe et al., 2019) presumably leading to higher fairness and equity and reduced bias (Gaur & Riaz, 2019; Kshetri, 2021). For instance, in their review of HR use of algorithms, Chowdhury et al. (2021) have suggested the objectivity potential, fewer mistakes, and the ability to predict employee behavior through extensive use of data as the main drivers of AL within organizations. Others have even suggested using algorithms to identify and close pay gaps across gender, race, and other protected classes by improving the accuracy of employee qualification measurements and predictions of future performance and retention (D. Anderson et al., 2022; Vrontis et al., 2022). Increasingly, however, empirical research emphasizes the “black box” nature of most algorithmic applications (Ajunwa, 2020; Durán & Jongsma, 2021), indicating opacity, bias, discrimination, and lack of accountability which could exacerbate the current power asymmetry and inequality within organizations (Engler, 2021; Köchling & Wehner, 2020; Lepri et al., 2018; Tambe, Cappelli, & Yakubovich, 2019).

Responding to the calls for interdisciplinary studies of using algorithms in employee management to identify ethical, societal, and fairness challenges (Vrontis et al., 2022), we discuss the power asymmetry and inequality implications of algorithmic control in organizations. AC can absorb the existing sources of employee power and distort power relations through the 6R mechanisms discussed in section 2. However, the introduction of AC into organizations and its replacement with existing organizational controls could also change power dynamics to benefit the employees or decrease inequality within organizations. Some sources of power that are eliminated or at least weakened through AC include demographic morphology and interpersonal style. Reducing the significance of interpersonal relationships and social and informational exchange in an informational setting by introducing AC could make established power sources such as age, sex, race, height, weight, and facial characteristics irrelevant, consequently leading to improved equality and power distribution. However, the extent to which these changes can compensate for the adverse effects discussed in section 2 needs more empirical inquiries.

The existing power maintenance mechanisms can also be disrupted by AC approaches leading to changes in power distribution. Power maintenance factors that could be affected by AC include exogenous factors such as system justification and attribution of positive traits to power holders and endogenous factors such as effect and physiology, cognition, and behavior (Anderson & Brion, 2017). Effects of AC are not bounded to organizations. Personal data collected for algorithmic management can be used to predict and control people's behavior which poses an extensive threat to individuality and the fabric of democracy. Furthermore, AC raises important policy questions regarding collecting personal data, which are limited in some areas under policies such as GDPR and CCPA. And finally, challenges may arise from a computing and knowledge management perspective. For example, managerial algorithms may be better than humans in organizing and distributing the work. But they are not yet capable of understanding the group dynamics and emotional relations between employees. In terms of knowledge management, the big stream of collected data raises important challenges in terms of storage and security.

Workplace privacy, defined as “Workers judge AC practices as appropriately respecting their personal information during data collection, storage, and use,” is one of the perceived legitimacy dimensions identified by Wiener et al. (2021), along with fairness and autonomy in the context of platform-based companies (p. 6). In organizational behavior literature, privacy is conceptualized as control over the release and use of personal information, the ability to regulate one's social interactions, isolation from the unwanted environment, and autonomous behavior (Bhave et al., 2020). This notion of privacy covers information privacy, workplace privacy, and the autonomy of the employees. These three dimensions of privacy are interrelated and affect each other. Importantly, the invasion of information privacy is more significant with increasing reliance on information technology in organizations. Also, information privacy and power are shown to be intertwined phenomena (Citron & Solove, 2021). The more information a party has about the characteristics, behavior, attitudes, and emotions of the other parties, the more power it obtains over them. Therefore, the privacy implications of the expansion of AC deserve more deliberation.

Technological trends and data privacy laws, as Bhave et al. (2020) discussed, are two major developments with privacy implications for organizations and employees. Improvements in technologies and methods of data collection, processing, and sharing have transformed the privacy challenges in organizations. A massive amount of granular data can be collected in continuous time through mobile apps, sensory devices, RFID and GPS applications, social media platforms, and internal knowledge management platforms. These data are sometimes collected outside the workplace and might not be job-related, such as data on employees' personal interactions on social media. Further, organizations could afford to make inferences about the employees at the individual group and department levels without their knowledge (Schafheitle et al., 2020). These affordances create new risks and liabilities for the organizations, including risks of a data breach, consequent legal liabilities, and non-compliance with privacy regulations.

Privacy regulations are relevant to algorithmic management from multiple perspectives. First, to facilitate organizational management, some organizations might want to link different types of information about employees. For example, suppose an organization has an internal medical care unit for its employees. In that case, it might be tempting to link employees' health information to their working schedule in order to distribute the work effectively and optimize employees' productivity. However, this might bring different problems for the organization because there are different policies for protecting individuals' health information vs. other types of information which complicates the idea of linking information, especially if a third-party analytics company is involved. Second, because of different policies around the world, it could be difficult for international organizations to be consistent in their treatment of employees. For example, employees in the EU are protected under GDPR. Therefore, they can claim their right to privacy on any type of personal information, including their right to opt out from their personal data being collected and processed. This might not be true for employees in regions without strict privacy and data protection regulations. These examples show some of the challenges that information privacy policies might bring for organizations, which require specific attention from organizations who are involved in collecting and use of employees' personal information. Organizations with employees residing in different locations with different data protection laws should assess the implications of different treatment of employees' data on the work outcomes.

One other aspect of AC that goes beyond the six dimensions discussed in section 2 is organizational control of the potential employee before they sign a contract with the company. As Schafheitle et al. (2020) report, there is a growing and strong demand for AI technologies that target the control of job candidates before their employment. This practice could be perceived as a stronger violation of the privacy of individuals because the data collected and used for decision-making are more personal and unrelated to the workplace. Automatic scanning of job applications, matching applicants with social media accounts and other external data sources like public records, or purchasing individual profiles from private data brokers for use in hiring decisions could raise privacy concerns not addressed within the current laws.

Increased capabilities of organizations to collect, store, analyze, and utilize employee data, also has a concerning drawback. Others, including competitors, individual hackers, cyber-criminal gangs, and even foreign adversaries, have also improved capabilities for accessing the organizations' data and utilizing it for their purposes. The costs of data breach incidents (IBM, 2019; Nathan & Scobell, 2020), ransomware attacks, and advanced persistent adversary attacks have been on the rise recently. The more employees' personal data the organizations collect and process, the more risks and vulnerabilities they have to cyber-attacks. Organizations must consider increased risks and vulnerabilities resulting from their aggressive reliance on AC when devising their policies. Adverse consequences of cyberattack could also harm the employee in cases of a data breach when stolen personal data are used for identity theft and related misuses. Further, the implications on employees' attitudes toward perceived invasive AC in this new environment need to be addressed in organizational control studies. Given the importance of human factors in organizations' cybersecurity success (Poehlmann et al., 2021), questions such as whether and how the perceived invasive control affects employees' compliance with the organization's cybersecurity guidelines and procedures.

Conclusion

AC's perceived efficiency and economic benefits spread its use cases within organizations to include everyday functions and interactions between employees and managers. Therefore, to study ethical implications and early realization of unintended consequences of this spread by academics and practitioners in organizational studies, human resource management, information systems, data analytics, and computer science. Algorithmic decision-making is often applauded for its accuracy and objectivity originating from its reliance on large amounts of granular data and advanced machine learning technology and its lack of prejudice, cognitive biases, emotional distortions, and other limitations of its human counterparts. Based on this objectivity assumption, the demand for algorithms to substitute or complement human decision-makers has increased. In the workplace context, it seems very appealing to replace an objective, unbiased, and therefore, a fair algorithm with a human supervisor with all the cognitive biases, sometimes unfair and arbitrary decisions, and personal interests that are often in contradiction with the interests of the supervisees. However, research and proactive have shown many social, ethical, legal, and economic consequences of algorithmic decision-making, including bias, discrimination, lack of transparency and accountability, and unfairness.

Transparency refers to the understandability and interpretability of the algorithm's results and how it works. It is the opposite of opacity. The lack of transparency can come from the creator's will to hide some information, such as proprietary techniques or intellectual property. The second source of opacity is the existing information barriers or digital divide where the majority of the users or stakeholders cannot understand the nuances of algorithms at work. Opacity is also an intrinsic feature of more advanced data analytics and predictive algorithms such as deep neural network models (Lepri et al., 2018). The relationship between transparency and information asymmetry, accountability, and power asymmetry is well-studied in the literature (Lyrio et al., 2018). Consider, for example, the case of using big data gathered from the web and other sources about employees to assign them a score for outcome variables, such as job satisfaction, absenteeism, intention to stay, perceived procedural justice, organizational commitment, and trust (Shah et al., 2017). While all these measures are the output of a usually unknown predictive algorithm with complex and messy input data, they can have significant consequences for subject employees.

Objective performance assessment, employee development, organizational socialization and engagement, and workforce planning are identified as the most popular objectives of AC (Boudreau & Cascio, 2017; Tursunbayeva et al., 2018). In addition, it has been argued that AC, based on a generally accepted set of rules, would increase transparency and leads to fairness (Möhlmann et al., 2020; Wiener et al., 2021). Although AC could bring many of the promised advantages to organizational management, its effects on organizational efficiency, employees' performance, and well-being should be evaluated more carefully. Most importantly, opaqueness, lack of understandability, trustworthiness, and accountability are characterized as intrinsic features of algorithms (Durán & Jongsma, 2021; Jarrahi et al., 2021; Kellogg et al., 2020). Accepting the assumption that AC can bring objectivity and transparency to the organizational control process could lead to an optimistic evaluation of the efficiency. This overestimation could create a false perception of control for employers, resulting in inefficient management and decision-making (Kellogg et al., 2020). Furthermore, employees might suffer from unintended consequences of managers' relying solely on algorithmic decisions about their performance. Literature on algorithmic decision-making has documented unfair and discriminatory decisions made by algorithms in areas of criminal justice (Hamilton, 2019; Peeters & Schuilenburg, 2018) and recruitment (Köchling & Wehner, 2020), which are in contradiction with the objectivity assumption.

Not different from many other social science questions, it seems there is no one simple answer to the question of the effect of AC on the inequality within organizations, as the answer depends on context, the organization’s ability to adopt the technology, values, socially desired outcomes, and many other factors. The survey of the literature shows that many underlying assumptions of proposing AC for organizations, including transparency and objectivity, are not justified. Embracing AC by organizations without meticulously examining that assumption in the context and specific conditions of the organization could result in detrimental consequences for both organizations and employees. The review of the related literature suggests that when adopted poorly, or when there exists a misalignment of incentives between employer and employees without proper legal and public policy protection in place, AC might exacerbate the existing power inequalities within organizations. There also exist concerns about the societal effects of gathering, processing, and making decisions based on granular data about employees.

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