Algorithms as work designers:

How algorithmic management influences the design of jobs

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Abstract

We review the literature on algorithmic management (AM) to bridge the gap between this emerging research area and the well-established theory and research on work design. First, we identify six management functions that algorithms are currently able to perform: monitoring, goal setting, performance management, scheduling, compensation, and job termination. Second, we show how each AM function affects key job resources (e.g., job autonomy, job complexity) and key job demands (e.g., workload, physical demands); with each of these resources and demands being important drivers of worker motivation and their well-being. Third, rejecting a deterministic perspective and drawing on sociotechnical systems theory, we outline key categories of variables that moderate the link between AM on work design, namely transparency, fairness and human influence (e.g., whether workers can control the system). We summarize our review in the form of a model to help guide research on AM, and to support practitioners and designers in the creation and maintenance of meaningful jobs in the era of algorithms.

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INTRODUCTION

Recent advances in artificial intelligence technologies have a considerable influence on people's work. Experts argue that the digitalization of workplaces is unprecedented and that we are in the "fourth industrial revolution" (de Ruyter, Brown, & Burgess, 2019; Ghislieri, Molino, & Cortese, 2018; Schwab, 2017). Researchers have begun to focus on the repercussions of these technological advances for HRM and management (Kellogg, Valentine, & Christin, 2019; Lindebaum, Vesa, & den Hond, 2019; Minbaeva, 2020; Murray, Rhymer, & Sirmon, 2020; Raisch & Krakowski, 2020; Tambe, Cappelli, & Yakubovich, 2019). Since most of the existing jobs are likely to be heavily transformed in the following years (Jarrahi, 2018; Raisch & Krakowski, 2020; Roos & Shroff, 2017), and many new forms of jobs are expected to appear (Paus, 2018; West, 2018), it is vital to ensure that the design of digital work promotes human well-being (Parker & Grote, 2020; Schroeder, Bricka, & Whitaker, 2019).

Fortunately, to help guide the design of digitalized work, there is a great deal of well-established theory and evidence regarding the work design parameters that lead to meaningful jobs (Hackman & Oldham, 1976; Humphrey, Nahrgang, & Morgeson, 2007; Parker, Morgeson, & Johns, 2017). Work design refers to "the content and organization of one's work tasks, activities, relationships, and responsibilities" (Parker, 2014, p. 47). This body of research has provided extensive evidence for the influence of work design characteristics such as job autonomy and task variety on employee's motivation and well-being, as well as on key HR indicators such as turnover and productivity (Chang, Wang, & Huang, 2013; Humphrey et al., 2007; Parker, 2014; Parker & Turner, 2002; Torraco, 2005). Scholars (e.g., Parker and Grote (2020); Demerouti (2020) have recently sought to apply work design research and theory to understand the impact of the digital revolution on people's work. We build on this perspective here, focusing specifically on understanding the impact of algorithmic management on work design and, as a consequence, on important outcomes such as well-being and motivation.

The management of employees via algorithms is one of the most disruptive forms of technological change currently being implemented (Duggan, Sherman, Carbery, & McDonnell, 2019; Kellogg et al., 2019; Lee, 2018; Rosenblat, 2018; Wesche & Sonderegger, 2019). Algorithmic management refers to "a system of control where […] algorithms are given the responsibility for making and executing decisions affecting labor, thereby limiting human involvement and oversight of the labor process" (Duggan et al., 2019, p. 6).

Existing research on algorithmic management tends to suggest that it generates more negative than positive outcomes for workers. In particular, AM has been associated with a reduction of workers' autonomy (Jabagi, Croteau, Audebrand, & Marsan, 2019; Mohlmann & Zalmanson, 2017; Toyoda, Lucas, & Gratch, 2020), and the creation of power asymmetry in information availability (Calo & Rosenblat, 2017; Jarrahi & Sutherland, 2018; Rosenblat & Stark, 2016; Shapiro, 2018). These consequences potentially explain why AM has also been shown to result in in negative emotions, unfairness perceptions, low trust (Lee, 2018; Zarsky, 2016), psychological contract breach (Tomprou & Lee, 2019), low job satisfaction (Brawley & Pury, 2016; Griesbach, Reich, Elliott-Negri, & Milkman, 2019), lower life satisfaction (Keith, Harms, & Tay, 2019), and reduced engagement in work (Bucher, Fieseler, & Lutz, 2019). This apparently dark portrait of AM, however, warrants additional research, and has limitations. First, the emerging literature on the topic is spread across different streams of research and conceptual approaches, and has mainly examined one algorithmic function at the time, lacking theoretical integration. Second, existing research often seems to be based on deterministic assumptions about the consequences of technology, implying pre-determined outcomes. Third, empirical research has focused on the context of gig work, such that AM in traditional work contexts has been overlooked.

In this paper, we address these limitations by reviewing the findings from empirical and descriptive studies of AM practices, drawing on work design theory to organize our analysis. We propose a holistic framework for understanding the effects of AM on work design, including moderators of these effects, and the associated outcomes. This framework can be tested and expanded to support systematic and theory-driven future research on the topic of AM (see Figure 1). Specifically, we first identify six HR and management functions that organizations can automate with algorithms (i.e. monitoring, goal setting, performance management, scheduling, compensation, and job termination). Second, drawing on existing evidence, we propose how these AM functions affect work design, in terms of key job resources and job demands. As indicated in our model, considerable evidence shows that these job resources and demands, in turn, affect workers' motivation, well-being, and performance (we do not review this evidence, but refer the reader to existing meta-analyses and reviews). Third, adopting a voluntarist rather than deterministic standpoint, we propose several moderators of this relationship between AM and work design (and hence outcomes). To identify these moderators, we draw on the socio-technical systems perspective of work design (Emery & Trist, 1978; Makarius, Mukherjee, Fox, & Fox, 2020). Altogether, the proposed model can not only can guide future research, but also can be used to help HR managers and system designers to ensure that the procurement and implementation of algorithmic management is done in a way that maintains or creates motivating work for workers.

Insert Figure 1 about here

In what follows, we describe algorithms and the functions of management they can perform, followed by how they affect work design. We then turn our attention to what we label as 'sociotechnical moderators', or the most promising parameters that can shape the influence of AM on work design, thereby providing a path for creating well-designed jobs.

ALGORITHMS AND THE FUNCTIONS OF MANAGEMENT THEY PERFORM

An algorithm is a "computational formula that autonomously makes decisions based on statistical models or decision rules without explicit human intervention, [such as] a sequence of instructions telling a computer what to do within a set of precisely-defined steps and rules designed to accomplish a task" (Duggan et al., 2019, p. 6). Algorithms are used in many data-based systems used in HRM and management (Cheng & Hackett, 2019; Duggan et al., 2019; Leicht-Deobald et al., 2019). First, *descriptive* algorithms are used to record past events and analyze their influence on present events, like the performance evaluation algorithms aiming to gather different kind of performance-related data and to compute an overall evaluation (Leicht-Deobald et al., 2019). Second, *predictive* algorithms focus on forecasting future behaviors or estimating the likelihood of an event occurring (Cheng & Hackett, 2019), such as the ones used to estimate the future performance or fit of candidates, or those algorithms used to set the goals, expectations or targets of current employees (Leicht-Deobald et al., 2019). Third, *prescriptive* algorithms select the best solution scenario out of different possibilities and recommend an action, or simply implement it (Cheng & Hackett, 2019; Leicht-Deobald et al., 2019), like the ones used to automate strategic HR decision-making (Jarrahi, 2018; Parry, Cohen, & Bhattacharya, 2016) or for task-allocation and scheduling decisions (Cheng & Hackett, 2019; Lee, Kusbit, Metsky, & Dabbish, 2015; Rosenblat, 2018).

Algorithms have been used for a long time, but their role is changing in important ways. The power of todays' algorithms driven by artificial intelligence is greater due to their ability to 'learn' autonomously and to handle big data (Beer, 2017; Kellogg et al., 2019; Schafheitle et al., 2020). Artificial intelligence algorithms can either be pre-programmed or powered by machine learning technologies (Leicht-Deobald et al., 2019; Wang & Siau, 2019; Wong, 2019). Machine learning refers to a field of study that enables computers to learn without being explicitly programmed (van Rijmenam & Logue, 2021; Wang & Siau, 2019). Instead of following determined rules like pre-programmed algorithms, machine learning algorithms start from very little programming and are trained on big and unstructured data sets. For instance, a machine learning algorithm aiming to forecast the performance of an employee would be trained using millions of employee records, learning from trial and error in performance ratings predictions and using every case of right or wrong prediction as data for improvement.

AI-powered algorithms differ from those previously used in traditional electronic management and HRM systems. First, their ability to learn from their success and errors without human intervention makes them attractive in terms of autonomous operation and continuous improvement (de Visser, Pak, & Shaw, 2018; Faraj, Pachidi, & Sayegh, 2018; Kemper & Kolkman, 2019). Second, AI algorithms have been found in some situations to outperform humans in reaching very high levels of accuracy in decision-making, and to handle big and unstructured data sets characterized by high velocity, volume, heterogeneity (Ananny & Crawford, 2018; Cheng & Hackett, 2019; Gillespie, 2014; Leicht-Deobald et al., 2019; Parry et al., 2016). Moreover, AI algorithms are often interconnected and interact autonomously between each other (Kellogg et al., 2019; Schafheitle et al., 2020). In sum, AI algorithms, largely powered by machine learning, differ from previous automated decision-making devices in their high level of autonomy (requiring little human input), their self-learning capacities, their potential for interconnectedness, and their ability to handle massive and heterogeneous data in order to perform description, prediction, and prescription tasks (Makarius et al., 2020; Murray et al., 2020). As we elaborate in this review, these attributes of AI algorithms mean they have the potential to impact work design in new, and often more extreme, ways (van Rijmenam & Logue, 2021).

Algorithmic management and its functions

In organizations of many kinds, it is increasingly the case that algorithms perform tasks traditionally reserved for managers or HR managers (Gal, Jensen, & Stein, 2020; Kellogg et al., 2019; Mateescu & Nguyen, 2019a). Lee et al. (2015) proposed the term algorithmic management (AM) to describe this phenomenon within the ridesharing industry. Since then, there has been growing interest from scholars in understanding the role of algorithms in managing human workers beyond this industry, and of the effects of such practice on the workers. Tomprou and Lee (2019) even suggest “the emergence of a new discipline” to describe the growing scientific interest in AM.

The early literature on the topic focused mainly on algorithmic management within the gig economy, defined as “an emerging labor market wherein organizations engage independent workers for short-term contracts (“gigs”) to create virtual jobs, often by connecting workers to customers via a platform-enabled digital marketplace" (Jabagi et al., 2019, pp. 192-193). However, recent reviews and conceptualizations (Kellogg et al., 2019; Mateescu & Nguyen, 2019a; Schafheitle et al., 2020) consider algorithmic management as a technological phenomenon that is not contingent on the type of organization and can be found in a large array of work contexts. In our review, we similarly identified literature about algorithmic management both in the gig economy and in other sectors.

Our model synthesizes six key managerial functions and HRM activities that algorithms have been used to perform management functions: ***monitoring*** (i.e., algorithms used in systems aiming to collect and report any data on employees during their work), ***goal setting*** (i.e., algorithms assigning tasks or rides, organizing employees' work, or setting performance or productivity targets), ***performance management*** (i.e., algorithms carrying out and/or displaying employees' performance ratings or providing automated performance feedback), ***scheduling*** (i.e., algorithms carrying out employee's schedules or sending nudges for suggested working times), ***compensation*** (i.e., automated calculation of pay based on algorithmically managed conditions and metrics), and ***job termination*** (i.e., algorithmic termination decision making and/or announcement).

The unpacking of algorithmic management through these six functions is based on the combination of empirical evidence for capabilities of algorithms in HRM and management domains (e.g., Mateescu & Nguyen, 2019a), and of conceptual descriptions of such capabilities and their consequences (Cheng & Hackett, 2019; Gal et al., 2020; Leicht-Deobald et al., 2019; Tambe et al., 2019)[3]. Specifically, the role of algorithms in

[3] Algorithms are also increasingly used to recruit and select staff. Because our focus is on work design, we consider only post-recruitment management of employees and therefore do not include this aspect in our algorithmic model.

performance management, compensation scheduling has been addressed by HRM scholars (Duggan et al., 2019; Schneider & Harknett, 2019; Strohmeier & Piazza, 2015; Tambe et al., 2019), whereas monitoring, goal-setting and job termination have been approached in the management field (Kellogg et al., 2019; Robert, Pierce, Marquis, Kim, & Alahmad, 2020; Schafheitle et al., 2020). Our model is based on evidence as to how these AM functions affect work design (summarized in Table 1), as we elaborate next.

THE EFFECT OF ALGORITHMIC MANAGEMENT ON WORK DESIGN

Among the different conceptualizations of work design (see Parker et al., 2017 for a review), we draw mainly on the popular job demands-resources model (J D-R model: Demerouti, Bakker, Nachreiner, & Schaufeli, 2001), emphasizing the importance of considering both job resources and job demands when designing work (Demerouti et al., 2001). Considerable evidence links job resources and job demands with workers' motivation, well-being and performance (for meta-analyses or reviews, see: Humphrey et al., 2007; Knight & Parker, 2021; Parker & Ohly, 2008).

Key job resources and job demands

Job resources refer to aspects of work that help individuals achieve their goals and which also help workers to deal with job demands (Demerouti et al., 2001). Job resources include a variety of aspects of one's job, among which we focus on the task, knowledge and social characteristics of the Morgeson and Humphrey (2006)'s model of work design. Task characteristics include (1) the autonomy one's has in decision-making related to the job, in scheduling decisions and in the determination of work methods; (2) the variety of the tasks one is required to perform; (3) the feedback received directly from the job regarding one's performance or work quality; and (4) task significance, or the degree to which the job influences the lives of others or is considered important (Morgeson & Humphrey, 2006). We also include role clarity as an important job resource, which refers to clarity of the expectations and tasks (Lyons, 1971). Knowledge characteristics include (but are not limited to) (1) job complexity one finds in work due to challenging nature (not too simple) of some tasks, and; (2) problem-solving opportunities requiring novel ideas or an active cognitive effort. Social characteristics include aspects to relatedness at work, among which we focus here on social support from peers.

Job demands are referred to as "those physical, psychological, social, or organizational aspects of the job that require sustained physical and/or psychological (cognitive and emotional) effort or skills and are therefore associated with certain physiological and/or psychological costs" (Bakker & Demerouti, 2007, p. 312). Based on the early evidence regarding the effects of AM on job demands, we focus on workload (e.g., the intensity of work and the amount of tasks to carry out), physical job demands (e.g., the use of physical strength required or the fatigue induced by the job), emotional demands (e.g., a job requirement to hide one's emotions), and job insecurity, which is increasingly viewed by scholars as an important and typical hindrance stressor and demand emanating from work (Van Laethem, Beckers, de Bloom, Sianoja, & Kinnunen, 2019; Wang, Le Blanc, Demerouti, Lu, & Jiang, 2019; Wu, Wang, Parker, & Griffin, 2020), defined as a "concern about the future permanence of the job" (van Vuuren & Klandermans, 1990, p. 133).

Insert Table 1 about here

Effects of AM functions on key job resources and job demands

Here we discuss the effect on work design of each of the six AM functions in our model. It is important to note that some potential HRM-related functions, such as training and career management (see Tambe et al., 2019), were not included in the model due to a lack of empirical evidence (we, however, refer to these functions briefly when discussing the performance management function).

Algorithmic monitoring. Monitoring refers to the systems, people and processes used to collect, store or analyze and report the actions or performance of individuals or groups on the job (Ravid, Tomczak, White, & Behrend, 2020). One key advantage of artificial intelligence algorithms in monitoring is their ability to analyze and process automatically and rapidly massive amounts of heterogeneous data about workers' actions, behaviors or performance (Mateescu & Nguyen, 2019b). AI-driven algorithmic monitoring thus allows to collect and record a vast array of new information and metrics, such as emotions (Chan, 2018; Pinheiro, Ramos, Donizete, Picanço, & De Oliveira, 2017), movements, sleep time, physical and health condition, social media activity, internet browser history (Angrave, Charlwood, Kirkpatrick, Lawrence, & Stuart, 2016; Leicht-Deobald et al., 2019), employees' calendar (Chen, 2019), stress levels (de Vries, Kamphuis, Oldenhuis, van der Schans, & Sanderman, 2019; Freihaut & Göritz, 2020; Horton, 2020), posture, ergonomics and safety threats during work (Bootsman, Markopoulos, Qi, Wang, & Timmermans, 2019; Brustein, 2019), real-time work space usage (Eveleth, 2019) or desk usage (Morris, Griffin, & Gower, 2017; Waterson, 2016), cognitive or physical employees' workload (Heard, Harriott, & Adams, 2018), and workers' engagement in their work (Burnett & Lisk, 2019). Moreover, whereas traditional systems of electronic monitoring relayed the information to a manager, algorithms are often autonomous in processing the resulting outcomes of these data, or transferring real-time information to other algorithms of an integrated system (e.g. scheduling or goal setting algorithms), making it an important entry point of data used for AM (Evans & Kitchin, 2018).

Algorithmic systems also facilitate the monitoring of customer information, which is increasingly used in workers' management (Davenport, Guha, Grewal, & Bressgott, 2020; Levy & Barocas, 2018). For instance, retail stores can now use multiple-device systems to precisely track the traffic of consumers in each zone of a store surface (Davenport et al., 2020; O'Connor, 2016) in order to carry out zone assignment, to build up staff schedules based on forecasted occupancy, and to calculate sales / traffic ratio to be included in the performance appraisal of salespersons (Evans & Kitchin, 2018; Levy & Barocas, 2018).

Because data collected through monitoring devices is often used to assess their performance, workers sometimes tend to "work for data" (Evans & Kitchin, 2018; Schafheitle et al., 2020), focusing more on the tasks being monitored and eluding the ones that are not, which can hamper <u>task variety</u> (Tomczak, Lanzo, & Aguinis, 2018). A similar consequence of narrow algorithmic monitoring systems is a greater emphasis on quantified work objectives at the expense of other and potentially meaningful aspects of one's job (Schafheitle et al., 2020), reducing the <u>autonomy</u> of workers in the choice of their work methods (Day, Paquet, Scott, & Hambley, 2012; Wang, Liu, & Parker, 2020), as observed in previous studies in algorithmically-monitored contexts (Leclercq-Vandelannoitte, 2017; Levy, 2015; Moore & Hayes, 2018; Pritchard, Vines, Briggs, Thomas, & Olivier, 2014; Pritchard, Briggs, Vines, & Olivier, 2015). Such systems used, for instance, to monitor and optimize warehouse workers hands and arms movements (Engler, 2018; Yeginsu, 2018), or to track different features of parcel delivery process such as the geolocation, the cleanliness of the trucks (Woyke, 2018) and the weight and size of each package (Rosenbush, 2018) are likely to simplify workers jobs or solving problems for workers, hampering job complexity and problem-solving opportunities. Similarly, in some call centers, voice recognition systems now capture instantly the emotions displayed by both the consumer and the agent, allowing to assess the real-time appropriateness of the agent's emotional response and the extent to which it matches the consumer's emotional state (De La Garza, 2019; Hernandez & Strong, 2018; Martin, 2019b; Roose, 2019). As a result of this assessment, the system shows instant instructions about particular emotional cues to be displayed or of speech rhythm adjustment, taking away workers' challenge to identify customers' mood and to use their judgment or creativity in the response (De La Garza, 2019; Hernandez & Strong, 2018; Martin, 2019b). Such monitoring of numerous features of employees' attitudes, behaviors, performance, and emotions has largely been viewed as a pervasive form of surveillance, focused on controlling employees (Mateescu & Nguyen, 2019b), which can correspond to a stress-related emotional demand.

Algorithmic goal setting. The wide range of data collected through algorithmic monitoring can be used to set workers' goals. The algorithmic goal setting function includes two aspects: task assignment and performance target setting. For instance, in the case of package and courier delivery, ridesharing services or app-based food delivery services, algorithms link employees' real-time geolocation information to on-the-flow task-related information (e.g., customer requests, new order, priority change, deadline approach) and to customer interface to provide precise and update expected delivery time (Duggan et al., 2019; Griesbach et al., 2019). Algorithmic task allocation is largely found in the gig economy and platform work (Gerber & Krzywdzinski, 2019; Lee et al., 2015;

Rosenblat, 2018), and in traditional work sectors like telecommunication (Leclercq-Vandelannoitte, 2017), electronics (Gershgorn, 2015; Hitachi, 2015), public transports (Hodson, 2014), and parcel delivery (Stevens, 2015). In other cases, algorithms are used to set the performance targets or rate, based on data such as previous performance, demand, traffic, weather, etc. (Griesbach et al., 2019; Guendelsberger, 2019). The most compelling examples, among many others, are warehouse workers parcel manipulation targets (Guendelsberger, 2019) and parcel delivery targets for drivers (Rosenbush, 2018; Woyke, 2018).

The impact of the use of AM to set goals on the reduction of workers' autonomy has been outlined by many scholars, namely in gig-work where autonomy in task selection is often viewed by externals as a major advantage of platform-based work (Curchod, Patriotta, Cohen, & Neysen, 2019; Gerber & Krzywdzinski, 2019; Griesbach et al., 2019; Rosenblat, 2018; Shapiro, 2018). In gig work, the algorithmic task allocation process is highly contingent on demand or customer satisfaction scores (Gerber & Krzywdzinski, 2019; Gregory, 2020; Griesbach et al., 2019). Workers have also very little freedom to accept or decline algorithmic assignments, because the acceptance rate and average time to accept assignments are indicators used by algorithms in the calculation of performance scores and in the determination of future assignments (Allen-Robertson, 2017; Gandini, 2019; Gregory, 2020; Griesbach et al., 2019; Lee et al., 2015; Rosenblat, 2018; Shapiro, 2018; Veen, Barratt, & Goods, 2019), or because the algorithmic system only show tasks available in a specific space zone (Heiland, 2021). Algorithmic goal setting has also been found to influence workers' autonomy and job complexity in traditional (non-gig) work setting. For instance, Brione (2017, p. 12) reports the case of manufacturing plants using a task planning algorithm with the purpose of better sequencing work, avoiding bottlenecks and meeting all the deadlines, and observes a reduction of workers' autonomy in the choice of tasks and method, as well as a simplification of tasks.

Having no control over the tasks or targets you are assigned to has the potential to result in an increase of work demands, namely in terms of physical demands and workload. Reyes (2018) namely reports how an algorithmic system used to dispatch room cleaning assignments based on instant clients' arrival time has taken away housekeepers' autonomy to organize their day and made their jobs more physically demanding, as it obligates them to zigzag across hotel floors and areas, carrying their heavy equipment. In the same vein, high-tech tools used in warehouses to identify the sequence of package manipulation movements serve as the basis for the setting of the ever-increasing performance standards regarding the number of packages to be manipulated per hour (Guendelsberger, 2019; Liao, 2018). Employees have reported the use how such precise technology result in an untenable workload due to inflated expectations of items' manipulation pace (Burin, 2019; Yeginsu, 2018). Previous studies among gig workers have further reported that algorithmic task allocation also often results in job insecurity, (Griesbach et al., 2019; Lehdonvirta, 2018; Veen et al., 2019; Wood, Graham, Lehdonvirta, & Hjorth, 2019) and increased workload (Gregory, 2020), since the flow of tasks (crowdsourced tasks, deliveries, rides) assigned by the platform is likely to vary substantially from one day to another without any apparent reason or explanation (Griesbach et al., 2019; Rosenblat, 2018) and because task assignment is based on previous records regarding the number of deliveries performed and the acceptance rate (Gregory, 2020). Since most of these food deliverers run by bike, this obligation to maintain high delivery pace reflects into increased physical demands (Gregory, 2020).

Algorithmic performance management. Descriptive algorithms are likely to reinvent the world of performance management (PM) in multiplying the metrics available to precisely quantify various facets of employees' actions, emotions, performance, behaviors, attitudes and physical state (Angrave et al., 2016; Tambe et al., 2019), but also customer-related information such as satisfaction and traffic (Evans & Kitchin, 2018; Levy & Barocas, 2018). Some studies have described how these metrics can play a central role (if not the entire role) in the performance management process of both traditional workers (Bakewell et al., 2018; Dhir & Chhabra, 2019; Evans & Kitchin, 2018; Kirven, 2018; Levy & Barocas, 2018) and gig workers (Gerber & Krzywdzinski, 2019). Moreover, predictive artificial intelligence algorithms, like the famous IBM Watson, are also used to forecast the future performance of employees based on multiple data sources such as past performance, existing and potential projects, and recent and future training opportunities (Angrave et al., 2016; Edwards & Edwards, 2019; Greenfield, 2018; Kirimi & Moturi, 2016; Sajjadiani, Sojourner, Kammeyer-Mueller, & Mykerezi, 2019). This forecasted performance is often used as the basis to set future goals or expectations (Angrave et al., 2016; Edwards & Edwards, 2019), to estimate the training needs (Horesh, Varshney, & Yi, 2016), to determine pay raise (Greenfield, 2018) or to promote employees to managerial positions (Mallafi & Widyantoro, 2016).

In terms of work design, algorithmic PM is, on the one hand, likely to augment the "amount" of feedback from the job and to align it more precisely on employees' actual performance. Because these metrics are generally easy to understand and straightforward (see Rosenblat & Stark, 2016, pp. 73-74 for examples of platform feedback notification), they also may increase the clarity of the expectations toward them, fostering role clarity. On the other hand, gig work researcher report that workers often react negatively to the feedback provided by the algorithm, most of the time perceived as unfair, opaque, lacking transparency, or resulting from irrelevant metrics (Gregory, 2020; Rosenblat, 2018), which could, rather yield confusion about the employer's or platform's expectations towards employees, reduce the quality of feedback and role clarity. The metrification of work in traditional work settings has also been found to lead to perceived reductionism (Newman, Fast, & Harmon, 2020), to reduced work meaningfulness, or lower task significance (Moore & Robinson, 2016; Moore, 2017). By the same reasoning, it is likely that precise and numerous performance metrics lead workers to focus more on the tasks and activities that are valued by these metrics, reducing their autonomy in organizing their work and priorities (Moore & Robinson, 2016; Moore, 2017).

Moreover, algorithmic systems facilitate high contingency of performance scores on customer satisfaction ratings, both in gig work (Curchod et al., 2019; Gerber & Krzywdzinski, 2019; Griesbach et al., 2019) and in traditional work settings such as restaurants (O'Donovan, 2018), retail (Evans & Kitchin, 2018; Levy & Barocas, 2018), or telecommunications (Bakewell et al., 2018). The strong impact of these ratings, largely questioned about their volatility, the reliability and validity (Gerber & Krzywdzinski, 2019; Greenwood, Adjerid, & Angst, 2019; Luca & Zervas, 2016; Orlikowski & Scott, 2013; Rosenblat, Levy, Barocas, & Hwang, 2017), has been associated with workers' perception of job insecurity (Curchod et al., 2019; Veen et al., 2019). Literature also suggest that, like the call centers' emotional state monitoring described above and involving continuous requests of rapid emotional shifts, the greater use of customer monitoring and data in workers management require them to display exaggeratedly and sustained positive emotions in their online interactions with customers, increasing the risk of emotional demands (Van Oort, 2019). The increased use of instant and short-term performance metrics can also result in the perception of being perpetually evaluated. Levy (2015) shows how truck drivers report increased workload after the implementation of daily performance assessment indicators In addition, performance metrics are increasingly used to show daily within- or between-team rankings of best performers, which has been found to stimulate a climate of competition between coworkers, depleting team member social support (Leclercq-Vandelannoitte, 2017; Levy, 2015). According to Bakewell et al. (2018) and Guendelsberger (2019), the use of top performers' scores as the ever-increasing standard of performance is likely to result in perpetually higher expectations and work intensification.

Algorithmic scheduling. The main affordance of an AI-augmented scheduling process is to determine, for a specific timeframe, the best match between labor requirements and supply. Both needs and supply rely on algorithmic estimation, with the precise prediction of needs in workforce based on information such as expected or real-time customer traffic, deadlines, real-time monitoring of fluctuating demand, weather forecasts, or on previous occupancy at the same date (Cheng, Rao, Jiang, & Zhou, 2015; Hoshino, Slobodin, & Bernoudy, 2018). Calculation of the best matching labor supply is based on information such as the availabilities of workers (or real-time app-active workers, in the case of platforms), their respective performance scores and their previous customer ratings, predicted performance, location or skills set (Cheng et al., 2015; Levy & Barocas, 2018;

Moore & Hayes, 2018). Companies can also use algorithmic systems to regulate the supply of workers by implementing the scheduling decisions and automatically sending the schedule to workers (Evans & Kitchin, 2018; Griesbach et al., 2019). The companies' objectives in delegating scheduling to algorithms is generally to create on-demand and just-in-time schedules quickly and automatically.

Researchers have found that algorithmic scheduling activities may limit workers' voice and the active role in the determination of their schedule, reducing their level of <u>autonomy</u> (Jabagi et al., 2019; Lehdonvirta, 2018; Moore & Hayes, 2018). This can occur through direct scheduling decisions (Uhde, Schlicker, Wallach, & Hassenzahl, 2020), or through scheduling nudging, particularly common in gig work (Gal et al., 2020; Mateescu & Nguyen, 2019a). The actual evidence regarding scheduling nudges, automated incentives displayed to workers to encourage them to work in specific times, shows that these incentives tends to systematically orient workers toward certain schedules due to the high cost of overriding the nudges (Griesbach et al., 2019; Lehdonvirta, 2018; Mateescu & Nguyen, 2019a; Rani & Furrer, 2020; Rosenblat, 2018; Rosenblat & Stark, 2016; Scheiber, 2017). Also, in complex schedule-making contexts such as healthcare, the inability to intervene in automated scheduling decisions can alter <u>social support</u> in taking away the flexibility for team members to exchange shifts or to make friendly schedule arrangements amongst them (Uhde et al., 2020).

Furthermore, because scheduling algorithms are often configured to base their decisions either on expected customer demand or/and on past employee performance, their use can lead to acute <u>workload</u> pressure, <u>physical demands</u> and <u>job insecurity</u>. For instance, in the retail industry and restaurants, customer satisfaction or other performance metrics are increasingly used by scheduling algorithms, such that low performers usually have poor schedules or very few guaranteed hours (Kantor, 2014; Levy & Barocas, 2018). Gregory (2020) showed that the Deliveroo platform displays automated nudges to encourage biking workers to log on in case of extreme adverse temperature food, resulting in physical strain or acute risk of accident. Workers have further complained about the effects of these on-demand, fluctuating and uncertain algorithmic schedules (Kantor, 2014; O'Connor, 2016; O'Donovan, 2018; Van Oort, 2019), describing how these changing shifts generate more job insecurity. Similarly, algorithmic scheduling may facilitate the implementation of an organizational strategy towards zero-hours contract (Fleming, 2017; Moore & Hayes, 2017, 2018), resulting in lower job stability.

Algorithmic compensation. As a result of the functions referred to above, algorithmic management can also be used to set workers' pay. First, algorithmic performance management based on metrics serves as a basis to determine financial incentives or bonuses (Griesbach et al., 2019; Rani & Furrer, 2020). Second, depending on the organization's strategy, it can render compensation more contingent on customer satisfaction, given the increasing role of customers in performance ratings (Wood et al., 2019). Furthermore, an emerging base for bonus or pay raise allocation is the algorithmic prediction of hypothetical future performance. In sum, in most observed cases, algorithmic compensation facilitates the enactment of a performance-based and demand-based management strategy. For many gig-work platforms, workers' compensation is almost entirely computed by algorithmic systems. An important number of these workers have complained or protested against sudden and unexplained drops in their wage (Lyons, 2020; ShiptShoppers, 2020; Siddiqui, 2019) or in their tips as displayed by the app (Captain, 2019).

In terms of work design, algorithmic compensation might contribute to reduce the autonomy of the workers in constraining them to work longer hours and decrease the control they have on the rewards they gain from work (Goods, Veen, & Barratt, 2019; Griesbach et al., 2019; Moore & Hayes, 2017, 2018; Rani & Furrer, 2020; Wood et al., 2019). Autonomy in the sense of self-determination theory (Deci & Ryan, 2000) refers to the perception of engaging in activities freely chosen, for reasons that are intrinsically valued by the individual, and satisfying one's curiosity or pleasure in doing it. In orienting efforts towards activities that will be financially rewarded, performance-based compensation lowers the perception of autonomy and is more likely to generate a controlled and extrinsic type of motivation (Gagné & Forest, 2008).

The study by Newman et al. (2020) also showed that algorithm-based pay decisions made be perceived as reductionistic, and that such rewarding of quantified, unsignificant an decontextualized aspect might alter task significance. Another study observed that algorithmic compensation encourages the workers "to internalize a logic of efficiency and productivity, infusing an ideal of hyper-meritocratic justice" (Galière, 2020, p. 7), which could practically result in the embracement of higher workloads.

Algorithmic job termination. As the final step of an algorithmic management system, the role of algorithms in job termination is twofold. First, algorithms can make the decision to terminate the employment of a worker and automatically notify the employee. Mainly found in the gig economy, this procedure starts with the platform notifying a worker of unsatisfying ratings and probability of account deactivation if no improvement, followed by official account deactivation (Gerber & Krzywdzinski, 2019; Griesbach et al., 2019; Rosenblat & Stark, 2016). Some cases have also been reported in traditional work settings

(Jee, 2019; Lecher, 2019). Second, if not taking or implementing the termination decision, algorithms may facilitate employees' dismissal through the prediction of employee behaviors such as departure (Punnose & Ajit, 2016; Rosenbaum, 2019; Sajjadiani et al., 2019; Sikaroudi, Mohammad, Ghousi, & Sikaroudi, 2015; Zhao, Hryniewicki, Cheng, Fu, & Zhu, 2018), performance (Edwards & Edwards, 2019; Greenfield, 2018; Sajjadiani et al., 2019), or deviant behaviors such as fraud (Son, 2015).

Overall, the ability of algorithms to decide, implement, or facilitate job termination makes it easier for employers to proceed to job termination, which could potentially influence job insecurity perceptions. According to some authors, this is a particularly salient in highly metrified contexts, like the service-industry (Van Doorn, 2017; Van Oort, 2019) or for workers who are less subject to attain the ever-increasing quantitative standards (Rani & Furrer, 2020; Williams & Beck, 2018).

HOW CAN ORGANIZATIONS ENSURE THAT AM ENABLES AND SUSTAINS WELL-DESIGN JOBS?

The above discussion of AM functions and their consequences suggests that the outcomes for work design are principally negative, with AM tending to lower job resources and to increase job demands. However, we assert that focusing solely on the negative consequences of algorithmic management is not a fruitful long-term approach. Rather, we embrace a (moderately) voluntarist rather than deterministic approach to apprehend the consequences of algorithmic management. As summarized by Strohmeier (2009), moderate voluntarism corresponds to the belief that the consequences of technology in management are mainly the result of organizational choices and strategies behind technological design and implementation, and that stakeholders can shape these consequences. This approach contrasts with determinism, which assumes that technology itself is agentic and responsible for the consequences experienced by workers, considering these consequences as uniform, constant across contexts and individuals, and barely changeable or manageable[4] (Orlikowski, 1992; Strohmeier, 2009). Moderate voluntarism is also distinct from strict voluntarism, which would reject any assumption of agency in algorithms and would rather consider them as instruments available for organizations to facilitate the implementation of their strategy, goals or ideology, considering worker-related consequences will be context specific and depend on the organizational agenda behind their use of algorithms in management (Orlikowski, 1992; Strohmeier, 2009).

Our moderate voluntaristic point of view leads us to postulate that the use of algorithmic management has consequences on workers, but that these effects can be influenced and managed by the decisions of stakeholders in organizations or institutions, as well as (to some extent) by the actions of individuals themselves. Consistent with this idea, one of the authors of the JD-R model stated that “digitalization and automation can contribute to stimulating and “healthy” jobs if their implementation is designed in a way that increases resources and reduces demands, and if people are in control and craft their use of the system” (Demerouti, 2020, p. 1). In what follows, we discuss how it is possible to design and implement AM in a way that pays greater attention to human and social aspects, and thereby enhances or at least does not further erode the quality of work design for workers.

[4] Most authors consider that only the advent of strong artificial intelligence (also called general AI), involving fully agentic and autonomous AI algorithms with potentially greater capabilities than human beings, could reasonably lead one to adopt a strict determinism perspective (Braga & Logan, 2017; Clifton, Glasmeier, & Gray, 2020). However, although AI technologies have increasingly advanced capabilities, most experts concur that strong AI is either not likely to happen in the near future, or is unlikely to happen at all (Hagendorff & Wezel, 2019; Wang & Siau, 2019).

Sociotechnical moderators

We reviewed the literature on AM in order to shed light on the most promising moderating mechanisms of the effects of algorithmic management on work design. Our research was guided by sociotechnical systems theory (STS: Cherns, 1976; Emery & Trist, 1978), which proposes that organizations perform better when their design jointly optimizes the social systems (i.e., the humans within and around the organization) and the technical system (i.e., technologies and mechanics supporting work processes) (Cherns, 1976; Emery & Trist, 1978). Some scholars have begun to apply STS theory to AI and the digitalization of work (Makarius et al., 2020; Parker & Grote, 2020; Shin & Park, 2019; Winby & Mohrman, 2018), stating that the fast pace of the recent technological progress has created an disequilibrium between the two components, such that technical systems and humans are often not jointly optimized. Makarius et al. (2020) elaborated a model of AI-employee integration to create sociotechnical capital, which refers to the advantage for companies and for individuals that results from the successful collaboration of AI and people in organizations. These authors claim that sociotechnical capital can only be optimized when AI technologies and employees act as a tightly coupled system exhibiting increased responsiveness. In their categorizations of the degrees of interaction between AI and people, AM is positioned in the *autonomous AI* type, which involves only some interaction and responsiveness, and consequently only results in *moderate* sociotechnical capital (p. 263).

Following this statement, and in accordance with the postulates of STS theory, the logic of our model is that algorithmic management could either enhance or hamper the achievement of quality work design, and hence impact individual outcomes and indeed firm productivity (or sociotechnical capital), depending on the interplay of technical characteristics and human workers. More specifically, as depicted in our model, we identified three critical and potentially inter-connected such parameters, which function as socio-technical moderators of the link between AM and its impact on work design: System transparency, system fairness, and human influence. We next describe each and illustrate how they can mitigate the effects of AM. Table 2 provides more detail about how the parameters apply to each of the AM function specifically.

Insert Table 2 about here

System Transparency

The importance of algorithmic transparency in shaping employees' attitudes towards algorithms has received great attention from scholars (Ananny & Crawford, 2018; Edwards & Veale, 2017; Glikson & Woolley, 2020; Lepri, Oliver, Letouzé, Pentland, & Vinck, 2018; Rahman, Ranganathan, & Rosenfeld, 2019; Schafheitle et al., 2020; Schildt, 2017; Shin, 2021; Shin & Park, 2019). Transparency refers to the degree to which explanation is provided with regards to ***why*** and ***how*** an algorithmic system is used (Brown, Davidovic, & Hasan, 2021; Pieters, 2011). The *why* reflects transparency about the existence or presence of an algorithmic system and the rationale behind the usage or implementation of an algorithmic system for a specific task, which thus fosters employees' awareness of the system (Pieters, 2011; Shin & Park, 2019). The how concerns and explainability regarding the functioning of the system and the process leading to algorithmic decision-making, allowing understandability of the technology (Lepri et al., 2018; Pieters, 2011). Most of the empirical research on algorithmic transparency has focused on the *how*, reflected in the explainability, interpretability and, ultimately, in the observability of algorithms (Miller, 2019; Robert et al., 2020; Shin, 2021; Shin & Park, 2019). For instance, in a study among telecommunications salespeople, Pachidi, Berends, Faraj, and Huysman (2019) found that employees' frustration of having to follow algorithmic recommendations was due to the inexplicability of these recommendations. In the same vein, algorithmic feedback has been found to increase workers' productivity when displaying performance ratings that are understandable and rely on transparent data (Bernstein & Li, 2017).

In terms of work design characteristics, when AM systems are implemented, if steps are taken to enhance people's understanding of the algorithmic system governing their work, we propose this will enhance workers' sense of <u>autonomy</u> over their tasks relative to not having such system transparency. For instance, the review by Backhaus (2019) revealed that a comprehensive announcement and rational explanation about a monitoring system can prevent its negative impact on employees' sense of control. Having knowledge about what is monitored and what this information will be used for is likely to give employees more decision options regarding work methods. Also, Heiland (2021) concludes that transparency in space assignment and zones changes for gig couriers workers would allow them to more understand, plan and accept their tasks and work, and to ultimately optimize their profit. Moreover, in line with Gal et al. (2020)'s explanations of the perils of algorithmic opacity in management, we argue that transparency regarding the criteria used in automated performance management may, for instance, determine the extent to which the PM process will result in helpful <u>feedback from the job</u> and <u>role clarity</u>.

In the same vein, Gregory (2020) showed that gig food deliverers feel obligated to follow the scheduling nudges displayed by the app and to sometimes work in adverse weather or very difficult conditions (<u>physical demands</u>), mainly because they don't know to what extent compliance to these incentives is reflected in performance scores or in future assignments. Transparency and the explicability of decisions are also likely to reduce the perception of job uncertainty resulting from algorithmic performance management and job termination, in making those decisions more predictable for workers.

System Fairness

The extent to which management algorithms and their decisions are perceived as fair is a fundamental element which, like transparency, has received considerable interest from scholars (Hughes, Robert, Frady, & Arroyos, 2019; Jabagi, Croteau, & Audebrand, 2020; Lee, 2018; Robert et al., 2020; Shin & Park, 2019; Wong, 2019). Although the conceptualizations of algorithmic fairness differ among authors, its most common and accepted components are the absence (or minimization) of bias and discrimination (Choudhury, Starr, & Agarwal, 2020; Cowgill & Tucker, 2020; Jean, 2020; Lepri et al., 2018; Robert et al., 2020; Shin & Park, 2019; Wong, 2019), the accuracy and appropriateness of decisions (Shin, 2021; Shin & Park, 2019), the relevance, reasonableness or legitimacy of the criterion or information used by the algorithms as an input to make decisions (Robert et al., 2020), and the privacy of the data and decisions (Fast & Jago, 2020; Schafheitle et al., 2020; Zuboff, 2015).

Algorithmic fairness is likely to influence how AM impacts work design. In terms of bias minimization, for instance, a system used to make automated job termination or scheduling would probably lead to more job insecurity when these decisions are biased or discriminatory, as it has been found by some researchers (Rani & Furrer, 2020; Van Doorn, 2017; Van Oort, 2019) or reported by media (e.g., Geiger, 2021). In terms of accuracy or appropriateness of decisions, we argue that, for example, scheduling incentives (or nudges) is likely to lead to higher workload for gig workers in the extent to which these incentives are accurate or not, that it if they correctly point out fruitful work times (Mateescu & Nguyen, 2019a; Rosenblat, 2018). In the opposite case, being forced to comply with inaccurate nudges would lead workers to work more for unsatisfying income. On another note, Pritchard et al. (2014) and Pritchard et al. (2015) described how some London bus drivers ended up accepting their algorithmic performance management system because the system takes into account changes in the quality of the road surfaces and the bus suspension when rating the overall quality of driving, resulting in a more accurate and appropriate performance rating and feedback. Bus drivers have access to a detailed and confidential breakdown of their areas of possible improvement, which seem to be perceived by drivers as feedback from the job and role clarity improvement.

In terms of relevance, reasonableness or legitimacy of the criterion, for instance, recent studies have shown that the reasonableness of the information collected through monitoring systems (e.g., intrusiveness, range and frequency of monitoring) shapes its impact on workers' reaction and autonomy (Charbonneau & Doberstein, 2020; Wang et al., 2020). Unreasonable monitoring systems foster the datafication of work, or the "working for data" phenomenon, viewed as the orientation of workers' efforts and energy towards the monitored or quantified aspects of the job (Evans & Kitchin, 2018; Gal et al., 2020; Schafheitle et al., 2020), which are presumably not the most meaningful, complex or valued ones. In that sense, the reasonableness (level of intrusiveness, range of information collected) of the system is likely to attenuate the impact of monitoring on task variety and significance and to preserve the ability of workers to organize their tasks and methods. Likewise, the more aspects of the work remain unmonitored, lower are the chances for monitoring system to result in an oversimplified job (job complexity) with few problem-solving opportunities. The relevance, reasonableness and legitimacy of the metrics used in automated decisions also play a central role in shaping work design outcomes. For example, emotional demands and higher workload might be triggered by performance management or compensation algorithms only if the system overemphasizes the importance of metrics such as customer satisfaction, forcing employees to display disproportionate positive emotions towards customer. Similarly, the extent to which schedules or goal-setting decisions are based on previous performance could shape the burdens associated with those decisions in terms of workload or physical demands. In the same vein, job insecurity could result from algorithmic task allocation and scheduling only if those decisions are precisely based on the demand for services as captured by the algorithm, like in the extreme cases of zero-hours contracts reported by (Moore & Hayes, 2017, 2018).

In terms of privacy of data and decisions, social support could be hampered by the rankings created through algorithmic performance management if these rankings or performance scores are visible to the team members or used to create competition, as reported by Leclercq-Vandelannoitte (2017) and Levy (2015).

Human influence

Three important features of the algorithmic management system fall into a category that we label as the human influence on the system, referring to the ability for workers (1) to have a voice or to exert control over the system, (2) to opt out of the system if wanted, and to (3) to provide an input or to contribute to the system. These aspects are largely inspired from the emerging human-in-the-loop literature about algorithmic decision-making (Aoki, 2021; Grønsund & Aanestad, 2020).

First, the capacity to influence or exert some form of control over the system might considerably improve the autonomy, task significance and job complexity of workers exposed to AM systems. A lab study by Dietvorst, Simmons, and Massey (2016) showed that being empowered to change or intervene in an algorithmic decision can overcome the aversion reaction sometimes developed by algorithm' users. Their results further indicate that even a very small amount of power of intervention or modification can significantly modify one's reaction and performance when working with the algorithm. For instance, the ability to check or to comment on collected data has been identified as been identified as a key feature to improve acceptance of monitoring systems by employees (Backhaus, 2019), and is likely to foster their sense of autonomy in their work. Also, the reduction of autonomy and job complexity observed by Brione (2017) after the implementation of automated work sequencing system in manufacturing plants was namely attributed to the fact that workers were no longer involved in the challenges related to the organization of tasks.

Also, for gig workers like ridesharing drivers or delivery workers, having the power to decline tasks without implicit or explicit penalties or prejudice could prevent workers from the accumulation of frustrating, low-paid or alienating tasks (Gerber & Krzywdzinski, 2019). In cases where providing employees with the control to intervene in the algorithmic decision would not be manageable, giving workers a voice to question, discuss or contest automated management decisions might also help them to maintain adequate levels of job autonomy. Evidence shows the advantages of providing employees with a staff application to modify algorithmic scheduling or task assignment decisions, to pick a better task assignment or to swap shifts with coworkers without penalties (Bakewell et al., 2018; Williams, 2017). In the same vein, Uhde et al. (2020) provided evidence for the beneficial role of a collaborative automated scheduling system among nursing teams. Their findings indicate that, instead of hampering social support between nurses, the easiness to use the system to swap shifts in order to accommodate coworkers triggered a positive team climate and a reduction of interpersonal conflicts, increasing social support.

Such workers voice or control might only be possible if there is human responsibility in the decision loop. For instance, the importance for organizations to have an "algorithmic auditor", responsible for the surveillance, control, auditing and altering of management algorithms is rapidly gaining interest in recent literature (Brown et al., 2021; Grønsund & Aanestad, 2020). The ability to contest prejudicial or erroneous algorithmic compensation or termination decisions might also help to protect workers' autonomy, as well as lower the probability of stressful job demands such as job insecurity.

Second, the possibility for employees to use their judgement when something goes wrong and to switch off the system for a short period is likely to make an important difference in their reaction to an algorithmic monitoring system, as observed in the Backhaus (2019) meta-analytical review. For instance, the UPS ORION algorithm, which closely monitors truck drivers, decides their route and perform a plethora of other functions, is somehow optional. Drivers have the freedom to decide every morning whether they wish to use ORION or not. Moreover, in case of disagreement with an ORION's decision regarding a route, or in case ORION' decision is jeopardizing driver's safety for any reason, drivers are asked to prioritize their own judgement (Holland, Levis, Nuggehalli, Santilli, &

Winters, 2017; Rosenbush, 2018; Stevens, 2015). We expect that this ability to opt out of the automated system or of its decision will increase job autonomy and maintain problem-solving opportunities.

Third, work design characteristics such as job complexity and task variety, and autonomy are also likely to be maintained or enhanced if employees are invited to contribute to the system. Back to the UPS ORION example, for each case of employee request of circumventing ORION's decision, engineers pursue investigation in the aim of improving ORION and sometimes ask drivers' input (Rosenbush, 2018; Stevens, 2015; Woyke, 2018). Similarly, Gershgorn (2015) reports that the Hitachi task assignment algorithmic system is fed by workers' input. Warehouses workers and technicians are asked to share their tips and their recent problem-solving experiences with the system in a continuous improvement objective. A participatory approach of monitoring (e.g., "previous interviews with employees on what aspects of their job could or should be used for monitoring") has indeed been observed as important feature to maintain employees' sense of control (Backhaus, 2019). Similarly, Newman et al. (2020) noted that automated decision such as performance evaluation are perceived as less reductionistic (i.e., more meaningful or significant) when there is room for human input in those decisions.

DISCUSSION AND CONCLUSION

The contributions of our model and review are multiple. First, albeit preliminary, the evidence reviewed clearly highlights the influence of AM on work design characteristics, with most of this influence appearing to be negative. In unpacking the phenomenon of algorithmic management and its six (actual) functions, we develop a more holistic approach of algorithmic management, allowing its examination across the distinctly operating components rather than as a monolithic piece. Several conclusions are noteworthy in this regard. For instance, while the impact on workers' autonomy is consistently negative across the six functions, the effect of each AM function on other job resources and demands is highly variable, suggesting the importance of considering functions separately. Also, algorithmic performance management (PM) and scheduling seem to have more salient consequences on job demands than job resources, whereas for the other functions, there is more evidence of effects on job resources. Similarly, PM is also the function for which there is the most evidence for a bright side, with a potential improvement of role clarity and feedback from the job. Overall, more research is needed to validate and deepen these observations regarding the outcomes of AM for workers. We recommend that research be clear which functions they are investigating and, as far as relevant, that the effects of multiple functions of AM are assessed. We also recommend that researchers systematically investigate the effects of AM functions on a range of pertinent job demands and job resources. Ultimately, workers' well-being, motivation and performance are key outcomes to strive for. Our model positions work design as an important mediator of such outcomes, and therefore provides guidance as to which features of work will need attention when designing and implementing AM.

Second, an implication from our model is that the effect of AM on work design and its outcomes is not likely to be unchangeable or unmanageable. That is, there are potentially important moderating factors to do with the way that AM is designed and implemented that could mitigate AM's negative effects and enhance its positive effects. However, although promising in theory, there is a clear need for future research about the role of these STS moderators in the link between AM and work design. To date, the evidence for the effect of these elements is limited, and our propositions are largely based on extrapolating from other fields of research (computing and data science, namely). In particular, there is a lack of intervention research that actually examines whether making these sorts of changes to real systems in a proactive way indeed positively impacts work design and outcomes. Further research on these moderators will help to realize concrete solutions for stakeholders in their design and implementation of algorithmic management strategies in order to maintain high quality of work design, preserving autonomy, meaningfulness and tolerable demands for workers.

Limitations and future research

Our model was based on state of the art of the actual knowledge. However, technological developments will require a constant reevaluation of the components of the model. Additional AM functions and moderators of their effect on the work design might well be important in the future. In addition, a limitation of our model arises from the difficulty in balancing comprehensiveness and parsimony. For example, several further outcomes of work design could be included in the model, yet we have not done so as the evidence base currently does not exist. Regarding the moderators of transparency, fairness and human influence, the need for parsimony led us to focus on these key system features, although we recognise there is likely to be a moderating role of individual differences and of wider contextual elements such as organizational culture and labor market variables. We recommend future research on these additional elements. We also propose that intervention studies are key to better capturing the tangible effect of these moderators (see Parker & Grote, 2020). The potential interrelationships amongst the three proposed moderators is a further avenue to consider. For instance, fostering transparency about the use and content of algorithmic systems might naturally contribute to lower biases (fairness), and allowing more human influence over the system is likely to trigger automated decisions that are seen as fairer.

Finally, the three proposed categories of moderators present significant practical challenges. For instance, transparency in the decisions of very complex machine learning algorithms with limited room for explainability is very difficult (and perhaps impossible) to achieve, and, if achieved, could be very demanding in terms of cognitive load for workers (Gal et al., 2020; Stohl, Stohl, & Leonardi, 2016). One of the advocated solutions to this issue is to provide transparency in the data (i.e., data visibility), which could however conflict with the need to preserve the privacy of the data (Stohl et al., 2016; Zuboff, 2015). The provision of fair algorithms, especially machine learning algorithms, is also a complex and challenging issue for computer scientists and managers (Jean, 2020; Lepri et al., 2018), and choices and decisions may depend on ethical orientations (Gal et al., 2020; Gibert, 2020; Martin, 2019a; Mittelstadt, Allo, Taddeo, Wachter, & Floridi, 2016). Also, keeping humans in the decision loop and preserving human voice is certainly important, but too much voice could impair at some point the benefits of automated decision-making and lead to a heavy and unfruitful decision-making process. These practical issues all warrant further attention.

The potential interrelationships between the three proposed moderators also warrant attention in future research. For instance, fostering transparency about the use and content of algorithmic systems may naturally contribute to lower biases, and allowing more human influence in the system is likely to trigger more relevant and legitimate automated decisions. In sum, research of the role and on the operationalization and interconnectedness of these constructs is nascent and warrants further development.

Conclusion

Building on previous research on algorithmic management, and drawing on well-established conceptual frameworks (job demands-resources model and sociotechnical systems design), we have proposed a conceptual model to enhance knowledge development and application about AM. We argue that such model is necessary at this stage of the development of the discipline in order to guide research that can leverage concrete and tangible improvements in AM implementation in organizations.

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Figure 1. Conceptual model

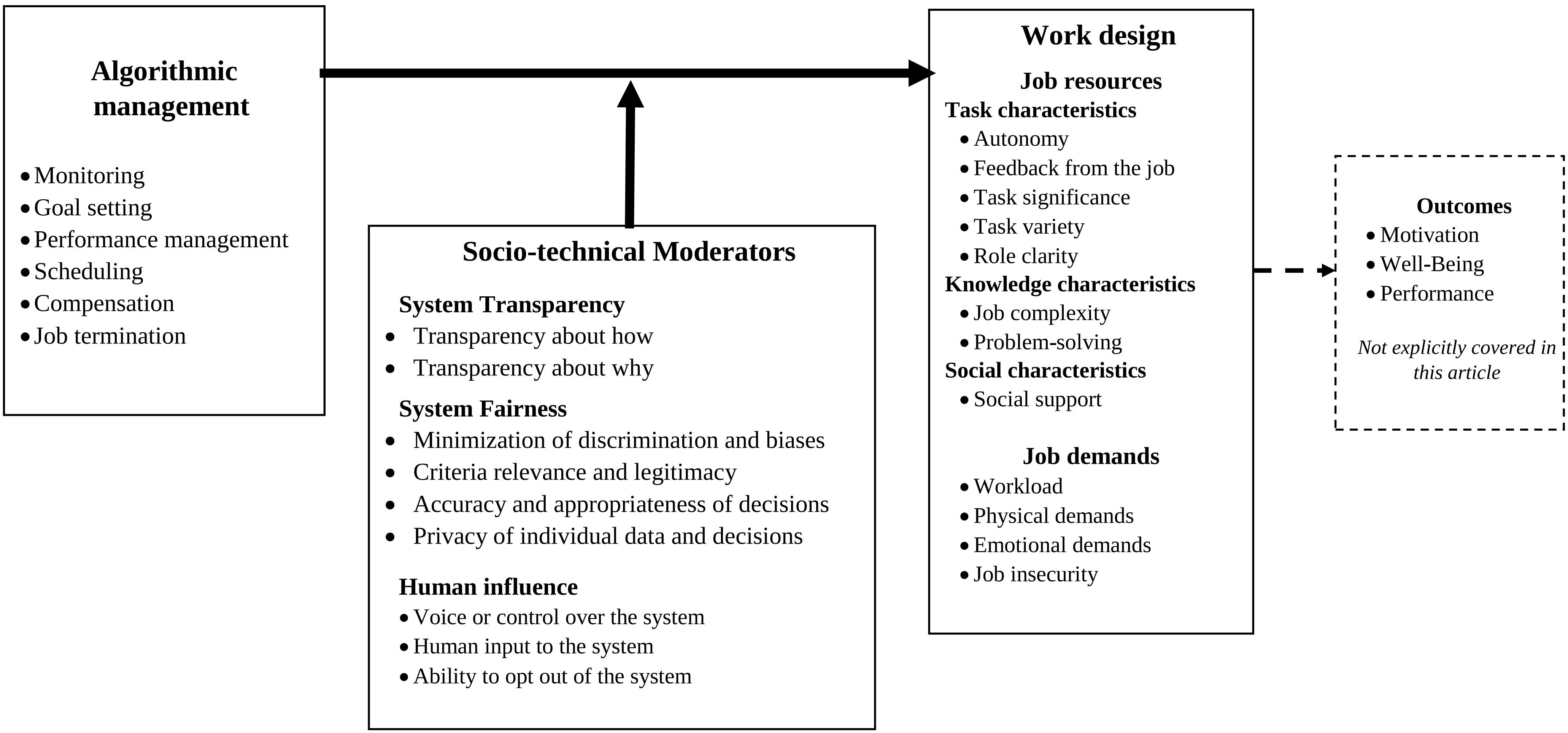

Table 1. Evidence for the relationships between AM and work design

AM functions	Potential effects on work design	References (non-exhaustive)
Monitoring	Autonomy, Task variety and significance (-)	Moore and Hayes (2018); Brione (2017, p. 14); Leclercq-Vandelannoitte (2017); Levy (2015); Pritchard et al. (2014); Pritchard et al. (2015)
	Job complexity (-)	Yeginsu (2018); Woyke (2018); Woyke (2018)
	Problem-solving (-)	De La Garza (2019); Hernandez and Strong (2018); Roose (2019)
	Emotional demands (+)	Gandini (2019); Van Oort (2019); Roose (2019); De La Garza (2019)
Goal setting	Autonomy (-)	Heiland (2021) ; Curchod et al. (2019); Griesbach et al. (2019); Rosenblat (2018); Veen et al. (2019); Gerber and Krzywdzinski (2019); Shapiro (2018)
	Job complexity (-)	Brione (2017, p. 12)
	Physical demands (+)	Reyes (2018), Gregory (2020)
	Workload (+)	Liao (2018); Burin (2019); Yeginsu (2018); Guendelsberger (2019), Gregory (2020)
	Job insecurity (+)	Griesbach et al. (2019); Lehdonvirta (2018); Wood et al. (2019); Veen et al. (2019)
Performance management	Feedback from the job (+/-)	Rosenblat and Stark (2016)
	Role clarity (+ / -)	Rosenblat and Stark (2016); Bernstein and Li (2017)
	Task significance (-), Autonomy(-)	Moore (2016, 2017); Newman et al. (2020)
	Social support (-)	Leclercq-Vandelannoitte (2017)
	Job insecurity (+)	Veen et al. (2019); Wood et al. (2019); Evans and Kitchin (2018); Williams and Beck (2018); Levy and Barocas (2018); Levy (2015)
	Workload (+)	Levy (2015); Leclercq-Vandelannoitte (2017); Bakewell et al. (2018)
Scheduling	Autonomy (-)	Moore and Hayes (2018); Lehdonvirta (2018); Rosenblat (2018); Scheiber (2017); Rani and Furrer (2020)
	Social support (-)	Uhde et al. (2020)
	Workload (+)	Lehdonvirta (2018); Levy and Barocas (2018)
	Job insecurity (+)	Van Oort (2019); Moore and Hayes (2017)
	Physical demands (+)	Gregory (2020)
Compensation	Autonomy (-)	Moore and Hayes (2017, 2018); Griesbach et al. (2019); Wood et al. (2019); Goods et al. (2019); (Rani & Furrer, 2020)
	Task significance (-)	Newman et al. (2020)

Job termination	Job insecurity (+)	Griesbach et al. (2019); Van Doorn (2017); Van Oort (2019); Gerber and Krzywdzinski (2019)

Table 2. Proposed effect of the socio-technical moderators based on the actual evidence for the relationship between AM and work design

AM functions	Effects on work design	Mostly when… (moderating effect)
Monitoring is associated with	Lower autonomy	Transparency or human influence is low (inability to opt out, no voice over the system, no access to data).
	Lower task variety, task significance, job complexity, problem-solving opportunities	Fairness is low (unreasonable information collected), no human influence (no participatory decisions).
	Higher emotional demands	Fairness is low (unreasonable information collected)
Goal setting is associated with	Lower autonomy	Fairness is low (based on customer satisfaction), human influence is low (no voice or input, inability to opt out)
	Lower job complexity	Human influence (no input in task planning or decision)
	Higher physical demands or workload	Fairness is low (decisions based on best performers standards)
	Higher job insecurity	Fairness is low (demand-based task allocation)
Performance management is associated with	Higher or lower role clarity and feedback from the job	Depending on the degree of accuracy of decisions, and on the relevance and transparency (explainability) of the criteria.
	Lower autonomy and task significance	Fairness and human input are low (unreasonable importance of metrics)
	Lower social support	Fairness is low (data and rankings visible to coworkers)
	Higher job insecurity	Fairness is low (largely based on customer ratings); transparency is low (decisions are unexplainable and unpredictable)
	Higher workload	Fairness is low (unreasonable importance of metrics)
	Higher emotional demands	Fairness is low (unreasonable importance of customer ratings)
Scheduling is associated with	Lower autonomy	Transparency is low (unknown impact of overriding scheduling nudges) Human influence is low (no voice in decisions)
	Lower social support	Human influence is low (no flexibility for modification or adaptation)
	Higher workload	Fairness is low (performance-based schedules, inaccurate nudging)
	Higher physical demands	Transparency or fairness is low (criteria behind scheduling nudges is unknown or unreasonable)
	Higher job insecurity	Fairness is low (demands-based schedule)
Compensation is associated with	Lower autonomy	Transparency is low (explainability of decisions), fairness is low (unreasonable pay-for-performance), no human influence
	Lower task significance	Fairness is low (criteria is irrelevant, unreasonable pay-for-performance)
	Higher workload	Fairness is low (unreasonable pay-for-performance)

Job termination is associated with	Higher job insecurity	Transparency is low (decisions are unexplainable and unpredictable) Fairness is low (criteria is irrelevant; biased decisions). No human influence