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The duality of algorithmic management: Toward a research agenda on HRM algorithms, autonomy and value creation

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ABSTRACT

This study proposes the 'duality of algorithmic management' as a conceptual lens to unravel the complex relationship between human resource management (HRM) algorithms, job autonomy and the value to workers who are subject to algorithmic management. Against tendencies to present algorithmic management as having predetermined, undesired consequences (e.g. restriction of job autonomy, poor financial compensation and deteriorating working conditions), our 'duality of algorithmic management' perspective offers two amendments to the dominant thinking on HRM algorithms and their outcomes to workers. First, we showcase how algorithmic management simultaneously restrains *and* enables autonomy and value to workers – with the latter referring to both use (i.e. non-monetary benefits) and exchange value (i.e. monetary benefits) that workers derive from working (under algorithmic management). In doing so, we make the case that the desired consequences of HRM algorithms to workers co-exist alongside the undesired consequences that the literature has mostly reported on. Second, we argue that algorithmic management is shaped by, as much as it shaping, the autonomy and value to workers. We do so by highlighting the 'recursivity' of algorithmic management that occurs when software designers and/or self-learning algorithms reinforce or limit worker acts for (re)gaining job autonomy and/or creating value out of HRM algorithms. We conclude this paper with the presentation of avenues for future research into the duality of algorithmic management, which sets the stage for a future line of inquiry into the complex interrelationships among HRM algorithms, job autonomy and value.

1. Introduction

Human resource management (HRM) activities are increasingly executed by software algorithms, that is, a set of computer-programmed steps to automatically accomplish a task by transforming data into output. Inputs that amount to the data coming from workers (e.g. via their social media accounts, smartphones or sociometric badges) (Garcia-Arroyo & Osca, 2019; Strohmeier, 2018), allow organizations to operate software algorithms for generating HRM-related outputs. These algorithm-enabled HRM outputs are mostly related to (automated) decision making in areas such as staffing (e.g. resume screening and text-mining), training (e.g. prediction of skill gaps), compensation (e.g. online job ranking and calibration), appraisal (e.g. processing data on worker performance) and workforce planning (e.g. assigning workers to shifts) (Cheng & Hackett, 2021; Kellogg, Valentine, & Christin, 2020; Leicht-

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Deobald et al., 2019; Newlands, 2021; Strohmeier & Piazza, 2015). It is the collection of these diverse algorithm-enabled HRM activities that has been broadly referred to as 'algorithmic management' (Duggan, Sherman, Carbery, & McDonnell, 2020; Lee, Kusbit, Metsky, & Dabbish, 2015; Meijerink, Boons, Keegan, & Marler, 2021; Möhlmann & Zalmanson, 2017).

Since HRM algorithms augment and/or automate decision-making about workers, academics have begun to examine how workers are impacted by algorithmic management. This strand of research has made several conceptual contributions, two of which are mostly important for, and extended by, our current study. First, researchers showed that algorithmic management limits job autonomy and value to workers (Gandini, 2019; Kellogg et al., 2020; Newlands, 2021; Veen, Barratt, & Goods, 2019; Zuboff, 2019). Here, we refer job autonomy (hereafter: autonomy) to as the freedom of workers to exercise control over aspects of their work (Langfred, 2007). Value to workers refers to the monetary (or exchange value; e.g. income) and non-monetary benefits (or use value; e.g. personal growth, identity and accomplishment) that employees derive from their work (Maatman, Bondarouk, & Looise, 2010; Meijerink & Bondarouk, 2018). Scholars argue that algorithmic management reduces autonomy and value to workers, among other reasons, through automating wage theft (Van Doorn, 2019), creating information asymmetries that curb workers' leeway to make optimal (economic) decisions for themselves (Rosenblat, 2018; Shapiro, 2018), decreasing human sensemaking where algorithms crowd out human freedom (Leicht-Deobald et al., 2019), and disciplining without room for personal growth and development (Kellogg et al., 2020). While studies into these downsides of algorithmic management are important, they reinforce negative deterministic assumptions about algorithmic management as having predetermined, undesired consequences to workers. We argue that HR management by algorithms is more complex than reinforcing negative outcomes for workers only. Instead, HRM algorithms can simultaneously offer value to, and foster autonomy for, workers. There is a growing body of knowledge to support this non-deterministic view on HRM algorithms. For instance, software algorithms embed organizational resources such as data, rules, and procedures that limit worker autonomy (Orlikowski & Scott, 2015; Strohmeier, 2018) while simultaneously offering workers the freedom to create value for themselves out of HRM activities (Meijerink & Bondarouk, 2018). Moreover, although HRM algorithms limit worker freedom, research shows that not all activities performed by workers can be monitored by algorithmic management systems such that selected worker behaviors remain at the discretion of workers (Gal, Jensen, & Stein, 2020; Newlands, 2021; Wood, Graham, Lehdonvirta, & Hjorth, 2019). This implies that HRM activities, when put into hands of software algorithms, not only restrain/limit, but simultaneously enable/offer autonomy and value to workers.

Second, researchers have observed how workers attempt to regain autonomy and value by offsetting algorithm-enabled control

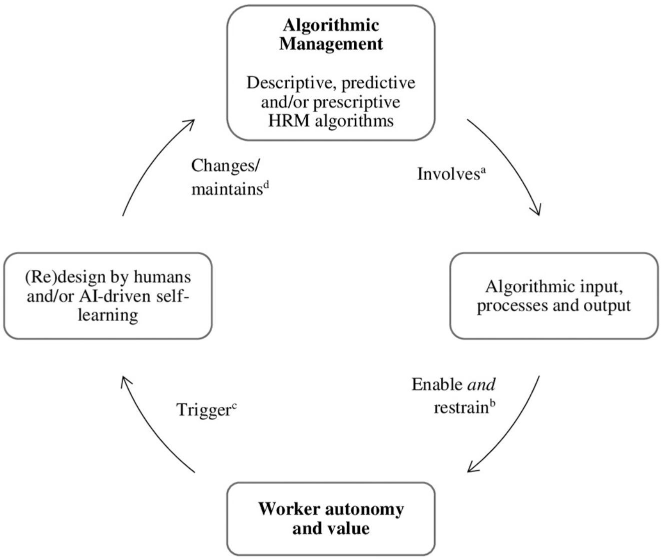

Fig. 1. The duality of algorithmic management.

a) HRM algorithms are embedded with rules and resources such as worldviews, meanings, assumptions, power relationships, procedures, norms, and values. These so-called structural properties of algorithmic management manifest as algorithmic input (i.e. machine-readable data about worker attributes and behaviors), algorithmic processes (e.g. software code for automated data processing) and algorithmic output (e.g. information, statistics or predictions that humans input in decision-making processes as well as automated decision-making and -execution).
b) The structural properties of algorithmic management are simultaneously restraining and enabling to workers. Specifically, HRM algorithms enable and restrain autonomy and value to workers because of the duality in algorithmic input, processes and outcomes.
c) Worker acts such as value co-creation and algoactivism for (re)gaining autonomy may trigger human managers/software designers to (re)design HRM algorithms. Such (re)design attempts may serve to further support workers in gaining autonomy and/or creating value or restrain workers in doing so. Propelled by artificial intelligence and self-learning, HRM algorithms can also change when inputted with worker data that reflect worker acts to (re)gain autonomy and/or (co-)create value with selected stakeholders.
d) The structural properties (i.e. rules and resources embedded in HRM algorithms) of HRM algorithms are sustained or changed, depending on whether software designers and self-learning processes reinforce or go against worker acts to gain autonomy or (co-)create value.

through so-called 'algoactivism' (Kellogg et al., 2020). This involves novel tactics of resistance such as 'data obfuscation' to sabotage software algorithms by feeding them with misleading data (Newlands, 2021), or scripts that workers deploy to monitor their online workplaces (Irani & Silberman, 2013). Ultimately, these tactics are believed to prevent employers from capturing excessive amounts of (monetary) value and stripping away autonomy from workers subject to algorithmic management (Gandini, 2019; Kellogg et al., 2020; Shapiro, 2018; Veen et al., 2019). We argue that these insights open the road for future research to study the ill-explored recursive implications for software algorithms at work. Here, the notion of 'recursivity' (Orlikowski, 1992) reflects a cyclical process in which algorithmic management is shaped and influenced by, as much as it shaping and influencing, the autonomy and value to workers (see Fig. 1). There are empirical observations that support such an assumption about the recursive nature of algorithmic management. First, HRM algorithms are fed with data about workers' behaviors (Garcia-Arroyo & Osca, 2019; Strohmeier, 2018), including their responses to algorithmic management, thereby shaping the functioning of software algorithms at work. Secondly, software developers may decide to alter software algorithms to counter the resistance to algorithmic management by workers. Provided that workers' algoactivism serves to (re)gain autonomy and value (Kellogg et al., 2020), we argue that algorithmic management does not unilaterally (pre-)determine autonomy and value to workers. Instead, when engaging in algoactivism for dealing with the autonomy- and value-related consequences of algorithmic management, workers shape the nature of algorithmic management. Put differently, algorithmic management is both the driver *and* the outcome of autonomy and value to workers. To illustrate this, we develop a conceptual lens that allows future studies to go beyond deterministic views on algorithmic management.

Specifically, we aim to develop a conceptual lens that affords to see autonomy and value as being limited *and* fostered by algorithmic management, while simultaneously shaping (or: having recursive implications for) the working of algorithmic management. To do so, we draw on the concept of duality of technology which holds that technology is the product of human action, while at the same time enables and restrains that action (Leonardi, Nardi, & Kallinikos, 2012; Orlikowski, 1992). It originated as a response to the call to go beyond deterministic thinking on the consequences of technology (Leonardi et al., 2012; Orlikowski, 1992) and therefore fits our aim to conceptually show that HRM algorithms are the product of autonomy and value to workers, while at the same time fosters *and* limits that autonomy and value. In line with this, we propose the concept of *duality of algorithmic management* which holds that algorithmic management simultaneously enables and restrains autonomy and value to workers, which reciprocally shape algorithmic management (see Fig. 1). On the way toward our goal, we offer two contributions to the literature. First, we provide an overview of the use of algorithms in HRM and offer a much-needed conceptual lens that allows to see how worker outcomes are recursively related to, rather than (pre-)determined by, algorithmic management. Second, we formulate questions for future research into the duality of algorithmic management, thereby setting a research agenda on the complex and non-deterministic interplay between HRM algorithms, autonomy and value to workers.

This paper is structured as follows. We start with defining software algorithms at work and review the literature on algorithmic management to highlight the controlling potential of software algorithms and the resistance of algorithmic control by workers. This is followed by an outline of the notion of the duality of algorithmic management. We finalize with the presentation of a duality-inspired research agenda on how algorithmic management enables and restrains autonomy and value to workers that reciprocally shape algorithmic management.

2. Algorithmic management: implications for autonomy and value

2.1. Unpacking the notion of algorithmic management: from inputs to decision-making

In the literature, algorithmic management has been defined as a system of control that relies on machine-readable data and software algorithms that support and/or automate managerial decision-making about work (Duggan et al., 2020; Lee et al., 2015; Meijerink et al., 2021; Möhlmann & Zalmanson, 2017). This definition highlights three important features of algorithmic management: (1) machine-readable data as input, (2) automated processing of data, and (3) decision-making and -execution as output:

2.1.1. Machine-readable data as input

As noted by Gillespie (2014), "algorithms are inert, meaningless machines until paired with databases upon which to function" (p. 169). Accordingly, software algorithms need to be inputted with data that a computer can process. With the advent of mobile technologies such as smartphones, smartwatches, GPS tracking, smart tools/workpieces, and sociometric badges, software algorithms at work can be fed with data about workers' behavior, location, performance, emotional states, social relationships and the like (Angrave, Charlwood, Kirkpatrick, Lawrence, & Stuart, 2016; Garcia-Arroyo & Osca, 2019; Strohmeier, 2018). These are considered to be 'big' data due to their sheer volume (i.e. number of bytes), velocity (i.e. speed at which data are collected) and variety (i.e. different types of data sources) (Cheng & Hackett, 2021; Garcia-Arroyo & Osca, 2019; Wenzel & Van Quaquebeke, 2018). Because of their sheer volume and multi-source nature, big data can impossibly be processed by humans and instead require software algorithms to be sorted, cleaned, combined and/or analyzed in an efficient manner. At the same time, although being voluminous and coming from various data sources, at best, these data conceive and gauge worker attributes (Newlands, 2021; Wenzel & Van Quaquebeke, 2018). This is the case as not all employee attributes are codifiable into machine-readable data. Therefore, the input that fuels algorithmic management can best be considered proxy data that capture neither the full lived experiences of workers, nor the workplace from which these data are collected (Newlands, 2021).

2.1.2. Automated processing of data

Algorithms are able to process big data at scale, and in real time, because they are composed of software codes that are run to turn data into output without (much) human involvement. In fact, software algorithms can be deployed to perform activities that computers can do more effortlessly than human managers, such as the cleaning, extracting, sorting, and filtering of data generated by workers (Garcia-Arroyo & Osca, 2019; Strohmeier & Piazza, 2015). Although software algorithms process data in an automated manner, algorithmic management nevertheless requires human involvement. For instance, the data that propels algorithmic management is generated by workers while performing (work-related) activities, like executing a job-related task, interacting with colleagues or taking a break. Therefore, depending how workers behave (at work), HRM algorithms may be fed with data that are different in kind. Besides workers generating the data that are inputted into software algorithms, this also involves programmers and/or human managers deciding what type of software code to operate, which parameters to include or what weight to assign to each parameter. Such decisions may not be disclosed to those subject to software algorithms, rendering algorithmic management opaque to workers (Burrell, 2016; Faraj, Pachidi, & Sayegh, 2018; Rosenblat & Stark, 2016). Especially online labor platforms like Uber and Deliveroo are known for strategically withholding information about their HRM algorithms in an attempt to control their workforces (Burrell, 2016; Pasquale, 2015; Rosenblat & Stark, 2016; Veen et al., 2019). Moreover, the opaqueness of software algorithms may increase further when they are built using artificial intelligence, which makes them 'self-learning' in that they automatically improve (e.g. by adjusting the weights of parameters) through experience (i.e. the data coming from workers). As noted by Burrell (2016), when operating on (big) data sets that include heterogenous properties of data, self-learning algorithms become so complex that they (even) become black boxes to their designers. In a response, academics and practitioners alike call for the use of explainable artificial intelligence (Adadi & Berrada, 2018; Arrieta et al., 2020), which refers to the "details and reasons a [algorithmic] model gives to make its functioning clear or easy to understand" (Arrieta et al., 2020: 85). In the case of algorithmic management, explainable HRM algorithms can be achieved by operating so-called 'white-box' algorithms that reveal the algorithm's structure and increasing the technical literacy of workers (Burrell, 2016). However, given that (1) workers differ in their technical literacy and thus abilities to understand the workings of HRM algorithms (Arrieta et al., 2020), (2) employers may be reluctant to operate white-box algorithms (Burrell, 2016; Rosenblat & Stark, 2016), and/or (3) software algorithms may operate on complex, large-scale data sets (Adadi & Berrada, 2018), we expect that algorithmic management remains, to varying degrees, opaque to workers (Pasquale, 2015).

2.1.3. *Decision-making and -execution as output*

HRM algorithms are used to solve an HR-related problem or, put differently, to realize a desired HRM outcome (e.g. to improve employee productivity, select the 'best' job candidate or ensure a sufficient supply of workers) (Cheng & Hackett, 2021; Meijerink et al., 2021; Strohmeier & Piazza, 2015; Van Esch, Black, & Ferolie, 2019). Accordingly, algorithmic management can be seen as a decision-making (support) tool that helps to select an appropriate solution (Kellogg et al., 2020; Leicht-Deobald et al., 2019). To illustrate this, Leicht-Deobald et al. (2019) distinguish three types of algorithms that afford HR-related decision making: descriptive, predictive and prescriptive algorithms. Although different sentiments can go with the names of these three types of decision-making, we below (see also Table 1) present an overview of exemplary algorithmic appliances for different HRM activities, close to the terminology of Leicht-Deobald et al. (2019).

First, descriptive algorithms help to analyze worker-generated data by means of data processing techniques (e.g. data extraction, sorting and cleaning) to integrate data from different sources and/or operate relatively simple statistics that show mean scores, distributions or associations between variables. This assists managers in overseeing relevant metrics like worker performance, absenteeism or personality traits. Accordingly, descriptive algorithms can be used for making decisions related to HRM activities such as recruitment and selection (e.g. resume screening, social media analysis), performance appraisal (e.g. computing multi-source performance scores) or training (e.g. evaluating the effectiveness of a training workshop).

Table 1
Examples of algorithmic-enabled HRM activities.

	HRM algorithm type			Example studies
	Descriptive algorithms	Predictive algorithms	Prescriptive algorithms	
Selection	Assessment of job candidates personality traits on basis of their social media profiles	Predicting job candidates potential and performance	Automated resume screening; automated suggestions which job candidate to invite for job interview	Cheng and Hackett (2021); Kellogg et al. (2020); Mallafi and Widyantoro (2016); Stoughton, Thompson, and Meade (2013); Strohmeier and Piazza (2015)
Training	Automated web-search of available training programs; evaluation of training effectiveness	Predicting the need for upskilling; prediction of workforce competence gaps	Automated instructions to poor performing workers	Cheng and Hackett (2021); Kellogg et al. (2020); Ramamurthy et al. (2015)
Appraisal	Sentiment analysis; aggregation and computing performance scores;	Predicting when projects go off track; predicting future worker performance	Alerting managers to take corrective actions; Automated sanctioning (e.g. deactivation) of poor performing workers	Jarrahi and Sutherland (2019); Kinder et al. (2019); Rosenblat (2018); Schweyer (2018); Strohmeier and Piazza (2015); Veen et al. (2019)
Compensation and benefits	Automated salary surveying; job ranking	Predicting desired compensation level	Surge pricing; automated variable pay; priority access to work assignments	Cheng and Hackett (2021); Griesbach et al. (2019); Meijerink et al. (2019); Veen et al. (2019)
Workforce planning	Construction of competency profiles; employee inventory	Turnover prediction; predicting future labor demand	Automated staff rostering; automated task allocation	Griesbach et al. (2019); Meijerink et al. (2019); Strohmeier and Piazza (2015)

Second, predictive algorithms are used for forecasting purposes by providing a score that represents the likelihood that an event or outcome will occur (Leicht-Deobald et al., 2019). This can involve the use of advanced regression techniques, machine-learning algorithms or data mining approaches (Davenport, 2013) that assist decision makers in areas such as recruitment and selection (e.g. predicting future potential of a job candidate), workforce planning (e.g. predicting turnover) or performance management (e.g. predicting future performance of a worker). Although such predictions may not be optimal, they can nevertheless assist (HR) managers in choosing a selected course of action (Cheng & Hackett, 2021).

Finally, prescriptive algorithms extend predictive algorithms by including simulations and scenario-based techniques to propose what should be done in the light of possible scenarios (Davenport, 2013; Leicht-Deobald et al., 2019). This serves two functions: (1) decision support with the algorithm proposing which scenario to follow and a human manager making the final call (e.g. a software algorithm that filters out job candidates on the basis of their resume and in turn, a human manager deciding on which job candidates to invite for a job interview), or (2) decision automation that involves a computer taking a decision without human intervention (Leicht-Deobald et al., 2019; Meijerink et al., 2021; Strohmeier & Piazza, 2015). The use of algorithms for automated decision-making is particularly prominent among online labor platforms like Uber, Deliveroo or Amazon Mechanical Turk that matchmake between freelance workers and organizations (Duggan et al., 2020; Lee et al., 2015; Meijerink & Keegan, 2019; Möhlmann & Zalmanson, 2017; Newlands, 2021; Rosenblat & Stark, 2016; Veen et al., 2019). Because they charge a fee per match made, online labor platforms have an interest to scale the number of freelancer workers on their platform. HRM algorithms are helpful here to automate automated decision making, limit transaction costs and control freelance workers at scale (Gandini, 2019; Rosenblat, 2018). In line with this, online labor platforms operate a wide range of predictive HRM algorithms to automate decisions in areas such as workforce planning (e.g. a software algorithm that automatically assigns activities to workers), selection (e.g. automated admission to the online platform on the basis of selected worker characteristics), compensation (e.g. surge pricing that determine the level of variable pay) and performance appraisal (e.g. dismissal/deactivation of poor performing workers). As such, when discussing the notion of algorithmic management in this study, we will often draw on examples coming from studies into online labor platforms and their use of HRM algorithms.

2.2. *Algorithmic management as a restraint of worker autonomy and value*

In existing studies into software algorithms at work, algorithmic management is predominantly conceptualized as a mean for managers to control workers, thereby limiting worker autonomy and value (Duggan et al., 2020; Gandini, 2019; Kellogg et al., 2020; Leicht-Deobald et al., 2019; Möhlmann & Zalmanson, 2017; Shapiro, 2018; Veen et al., 2019; Zuboff, 2019). This is in line with labor process theory which predicts that managers seek innovative ways to establish control over workers to capture the (monetary) value created by workers' labor (Gandini, 2019; Smith, 2015). Provided that the effort of workers enhance monetary value when turning inputs possessed by the employer (e.g. production facilities, raw materials, know-how) into products and services, it is in the interest of employers to control labor processes. Accordingly, labor process theorists have examined how employers use control mechanisms that involve directing, surveilling and disciplining workers to capture (monetary) value from workers (Barley & Kunda, 1992; Edwards, 1979; Thompson & Van den Broek, 2010). Along similar lines, HRM researchers have shown how high-control HRM systems afford employers to improve worker productivity through HRM practices such as well-defined jobs, training that emphasis compliance with rules and procedures, performance appraisal against preset behaviors, and contingent/hly pay (Arthur, 1994; Hauff, Alewell, & Hansen, 2014; Lepak & Snell, 2002; Walton, 1985). These control-enhancing HRM activities come at the expense of job autonomy in terms of the workers' freedom to exercise control over aspects of their work such as its content, location, timing, remuneration and/or performance standard (Langfred, 2007). Research shows that this limits workers' non-monetary value derived from work in terms of building a desired (work) identity, personal growth, being satisfied at work or experiencing a sense of accomplishment (Goods, Veen, & Barratt, 2019; Wood et al., 2019). Labor process theorists predict that this ultimately creates an antagonist relationship between workers and employers/manager, with the former seeking to resist managerial control, causing the latter to seek new ways to execute control over workers (Smith, 2015; Thompson & Van den Broek, 2010). In the literature, algorithmic management is regarded as an 'innovative' way for employers to reinforce control over workers (Gandini, 2019; Kellogg et al., 2020; Veen et al., 2019) by means of directing, evaluating and disciplining workers (Edwards, 1979; Kellogg et al., 2020):

Algorithmic direction entails employers using algorithms to offer only certain information to workers and/or making suggestions that make workers decide in line with the employers' interests (Kellogg et al., 2020; Rosenblat, 2018; Veen et al., 2019). It is the opaque nature by which algorithms turn input into output that affords this type of control that manifests in algorithmic-enabled HRM activities such as job design and selection. For instance, the ride-hailing platform Uber relies on algorithms to automatically allocate tasks to drivers. Drivers however are not presented with the complete overview of all available requests for a ride. This limits the degree of choice to workers through the creation of information asymmetries (Leicht-Deobald et al., 2019; Rosenblat & Stark, 2016). This reduces (monetary) value to Uber drivers – who are freelancers and therefore paid per ride – as they cannot select those rides that are most beneficial to them. Moreover, research into the meal-delivery platform Deliveroo shows that the address of consumers remain algorithmically concealed until a meal deliverer picked up the order from the restaurant, thereby avoiding that deliverers accept orders that are less (financially) lucrative to them (Meijerink, Keegan, & Bondarouk, 2021; Veen et al., 2019).

Algorithmic evaluation involves both the real-life, remote surveillance of worker behavior and the evaluation of worker performance by means of ratings and rankings (Gandini, 2019; Kellogg et al., 2020; Newlands, 2021; Strohmeier & Piazza, 2015). This is afforded by the variety and veracity of the big data that is inputted into software algorithms that semi-automate HRM activities such as performance appraisal, compensation and selection. For instance, Schweyer (2018) shows how the consulting firm Klick Health operates a machine-learning tool to calculate the average time that workers take to "complete a variety of tasks and alerts leaders when projects appear to be going off track" (p. 7). Software algorithms at work can also be used to perform text mining analyses on employees' opinions and sentiments in web-based documents, blogs and social network sites (Gegenhuber, Ellmer, & Schüßler, 2021; Strohmeier & Piazza, 2015). This limits workers' autonomy through identity and discourse control by managers (Alvesson & Kärreman, 2007). In line with this, online platform firms like Upwork, Fiverr and Amazon Mechanical Turk rely on software algorithms to aggregate customer ratings to identity poor performing workers and take corrective measures if needed (Jarrahi & Sutherland, 2019).

Algorithmic disciplining entails the use of software algorithms for rewarding and/or punishing workers (Kellogg et al., 2020) thereby enabling HRM activities such as performance appraisal and compensation & benefits. As an example, online platform firms automatically dismiss workers in case their performance ratings fall below a certain threshold (Rosenblat & Stark, 2016). This involves workers, who do repeatedly receive poor customer ratings, being either deactivated (i.e. losing access to the online workplace) or receiving fewer jobs (Jarrahi & Sutherland, 2019; Rosenblat & Stark, 2016; Shapiro, 2018). Workers that are subject to algorithmic disciplining often are easily replaceable by others and work on short, fixed-term contracts, meaning that the use of software algorithms at work creates precarious working conditions for them (Gandini, 2019; Kellogg et al., 2020; Wood et al., 2019). On the other hand, workers that are willing to comply with preset performance criteria may be algorithmically rewarded with more work and/or higher pay – often however at the expense of their autonomy in terms of freedom how and when to do their work (Lehdonvirta, Kässi, Hjorth, Barnard, & Graham, 2019; Meijerink et al., 2021; Möhlmann & Zalmanson, 2017; Wood et al., 2019).

The overview above shows that there have been a lot of studies into algorithmic management to show that are variety of HRM activities are augmented and/or automated by means of software algorithms. Although HRM algorithms differ by being either descriptive, predictive or prescriptive in nature, research evidence is converging around the idea that algorithmic management reduces workers' autonomy and (non-)monetary value, among other reasons, through the creation of information asymmetries (Rosenblat, 2018; Shapiro, 2018), decreased human sensemaking (Leicht-Deobald et al., 2019) and automated disciplining (Kellogg et al., 2020).

2.3. *Worker resistance to regain autonomy*

In parallel to the stream of studies on algorithmic control, there is a growing body of literature that shows how workers seek to regain autonomy through so-called algoactivism. We borrow the definition from Kellogg et al. (2020) and view algoactivism as the tactics employed by workers to resist the control that HRM algorithms afford (Kellogg et al., 2020). Research shows that workers seek to regain autonomy under algorithmic management regimes in at least two ways: through non-cooperation and data obfuscation (Irani & Silberman, 2013; Kellogg et al., 2020; Lee et al., 2015; Lehdonvirta, 2018; Newlands, 2021). *Non-cooperation* entails the ignorance of algorithmic direction and recommendation (Kellogg et al., 2020). For instance, workers on the Amazon Mechnical Turk platform crowdsourced an application called Turkopticon that enables workers to report and avoid malicious clients. In so doing, they can avoid contracting with clients that are algorithmically suggested to them by Amazon Mechnical Turk (Irani & Silberman, 2013). Moreover, research has shown that taxi drivers on the Uber platform reported not to be influenced by Uber's surge pricing mechanism that algorithmically directs drivers by offering higher pay in areas were customer demand increases. Rather that following algorithm-based recommendations, the Uber drivers relied on their own knowledge in deciding which city districts to do business in, thereby limiting the reduction in their autonomy (Lee et al., 2015; Rosenblat, 2018). Other Uber drivers however seek to engage in data obfuscation by collectively gaming the surge price algorithm by calling on others in online forums to log off from the Uber app (Möhlmann & Zalmanson, 2017). As another example of *data obfuscation*, Lehdonvirta (2018) showed that workers on platforms like MobileWorks and CloudFactory operate scripts that monitor the online marketplace and alert workers when suitable tasks became available, thereby seeking to gain the upper hand over the platforms' algorithmic control mechanisms (Kellogg et al., 2020). Along similar lines, workers seek to avoid the control exercised by automated screenshots taken of their computer screens, by installing a second monitor (Wood et al., 2019). In conclusion, while one stream of research has shown how algorithmic management limits worker autonomy and value, a second research stream showed that this can be negated by workers through algoactivism for resisting algorithmic control, (re) gaining autonomy and creating value out of HRM algorithms.

2.4. *Moving our understanding beyond notions of algorithmic control and resistance*

Based on the two streams of studies into algorithmic control and algoactivism, we will build our understanding of HRM algorithms further, in at least two ways. First, if we know that workers may resist algorithmic-enabled control and regain autonomy through algoactivism, we still need to investigate the implications this may have for the properties algorithmic management. After all, HRM algorithms are fed with data that are generated through workers' behaviors and actions at work (Garcia-Arroyo & Osca, 2019) – including their algoactivist acts. Accordingly, algoactivism may lead to changes in algorithmic management when workers feed HRM algorithms with obfuscated data to offset algorithmic control, which may change the weight and relevance of algorithmic parameters. Similarly, managers and software developers can decide to redesign software algorithms to offset resistance tactics of workers to regain autonomy under algorithmic management and create value out of HRM algorithms. Provided that algoactivism by workers serves to (re)gain autonomy and value from work, we expect that besides being shaped by, autonomy and value are equally shaping algorithmic management. Secondly, if we know that algorithmic management can restrain worker autonomy and value, now it is time to put emphasis on how software algorithms can simultaneously foster autonomy and value to workers.

Given the above, we argue that a one-sided research perspective – i.e. algorithmic management as a threat to worker autonomy or workers' resistance to it – that is predominantly informed by labor process theory is meaningful, yet does not echo the real life complexity of algorithmic management. In fact, overlooking this complexity creates the risk of ending up with a deterministic instrumental way of conducting empirical studies into the relationship between algorithmic management, autonomy and control. That is, current perspectives on algorithmic management imply that HRM algorithms predetermine autonomy and control to workers who cannot do more but to either accept or resist the algorithmic control they are subject to and undesired consequences that HRM algorithms bring. We argue that algorithmic management is more complex, while workers can engage in alternative courses of actions beyond algoactivism to increase autonomy under, and create value out of, HRM algorithms. To ensure future research can unpack this complexity and avoid reinforcing deterministic assumptions about algorithmic management as having predetermined, undesired consequences to workers, we propose a conceptual lens that puts the *duality of algorithmic management* at center stage. The dualistic perspective allows to see that algorithmic management limits *and* fosters autonomy/value, while simultaneously being shaped by the actions of workers to increase autonomy and value at work. In the remainder of this article we discuss the notion of duality of HRM algorithms, translate this to the duality of algorithmic management concept, and conclude with a duality-informed research agenda on the recursively relationships among algorithmic management, autonomy and value.

3. Duality of HRM algorithms: touching the base

We take the notion of duality from the scholarly stream of structuration thinking (after Giddens (1984)). Particularly, we were inspired by the notion of duality of technology that is originated as a response to the call to go beyond deterministic thinking on the relationship between technology and human (inter)action (Leonardi et al., 2012; Orlikowski, 1992). In deterministic studies, algorithms are seen as mediating mechanisms between action and organizational structures by providing workers with new opportunities and capabilities. The notion of duality changes this view. While the algorithm-determinist approach views activities as communications between people in organizations, duality thinking alters this understanding as it considers algorithms usage to be an action on its own that impacts the constitution of organizational structures. In other words, software algorithms – like any other technology at work – do not affect the organizational structures through communications; instead – their use is considered to be an action that changes the organizational structure (Orlikowski, 1992).

Following this scholarly tradition, we view algorithmic management neither as an objective force that determines actions/responses of workers nor being socially produced by them. Accordingly, we borrow and apply the central premise of the duality of technology to algorithmic management that human actions and their outcomes are enabled *and* constraint by algorithmic management (Leonardi et al., 2012; Orlikowski, 1992). Here, the idea is that HRM algorithms embed rules and resources such as worldviews, assumptions, norms, power relations or conventions (Giddens, 1984). For example, software developers draw on their knowledge, experiences, worldviews when designing technological artefacts thereby embodying algorithms with their meanings (Leicht-Deobald et al., 2019). Algorithms also can encompass some built-in power relationships because managers and designers make decisions what can and cannot be done with algorithms. Also, one can expect that rules are built into algorithms to legitimize selected actions, while delegitimizing others (like collecting or reporting private information about workers). As such, we propose algorithms at work to be seen as both enabling *and* restraining the actions of those engaging with algorithmic management.

The above implies that the duality of algorithmic management involves another notion – algorithms themselves develop gradually and recursively. Rather than merely enabling or restraining workers' action (obeying or resistance), algorithms themselves become a target of influence by workers, and therefore, are subject to change. Changes in algorithms – either through design or usage – are seen to be triggered by the so-called interpretive flexibility of software algorithms (after Orlikowski (1992)). As noted by Pinch and Bijker (1987), this concerns “the idea that technological artefacts are both culturally constructed and interpreted, that is flexibility is manifested in how people think of or interpret artefacts as well as how they design them” (p. 40). Interpretive flexibility allows users of algorithms to be conscious about the meanings, resources and norms/rules that are built into algorithms. Here, the idea is that users are able to change the properties of algorithms when they are aware of these properties and capable to modify them. Provided that algorithms are built by humans, workers are provided with selected worldviews, resources and rules which they draw upon in their day-to-day activities (Leicht-Deobald et al., 2019). Therefore, algorithms are socially constructed by workers through the everyday usage, making sense of, and/or deciding how to use selected technical features. In so doing, workers (users) reproduce and sustain the rules and resources embedded into HRM algorithms. It can also occur that users ascribe different meanings to algorithms or use them as a resource to achieve other outcomes than intended by designers. Over time, this may result in a structural change in algorithms whereby they lose their connection with individual users (Leonardi et al., 2012; Orlikowski, 1992).

Taken together, the above implies that the concept of algorithms' duality embody two notions: algorithms will enable and constrain actions of workers simultaneously; and in the course of usage algorithms will evolve and change their properties.

4. Duality of algorithmic management, autonomy and value

In line with the two notions outlined above, we propose the *duality of algorithmic management* to argue that HRM algorithms (1) both restrain *and* enable worker autonomy and value, and (2) are simultaneously resultant from workers' acts to uphold autonomy and create value out of HRM algorithms (see Fig. 1).

4.1. Algorithmic management as restraining and fostering worker autonomy and value

Provided that HRM algorithms are built and deployed on the basis of rules and resources, we argue that the structural features of HRM algorithms enable *and* restrain workers actions to gain autonomy and create value out of HRM algorithms. We see four reasons for this, because: algorithms (1) are fed with proxy data which are dual in nature, (2) incorporate automated processes which are dual in nature, (3) equate resources out of which workers create value, and (4) enable value co-creation between workers and other stakeholders (see right-hand side of our Fig. 1).

4.1.1. Duality in proxy data that fosters and restrains autonomy

HRM algorithms simultaneously restrain *and* enable worker autonomy because they are fed with data that only partially capture the experiences and reality of workers (Gal et al., 2020; Newlands, 2021; Wood et al., 2019). For instance, Newlands (2021) describes how algorithmic management of freelance meal deliverers creates a so-called 'data double'. Such data doubles represent a conceived technical reality that is an inaccurate description of the lived, embodied reality that workers face at work (e.g. icy conditions, road blocks or short-cuts) (Haggerty & Ericson, 2000). This offers leeway for workers to glitch control systems and constrains the organization to exercise control over workers. This occurs, for instance, when meal deliverers make use of short-cuts in delivery routes not encoded into digital maps. At the same time however, data doubles constrain freedom as it forces workers to act in line with the errorless technical reality of a digital map rather than acting freely in their lived, embodied reality (Newlands, 2021; Veen et al., 2019). Also, Wood et al. (2019) show how firms like Upwork and Fiverr, are unable to algorithmically monitor worker behaviors when their workers engage in non-routine tasks. To make up for this, these companies exercise control by algorithmically processing customer reviews. This leaves workers with little autonomy to escape output-based control regimes, but simultaneously makes them free to decide how they organize their work. Taken together, HRM algorithms can at best processes data on a *selected* number of employee attributes and behaviors to limit worker autonomy. However, since not all worker attributes and behaviors can be translated into machine-readable data, algorithms simultaneously offer autonomy to workers.

4.1.2. Duality in algorithmic processes that fosters and restrains autonomy

HRM algorithms further enable and restrain autonomy, since they are embedded with rules that are dual in nature. In our view, this duality manifests since algorithms (1) are embedded with selected norms and worldviews, and (2) when they are opaque and black-box in nature (Faraj et al., 2018; Pasquale, 2015). Here, algorithmic management limits freedom by compromising workers' sensemaking and imposing one dominant worldview encoded into software algorithms (Leicht-Deobald et al., 2019). In fact, when algorithms are opaque, workers might not even realize that their freedom is being restricted (Gal et al., 2020). At the same time, sensemaking researchers have shown that uncertainty and lack of information (e.g. about the rules embedded in HRM algorithms) make workers turn to their idiosyncratic experiences, expectations and motivational drivers to make sense of reality (Sonenshein, 2007; Weick, 1995). It is precisely the black-box nature of selected HRM algorithms that create uncertainty for workers. Accordingly, we expect that this triggers workers to attribute different meanings to the functioning and goals of algorithmic management (Orlikowski, 1992). This especially holds for workers that do not communicate with human managers that may limit autonomy through discourse and identity control (Alvesson & Kärreman, 2007). In this sense, besides being embedded with a restraining dominant worldview, black-box HRM algorithms (that fully automate decision making) also offer workers the freedom to make sense of the working of algorithmic management in different ways.

Furthermore, organizations may have to design HRM algorithms that restrain and enable worker autonomy. This especially goes for platform organizations like Uber and Deliveroo that need to balance between autonomy and control (Cameron, 2018; Meijerink et al., 2021; Shapiro, 2018; Wood et al., 2019). Namely, these organizations work with freelancers who – in line with their self-employed status – should be autonomous in their work. At the same time, online labor platforms need to control independent contracts to ensure customer needs are met. Online labor platforms need to strike a balance to avoid legal problems that center on the reclassification of freelance workers (see Meijerink & Keegan, 2019 for an overview of high-profile court cases on this issue). As such, the algorithmic management of platform firms should be inscribed with both control and freedom (Shapiro, 2018). In a study among Uber drivers, Cameron (2018) reports on this duality: some drivers experience that HRM algorithms limit their freedom, while others report that HRM algorithms afforded them autonomy in terms of making choices through the work process for maximizing earnings. Equally, meal delivery platforms like Deliveroo and Uber Eats have algorithms in place that control workers by creating lock-in effects. At the same time, as freelancers, these workers are free to work for different platforms and thus decide themselves to switch across online platforms as they see fit (Meijerink et al., 2021; Veen et al., 2019). Finally, Kinder, Jarrahi and Sutherland (2019) show how workers on the Upwork platform rely on the output of HRM algorithms to increase autonomy. These workers do so, by transferring their online reputation score (i.e. an overall customer satisfaction score generated by an algorithm) from the Upwork platform to their social media accounts. This enables them to attract clients from outside Upwork's platform and thus avoid Upwork's control mechanisms (Kinder, Jarrahi, & Sutherland, 2019). Taken together, this implies that besides limiting autonomy by controlling workers' interpretations and behaviors, HRM algorithms do simultaneously foster worker autonomy and freedom.

4.1.3. Algorithmic output as input for value creation by workers

Algorithmic management is further dual in nature while it restrains and enables value to workers. Here, we define value both in terms of monetary benefits – in terms of financial compensation for their work – as well as non-monetary benefits that are derived from work (e.g. social relationships, learning and enjoyment) (Bowman & Ambrosini, 2000; Lepak, Smith, & Taylor, 2007; Meijerink & Bondarouk, 2018). The literature has broadly discussed how algorithmic management limits monetary value to workers (Gandini, 2019; Smith, 2015; Veen et al., 2019). At the same time, algorithmic management can be simultaneously designed as an organizational resource that benefits workers. For instance, besides operating HRM algorithms that nudge drivers to work long hours and destroy value (e.g. fatigue, work-life imbalance), Uber also operates algorithms that assign rides with destinations close to their home (or another final destination) at the end of a taxi driver's shift (Rosenblat, 2018). This creates value for workers while it prevents them from long rides back home that are not financially compensated.

Furthermore, workers may leverage HRM algorithms to their advance, even if algorithmic management is not designed to create value for them. As an example, when demand outstrips supply, the meal-delivery platform Uber Eats offers minimum hourly rates (so-called 'hourly guarantees') of approx. €15 per/hour. Workers are algorithmically offered these minimum hourly rates when performing at least one meal delivery an hour and refrain from declining incoming orders (Veen et al., 2019). Meijerink, Keegan, and Bondarouk (2019) show that this algorithmic-enabled compensation scheme does benefit Uber Eats (i.e. more labor supply), but not the workers (i.e. demand outstrips supply, meaning that workers' income anyway exceed the minimum hourly rate). However, some workers were able to identify a bug in the system that allowed them to maximize income at minimal additional effort. Namely, during the first 50 min of each hour worked, these workers earned an income via a rivalry platform firm (e.g. Deliveroo). Only during the last 10 min, they switch to the Uber Eats platform. During these 10 min they perform one meal delivery and therefore, do not decline any orders. As such, they are algorithmically awarded the hourly guarantee of €15 by Uber Eats on top of the income generated via the rival platform (Meijerink et al., 2019). Along similar lines, Wood et al. (2019) show that online freelance workers with high online reputation scores on platforms like Upwork and Fiverr are able to attract many clients. They benefit from these algorithm-computed scores by sub-contracting some of the work to peers via the same online platforms at a lower hourly rate than charged to their client. Taken together, these examples show that the output of algorithmic management enable and restrain value to workers, depending on how they put this output to use.

4.1.4. *Algorithmic output as input for value co-creation*

Finally, algorithmic management has a dual impact on value derived by workers through enabling and restraining value co-creation between workers and relevant stakeholders. On the one hand, performance management algorithms may limit value to workers by allowing customers – that administer worker rating schemes – to exercise power over workers (Rosenblat & Stark, 2016). As an example, research has shown reductions in value to workers when workers financially reimburse/compensate customer to avoid or erase a bad customer review (Rosenblat, 2018). On the other hand, the same customer reviews also offer (use) value to workers. For instance, Cameron (2018) showed that algorithmic-enabled performance appraisal reminded workers of the pleasant interactions they had with customers. Moreover, in the case of platform workers on the Fiverr platform, performance management algorithms allow workers to build strong online reputations and trustworthy relationships with workers. Because of these trusting relationships, workers can transact with customers outside the online platform (so-called 'disintermediation'), avoid the intermediation fee charged by the platform and therefore, capture more monetary value from their labor effort (Kinder et al., 2019). As such, while algorithmic management limits workers to derive value from their work, for others it simultaneously increases value.

HRM algorithms can also be purposefully designed to foster value co-creation by using predictive algorithms that effectively matchmake workers with selected projects and/or customers. As an example, Gregory, Henfridsson, Kaganer, and Kyriakou (2021) discuss how organizations learn from user-generated data to enable value-added transactions in online marketplaces. Software algorithms help to process and analyze these data to learn which competences and experiences workers have and how this can serve algorithmically-identified customer needs, habits and routines. Ultimately, this allows to make better matches between workers and customers to ensure both parties co-create value (Chen & Horton, 2016). Here, organizations need to avoid capturing excessive amounts of value that is co-created by workers and customers. This especially holds for online labor platforms. Namely, to ensure that customers and workers remain willing to pay for a platform's intermediation services, the platform has to ensure both parties co-create and derive value from online market place transactions. Platforms that attempt to capture excessive amounts of (monetary) value from such transactions – by charging high intermediation fees – however run the risk that workers either earn too little and/or customers pay too much. This ultimately results in a situation where workers and customers are unwilling to pay for intermediation services and stop to co-create value in the platform's online market place. As such, when designing algorithmic management, online platforms have to balance between fostering value co-creation by platform users, while simultaneously capturing a portion of that value. Put differently, HRM algorithms need to both enable and restrain the value that workers derive from transacting with clients.

Taken together, the discussion above stresses that algorithmic input, processes/throughput and output are dual in nature. Accordingly, next to the idea that algorithmic management restrains autonomy and (monetary) value to workers, the duality of algorithmic management holds that it simultaneously fosters worker autonomy and value. Accordingly, we propose the following:

Proposition 1. HRM algorithms simultaneously enable and restrain the autonomy and value to workers subject to algorithmic management.

4.2. *The recursive implications of worker autonomy and value for algorithmic management*

Besides being shaped by HRM algorithms, autonomy and value equally shape algorithmic management. The latter we refer to as the recursive implications of autonomy/value for algorithmic management. We propose that worker autonomy and value creation have recursive implications for HRM algorithms by triggering (1) the purposeful redesign of software algorithms by humans and (2) automated changes in software algorithms by means of artificial intelligence (see left-hand side of our Fig. 1).

4.2.1. *The redesign of HRM algorithms by humans*

The autonomy to workers and value created out of HRM algorithms have recursive implications for the design of algorithmic management. Here, the idea is that software engineers change the structural features of HRM algorithms as a response to workers' engagement with algorithmic management. This can involve attempts to further enable or restrain worker autonomy and value. In the enablement scenario, when workers create value out of HRM algorithms in unanticipated ways, software designers may decide to add additional parameters to existing algorithms or create new algorithms to better aid workers in further reaping benefits. On the contrary, software engineers (upon the requests of their managers and/or capitalists) may also redesign software algorithms to avoid unwanted use of HRM algorithms for limiting freedom to workers. Research into algoactivism has shown that workers indeed ignore algorithmic direction (e.g. recommendations on which work activities to execute) or circumvent algorithmic disciplining to regain autonomy (Kellogg et al., 2020). These acts may motivate managers to revisit algorithmic control mechanisms. For instance, in an attempt to avoid so-called disintermediation – i.e. platform users engaging in transactions outside their online marketplace – the Upwork platform designed an algorithm that automatically searches for worker-client communication that is indicative of disintermediation attempts (Jarrahi & Sutherland, 2019). Moreover, to escape intermediation fees, platform workers and clients move transactions off-platform, which Upwork seeks to address by algorithmically deactivating accounts of workers who engage in disintermediation (Kinder et al., 2019). Along similar lines, and as noted by Gregory et al. (2021), "Uber tries to prevent fraudulent behavior such as prearranged trips between riders and drivers that limit open competition by letting its algorithms monitor signs of fake trips (e.g., requesting, accepting and completing trips on the same device or with the same payment profile, excessive promotional trips, excessive cancellations) in real time for faster prediction and action recommendations or sanctions to enforce rules more quickly" (p. 14). Finally, Griesbach, Reich, Elliott-Negri, and Milkman (2019) show that meal delivery workers consistently reject algorithmically-dispatched orders coming from restaurants with bad reputations. In an attempt to address this situation, meal delivery platforms change pay/compensation algorithms to induce workers to accept orders by algorithmically increasing delivery fees for orders coming from restaurants that workers previously did not want to work for (Meijerink et al., 2021). Taken together, this implies that worker actions to (re)gain autonomy and value have recursively implications for algorithmic management when designers attempt to suppress (or reinforce/support) these worker actions through HRM algorithm redesign.

4.2.2. Automated, AI-driven changes in HRM algorithms

Worker autonomy and value also change the structural features of algorithmic management when artificial intelligence is built into HRM algorithms. This most likely occurs with self-learning algorithms that automatically adjust the weight of software parameters depending on how workers engage with HRM algorithms for (re)gaining autonomy and/or creating value out of algorithmic-enabled HRM activities. For instance, Jarrahi and Sutherland (2019) show that workers ask clients to break down a project into smaller gigs to build their online reputation. This increases value to workers as online reputations are positively related with worker income (Lehdonvirta et al., 2019). If future clients in turn are more likely to hire workers with inflated reputations, matching algorithms may automatically increase the weight assigned to parameters such as 'number of previous gigs performed' when matchmaking workers and clients. Furthermore, workers leave digital traces when co-creating value with others. These are processed by self-learning algorithms to optimize automated decision-making (Gregory et al., 2021). For instance, in many online marketplaces, workers and clients give mutual ratings that indicate the level of satisfaction of both actors (Meijerink et al., 2019; Rosenblat, 2018). When coupled with other attributes that gauge worker and client needs, competences or interests, self-learning algorithms can processes mutual ratings to better predict which future matches will produce high-value outcomes for all parties involved. As these examples show, the acts of workers to (re)gain autonomy and value are fed into the (automated) redesign of HRM algorithms. Therefore, we propose the following:

Proposition 2. Besides being shaped and affected by HRM algorithms, autonomy and value equally shape (or: have recursively implications for) the structural features of algorithmic management.

5. Future research questions on the duality of HRM algorithms

In line with our duality of algorithmic management concept, we propose two avenues for future research to uncover the full complexity associated with the interrelations among HRM algorithms, autonomy and value: one on the enabling and restraining nature of algorithmic management, the other on the recursive relationship between algorithmic management and worker autonomy/value:

5.1. Future research questions on the restraining and enabling nature of algorithmic management

Although we predict that algorithmic management simultaneously enables and restrains autonomy/value, it is unlikely that HRM algorithms are enabling and restraining to a similar degree. That is, HRM algorithms that are designed to foster autonomy may still limit worker freedom, while control-enhancing algorithms may still afford some degree of autonomy to workers. As such, an interesting avenue for future research is to uncover under what conditions algorithmic management hinges on being more enabling or restraining. For instance, does this depend on the type of algorithm put into place? That is, can we expect differences in worker autonomy depending on whether organizations deploy descriptive/predictive algorithms where humans rely on algorithmic output in decision making processes but still make the final call versus prescriptive algorithms that fully automate decision making? Moreover, research shows that the type of algorithm-enabled (HRM) activity and complexity have implications for worker outcomes (Langer, König, & Papathanasiou, 2019; Nagtegaal, 2021). For instance, algorithmic decision making is shown to have negative implications for workers' justice perceptions (Newman, Fast, & Harmon, 2020) – a situation which is however negated in cases (e.g. automated interview training) when little is at stake for the worker (Langer et al., 2019) or when algorithmic HR-decision making involves little complexity (Nagtegaal, 2021). In fact, Nagtegaal (2021) shows that procedural justice increases when algorithms are used for automating HRM activities that are low in complexity (and vice versa). In such cases, the use of white-box HRM algorithms, that are transparent and reveal the algorithm's structure to workers (Burrell, 2016), may be desirable and effective as non-complex algorithmic decision making may be most comprehensible to workers. On the contrary, complex and high-stake decision making by algorithms should be black-boxed, or even better, be placed in the hands of a human decision maker (Langer et al., 2019; Nagtegaal, 2021). This presents interesting questions for future research into the implication of algorithmic management for autonomy and value, like: does the enablement versus restriction of autonomy depend on the level of complexity of algorithm-based HR decision making? Do HRM algorithms limit value to workers in high-stake scenarios and increase value when algorithmic decision making involves low stakes? Is worker autonomy/value enabled or restrained depending on the transparency of algorithmic management?

Another line of inquiry is to examine how the enabling and restraining potential of algorithmic management is affected by the institutional context in which they are applied. Provided that algorithms are embedded with rules and resources, we can expect them to reflect the institutional context in which they are applied (Orlikowski, 1992). While some legal jurisdictions are more stringent on the collection of worker data (e.g. GDPR in Europe) and limiting worker autonomy, others likely leave more room for corporations to control workers by means of algorithmic management. Here, future studies can apply the institutional logics concept to describe how ideal-type sets of norms, values and believe systems impact algorithmic management (Frenken, Vaskelainen, Fünfschilling, & Piscicelli, 2020; Meijerink et al., 2021). This would allow studies that examine whether the restraining or enabling features of HRM algorithms differ across the ideal-type institutional logics of the market, corporation, state or profession.

Since algorithms have interpretive flexibility, we expect that the autonomy and value coming from algorithmic management differ across workers. For instance, previous research has shown that employees derive value from HRM activities by integrating their personal resources (i.e. their knowledge, skills and abilities) with resources provided by the organization (e.g. relationships with colleagues, information technologies, operating procedures) (Meijerink & Bondarouk, 2018). As such, an interesting question is what personal and organizational resources employees draw upon to create value out of HRM algorithms? Such personal and organizational resources follow from HRM activities that are not necessarily automated by algorithms, such as training or team work (Van Beurden, Van De Voorde, & Van Veldhoven, 2020). To our knowledge, there is little research that examines the interactions between HRM algorithms and non-algorithmic HRM. This is surprising as research has shown that HRM activities in highly digitalized workplaces continue to be executed by human managers that operate alongside HRM algorithms (Meijerink et al., 2021; Newlands, 2021; Shapiro, 2018; Veen et al., 2019). Accordingly, we see the need for research that examines questions such as: How are non-algorithmic and algorithmic HRM activities working together? What is the best synergy? What role do HRM activities performed by human managers play in balancing whether HRM algorithms enable or restrain worker autonomy? What resources do non-algorithmic HRM activities offer to workers for allowing them to create value out of HRM algorithms? And, do changes in non-algorithmic HRM activities trigger changes in how workers make sense of and engage with algorithmic-enabled HRM activities?

Finally, we see possibilities for studies into how the enabling and restraining properties of algorithmic management are reflected in worker behavior. Here, we encourage future studies on new forms of algoactivism that offset the constraining potential of HRM algorithms (Kellogg et al., 2020). For instance, a group of Uber drivers recently announced to start a court case against Uber with the aim to obtain the worker data inputted into Uber's HRM algorithms. Using these data, these workers want to reverse engineer the algorithms they are subject to, which ultimately can start future court cases for limiting the control that Uber exercises over its drivers. In line with this, future studies can examine whether such acts impact the degree to which algorithmic management restrains autonomy. While some workers seek to reactively resist algorithmic control through algoactivism, others may take a more proactive approach to create value out of HRM algorithms. As such, we ask what makes some workers to (reactively) resist algorithmic management, while others seek to use algorithmic management to their own advantage? Such worker acts to create value out of HRM algorithms may have negative consequences for others. Earlier, we described how freelance workers exploit their peers by using their high online reputation scores to attract clients and in turn sub-contract that work to their peers at a lower hourly rate than charged to their client (Wood et al., 2019). This implies that for some workers, algorithmic management can be enabling, while for others it is restraining. Accordingly, future research may seek to answer questions like: To what extent does algorithmic management result into 'winners' and 'losers'? Is the creation of value out of HRM algorithms a zero-sum game to workers? What role does reflectivity and algorithmic output (e.g. online reputations) play in explaining whether HRM algorithms enable value creation to some workers, while limiting value to others?

5.2. Future research questions on recursive relationship among HRM algorithms, autonomy and value

We proposed that worker autonomy and value creation trigger automated changes in HRM algorithms and/or motivate software engineers to redesign the structural properties of algorithmic management (see Fig. 1). Although the use of self-learning algorithms in HRM may yet be limited (Cheng & Hackett, 2021), research into online labor platforms and their use of algorithmic management show that an uptake of artificially intelligence algorithms in 'traditional' organizational settings may be foreseeable in the near future (Prassl, 2018). If this were to happen, HRM algorithms are more likely to develop autonomously, depending on the worker-generated data that they are trained with and co-evolve along. This may minimize the role that interventions by human designers play the use and of HRM algorithms. In terms of the duality of HRM algorithms, it implies that the recursive implications of worker autonomy and value for algorithmic management is more likely to be based on automated processes than deliberate changes by human designers in cases when self-learning HRM algorithms are deployed. On the other hand however, as noted by Raisch and Krakowski (2021), even the most automated and autonomous algorithmic systems require human-made changes and include human managers 'in the loop' in cases when algorithms need to be optimized to realize a new desired state, perform a new/different task, or need to be compliant with novel regulatory regimes. This implies that the redesign of HRM algorithms always remains – to varying degrees – a responsibility of humans. In fact, human decision makers (like HR professionals and line managers) perform HRM activities (e.g. job interviews, appraisal talks or task allocation) alongside those automated by HRM algorithms. These human-performed HRM activities are likely to be dual in nature too in that they shape, and are shaped by, algorithm-enabled HRM activities. One the one hand, HRM algorithms have implications for human managers in case they perform HRM activities that are augmented and shaped by algorithmic output (e.g.

decision which job candidates to invite for an interview) or replaced by autonomous, algorithmic processes which makes their HRM role redundant or offers freedom to work on HRM activities that algorithms can/do not take over. On the other hand, HRM algorithms can be shaped by human-performed HRM activities as well. This occurs in cases when hiring decisions or performance evaluations that were made by human decision makers are used as training data for developing HRM algorithms. Taken together, this triggers research questions such as: What is having a bigger impact on the structural properties of HRM algorithms: automated changes of human-made changes? Will self-learning algorithms adjust differently to worker acts to regain autonomy in comparison to situations where software engineers redesign HRM algorithms? If software designers decide to change HRM algorithms, is this upon their own initiative, that of workers or a manager/capitalist? Do the worldviews of software engineers (and their managers) change when workers engage with algorithmic management in unintended ways? Or, will they change HRM algorithms to reinforce and superimpose their pre-existing worldviews onto workers? What rules and resources do software engineers change when redesigning HRM algorithms: algorithmic parameters, the weight of these parameters, the descriptive/prescriptive/predictive nature of algorithmic management? How do power relationships change when workers create autonomy and value out of HRM algorithms? And, will (automated) changes in algorithmic management ultimately bring about change in the degree/balance to which HRM algorithms enabled and restrain worker autonomy and value?

Since algorithmic management and worker autonomy/value are recursively interrelated, we see the need for longitudinal research on the evolution of algorithmic management. Here, interesting questions for future research are: Through which processes will the use and outcomes of algorithmic management become stabilized? What time does it take before workers make habitual use of HRM algorithms, meaning that the restraining and enabling features of algorithmic management remain unchanged? Or, will the structural properties of HRM algorithms never change provided that self-learning algorithms continue to adapt? How does the evolution of algorithmic management depend on the characteristics and (inter)actions of its users? For instance, will the differences in meanings attached to HRM algorithms become smaller among workers, designers and managers such that the use of algorithmic management becomes more or less stabilized? While power relationships between workers and managers/capitalist stabilize such that workers stop to resist algorithmic control, meaning that the enabling and restraining properties of HRM algorithms remain unchanged? And, what changes do external shocks such as the COVID-19 pandemic or the loss of court cases over worker rights under algorithmic management bring to HRM algorithms? Will such shocks change the meanings, worldviews, norms and rules embedded in HRM algorithms and thereby, bring alterations to whether algorithmic management enables or restrains worker autonomy and value? It is by answering such questions through which future studies can further untangle the deeper complexity associated to algorithmic management.

6. Conclusions

This conceptual study builds on two important observations made by earlier studies into algorithmic management: (1) that HRM algorithms limit worker autonomy and value through increased surveillance and control exercised over workers, (2) which workers seek to resist by means of algoactivism as a novel type of workers resistance vis-à-vis management/capitalist. Building further on these earlier contributions, we offer a deeper understanding of the complexity in the relationship between algorithmic management, autonomy and value. By outlining the duality of HRM algorithms and the 'duality of algorithmic management' concept, we showcased how algorithmic management simultaneously restrains and enables worker autonomy and value. Moreover, we propose that HRM algorithms are recursively interrelated with worker autonomy and value, when software designers and/or self-learning algorithms reinforce or limit worker acts for (re)gaining autonomy (e.g. algoactivism) and/or creating value out of HRM algorithms. On this basis, we discussed avenues for future research into the duality of algorithmic management. As such, we hope that this study sets the stage for a future line of inquiry into the complex interrelationships among HRM algorithms, autonomy and value.

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