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Algorithmic human resource management: Synthesizing developments and cross-disciplinary insights on digital HRM

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Introduction

Across different disciplinary boundaries, research into algorithmic surveillance (Newlands, 2020), people analytics (Gal et al., 2020; Marler & Boudreau, 2017; Tursunbayeva et al., 2018), human resource management (HRM) algorithms (Cheng & Hackett, 2021), and algorithmic control (Kellogg et al., 2020; Veen et al., 2020) is gaining traction. Moreover, these various concepts are studied alongside – and at times interchangeably with – related phenomena including Big Data (Garcia-Arroyo & Osca, 2019), artificial intelligence (Strohmeier & Piazza, 2015; Tambe et al., 2019) and online labor platforms (Duggan et al., 2020; Newlands, 2020; Veen et al., 2020). These terms and developments are often loosely linked to, or aggregated as, ‘digital HRM’ which, as a broad notion covers a multitude of topics and issues with unclear and ambiguous relations between them (Strohmeier, 2020b). Studies into HR analytics (Marler & Boudreau, 2017; Minbaeva, 2017; Tursunbayeva et al., 2018; Van den Heuvel & Bondarouk et al., 2017), HRM algorithms (Cheng & Hackett, 2021; Leicht-Deobald et al., 2019), and artificial intelligence (AI) deployed in HRM practices (Strohmeier & Piazza, 2015; Vrontis et al., 2021), while beginning to coalesce around key issues, tend to use different terms to describe seemingly similar content leading to...
a lack of construct clarity that may prevent the scholarly community from building a collective and coherent body of knowledge (Suddaby, 2010).

In addition to lack of construct clarity, academic research on selected digital HRM activities, and any, or all, of its related components, lags the popularity of this term in practice. For example, Cheng and Hackett (2021: 9) conclude that “the growth of scholarly interest in HR-related algorithms pales in comparison to the surge of applications in HR practice.” Similarly, reviewing the HR analytics literature, Marler and Boudreau (2017: 7-8) find that “while there are many more blogs, white papers, consulting reports and press reports, it does not appear that management researchers have focused a great deal of attention to the topic.” Finally, Strohmeier (2020a: 58) also observes that besides a couple of initial contributions that deal with algorithmic decision making (e.g. Cheng & Hackett, 2021; Leicht-Deobald et al., 2019), there are still too few contributions that deal with algorithmic decision making as a key issue.

To set the stage for this special issue which focuses on these related digital HRM topics, we propose adoption of the term ‘Algorithmic Human Resource Management’ (hereafter algorithmic HRM) to synthesize insights on issues of common concern including the growing use of digital data to support HR decision-making, the deployment of software algorithms that process digital data at work, and the partial or full automation of HR decision-making, all of which are profoundly shaping how labor is managed and HR practices are performed. We propose this term to highlight salient links between different types of digital HRM discussed in the literature (e.g. HR analytics; AI-enabled HRM algorithms) as well as the conditions that enable it (e.g. Big Data) and the organizations that rely on it (e.g. online labor platforms). Algorithmic HRM is a more narrowly-defined term than digital HRM which may also help foster stronger cross-disciplinary links with research from other fields examining how algorithms, digital data, and digital platforms are transforming HRM practice, work and labor processes. We first introduce the research on algorithmic HRM by examining three key features that characterize it and specify how it is related to digital HRM. Next, we introduce the papers in the special issue and show their connections with algorithmic HRM. Finally, we conclude by looking forward to the challenges and opportunities linked with algorithmic HRM in different organizational contexts, including online labor platforms that are studied by researchers from different disciplinary fields and who have not communicated extensively with each other.
Algorithmic human resource management

Building on previous work (Duggan et al., 2020; Kellogg et al., 2020; Lee et al., 2015; Leicht-Deobald et al., 2019; Newlands, 2020; Strohmeier, 2020a; Veen et al., 2020), we define algorithmic HRM as:

The use of software algorithms that operate on the basis of digital data to augment HR-related decisions and/or to automate HRM activities.

Our definition highlights three main features of algorithmic HRM: 1) the generation and use of digital data, 2) the deployment of software algorithms that process digital data, and 3) the partial or full automation of HRM-related decision-making. Using this definition, we regard algorithmic HRM as a specific subset/type of digital, or electronic, HRM (Bondarouk et al., 2017; Strohmeier, 2020b). Here, digital HRM “denotes the socio-technical result of the digitalization of HRM” (Strohmeier, 2020b: 352), with the digitalization of HRM referring to the process by which the potential of digital data about work, workers or HRM practices is used for HRM purposes (Parry & Strohmeier, 2014; Strohmeier, 2020b).

In the case of algorithmic HRM, this potential relates to the use of digital data for full or partially automated decision making in HRM. Accordingly, its first two features (i.e. digital data and use of software algorithms) imply that algorithmic HRM falls within the realm of digital HRM, while the third feature, automation of HRM-related decision-making, distinguishes algorithmic HRM from other forms of digital HRM.

Algorithmic HRM and the creation and use of digital data

Algorithmic HRM depends on digital data. Without data, software algorithms do nothing. For software algorithms to be able to “use” data, these data need to be presented as binary digits that a computer can read and process. As such, algorithmic HRM requires what (Strohmeier, 2020b) refers to as digitization - a process by which information is turned into digital data. An example of digitization is the conversion of paper-based worker records into digital worker data that are stored in HR information systems (HRIS). Moreover, the use of sensors and smart devices in the workplace including smartphones, smartwatches, GPS tracking, smart tools/workpieces, and sociometric badges enables organizations to further digitize worker-related data. Here, one can think about the generation of digital data that capture workers’ behavior, actions, location, performance, emotional states or social relationships (Garcia-Arroyo & Osca, 2019). Digitization by means of sensors and smart devices allows for the real-time collection of digital data that
come in large amounts and from a variety of sources. This is often referred to as ‘Big Data’. Data are considered ‘big’ when having the following three attributes: high volume, high velocity, and high variety, or the 3Vs of Big Data (Frizzo-Barker et al., 2016; Garcia-Arroyo & Osca, 2019; Wenzel & Van Quaquebeke, 2018). Accordingly, Big Data equates with data that is converted into a large number of bytes about a large pool of workers (high volume), is collected at a high level of speed (high velocity) and comes from different types of sources (high variety). Although some have questioned whether Big Data actually exists in HRM (Cappelli, 2017), a real-life – yet rare – example of what might come close to Big Data in HRM is the data on the tens of thousands of Amazon's warehouse and delivery workers that are collected on an ongoing, minute-by-minute, basis and that come from a wide range of different sources such as smart equipment (e.g. a truck), handheld devices (e.g. a workers’ smartphone), and consumers (e.g. online customer reviews).

**Algorithmic HRM and the role of automated data processing**

Given the sheer size and speed at which they are collected, Big Data are difficult to process efficiently in a manual manner. This is where software algorithms come into play for transforming data in an automated and efficient manner. We define software algorithms as a set of computer-programmed steps to automatically accomplish a task by transforming data into output (Cheng & Hackett, 2021; Strohmeier, 2020a). This involves algorithms that extract data from different databases, combine these data, and convert them into a common format with little or no human involvement. In an HRM context, an example is software algorithms used by the Upwork platform, as highlighted in one of the articles in our special issue (Waldkirch, Bucher, Schou and Grünwald, this issue). Upwork's algorithms combine behavioral data (e.g. number of tasks completed) and customer evaluations to arrive at a so-called Job Success Score (JSS) that claims to capture a worker’s job-related performance (Kinder et al., 2019). Accordingly, algorithms process data and by so doing they produce “information” that can be treated as new knowledge or not (Pachidi et al., 2021). This may include the use of relatively straightforward descriptive statistics derived from HRIS as well as more sophisticated regression-based techniques.

Only recently, HRM scholars have started discussing how these HRM algorithms can become adaptive and self-learning (for a review, see Vrontis et al., 2021). This is where the link between algorithmic HRM and artificial intelligence (AI) in HRM comes to the fore. In line with the work of others (Strohmeier & Piazza, 2015; Tambe et al., 2019), we
define AI in the context of HRM as a broad class of software algorithms by which a computer executes HRM activities that would normally require human cognition and intervention. While most software algorithms in HRM are likely to be static, meaning that computer-programmed steps remain the same irrespective of the data inputted (e.g. use of an Excel spreadsheet to rank job applicants or use of SPSS to predict turnover intentions), in the case of AI these evolve with the data they process based on, for example, machine learning (Strohmeier & Piazza, 2015; Vrontis et al., 2021). In this sense, the use of AI in HRM is a specific form of algorithmic HRM. An example of a self-learning algorithm in HRM is one that automatically adjusts which variables and the weights of variables or the order of computer-programmed steps for predicting a job candidate’s future performance within the organization. Along similar lines, food-delivery platforms such as Uber Eats and Deliveroo rely on self-learning algorithms that optimize the allocation of tasks to workers, using existing data on past availability of workers, weather conditions, travel time or customer habits (Newlands, 2020; Veen et al., 2020).

Notwithstanding their benefits such as adaptability, the use of software algorithms in HRM creates challenges (Gal et al., 2020; Leicht-Deobald et al., 2019; Tambe et al., 2019). For example, software algorithms are (or can be made) opaque to workers, and it may not be entirely clear how these algorithms learn, or the exact source of their learning, and how they add parameters or adjust parameter weights using the data to which they are dynamically adapting (Burrell, 2016). This becomes particularly problematic when data reflects existing biases towards selected groups of job candidates. Thus, algorithmic HRM has the potential to reinforce discrimination on the basis of, for example, gender, ethnicity or age at scale (Ge et al., 2016; Hannák et al., 2017) if it learns these are parameters that are associated with human decisions. More generally, IT developers and therefore end-user employees, managers or independent contractors are not aware of the basis upon which computer-programmed steps are taken and which data are drawn on when HRM algorithms generate a selected type of output (Gal et al., 2020; Leicht-Deobald et al., 2019). Consequently, researchers and practitioners alike are increasingly calling for more transparency (Schildt, 2017) and “explainability” (Gunning et al., 2019) in the development and use of software algorithms at work.

**Algorithmic HRM and automated decision-making as output**

Algorithm-based HR decision making refers to the use of software algorithms to select one option from a range of alternatives (Cheng &
Hackett, 2021; Leicht-Deobald et al., 2019; Strohmeier, 2020a). Software algorithms support HRM decision making in two ways, through providing information (or augmentation) and with automation (Leicht-Deobald et al., 2019; Raisch & Krakowski, in press).

Information is provided when algorithms create output that helps human decision makers to make more informed decisions. For example, this information could be in the form of descriptive statistics which provide additional insights into skill or diversity gaps in the workforce (Deloitte, 2020). Furthermore, HRM algorithms augment human decision making by offering predictions which are used to forecast how a current decision may impact future outcomes. These so-called predictive algorithms operate regression-based forecasting techniques that, for example, help managers predict which employees are likely to leave the organization (and thus how to make decisions about retention), or to predict the future performance of a job candidate (and thus help hiring managers with selection decisions) (Cheng & Hackett, 2021; Leicht-Deobald et al., 2019). The use of predictive algorithms may involve machine learning and data mining to explore patterns in the data that humans may not (or could not) have uncovered themselves (Raisch & Krakowski, in press; Tambe et al., 2019). Such algorithmically generated information can be used by HR decision makers to choose between different alternative courses of action. This is where algorithmic HRM and the field of HR analytics intersect. As noted by Marler and Boudreau (2017: 15), HR analytics is “a HR practice enabled by information technology that uses descriptive, visual and statistical analysis of data related to HR processes, human capital, organizational performance, and external economic benchmarks to establish business impact and enable data-driven decision making”. Key to HR analytics is that humans, albeit drawing on descriptive or predictive algorithms, make decisions and act on those decisions themselves (Ellmer & Reichl, this issue; Wiblen & Marler, this issue). Put differently, HRM algorithms can both automate and augment HRM decision making. Currently, in HR Analytics, algorithmic HRM primarily augments HRM decision-making in that human decision makers may choose not to act on algorithmic-enabled insights or choose alternatives that are not necessarily predicted to be optimal by an algorithm (Rasmussen & Ulrich, 2015; Tursunbayeva et al., 2018). But with increasingly sophisticated algorithms, particularly with advances in AI algorithms, some HR decisions are now made without human “decision-making”.

As AI-based algorithms become more widely used, algorithmic HRM is shifting decision-making responsibility from human to machine by automating decision-making processes where human managers are replaced. This occurs when prescriptive algorithms automate HR-related
decision making, putting the execution of HRM activities in the hands of a robot or computer (Duggan et al., 2020; Leicht-Deobald et al., 2019; Newlands, 2020). Prescriptive algorithms that automate HRM activities not only forecast what can be done in different scenarios, but also select and execute a course of action without (much) involvement by a human decision maker. Although the study of prescriptive algorithms that automate HRM activities is growing in number (Cassady et al., 2018; Duggan et al., 2020; Meijerink et al., 2021), other streams of literature, such as Sociology of Labor (Ellmer, 2015; Veen et al., 2020; Wood et al., 2019) and Organization Studies (Newlands, 2020; Pachidi et al., 2021), more extensively reveal how organizations fully automate managerial activities by means of prescriptive algorithms as well as the consequences of doing so for worker outcomes (Bucher et al., 2021; Pachidi et al., 2021). Where this shift from human to machine in decision-making is most prevalent is with online labor platforms such as Uber, Upwork and Deliveroo that automate HR-related decision making and execution in areas such as selection (e.g. an algorithm that grants or denies workers access to the Upwork platform), compensation (e.g. Uber’s surge price algorithm that adjusts workers’ pay on the basis of labor supply and demand dynamics), and task allocation (e.g. Deliveroo’s algorithm that dispatches orders to food deliverers without human involvement). As these examples show, algorithmic HRM includes the use of a broad array of digital HRM activities that now goes well beyond the use of descriptive/predictive algorithms that HR analytics scholars frequently study.

**Overview of papers included in the special issue**

The papers featured in this special issue mobilize concepts and ideas related to algorithmic HRM including using digital (big) data, augmentation and automation, maintaining control, or balancing machine and human decision-making autonomy. This section discusses the four special issue papers individually, which is followed by an outline of avenues for future research into algorithmic HRM across different types of organizations that are examined by the studies included in this special issue.

In the first paper, Myllymäki (this issue) reviews how current electronic HRM research (or: digital HRM research) has been theoretically framed and compares this to what research using a social-materiality theoretical perspective might add to our understanding of how HRM digitalization is affecting how HRM is practiced in organizations. One of her key arguments is that research into electronic/digital HRM needs to pay closer attention to how people are using digital technology. Researchers can gain a more nuanced understanding of the reciprocal
nature of ways in which people (human agency) and technology (material agency) enable, constrain, and control each other by applying a socio-material theoretical perspective. In line with her theoretical reflection, Myllymäki (this issue) does not directly address the notion of algorithmic HRM. The socio-material perspective that she outlines nevertheless has important implications for algorithmic HRM research. Seen through a socio-material lens, HRM algorithms are performative while triggering changes in social processes. Even in cases where HRM decisions are fully automated by means of software algorithms (as a material actor that has agency), these decisions have implications for the human agency of workers that are subject to the decisions ‘made’ by HRM algorithms. Vice versa, the actions of workers generate digital data that HRM algorithms processes, thereby triggering changes in the materiality of algorithmic HRM. Accordingly, the work of Myllymäki (this issue) stimulates questions such as how the materiality of HRM algorithms is integral to (socio-material) HRM processes, enables (or: augments) and restrains (or: automates) human agency, and how algorithmic HRM is enacted and changes as it interacts with those people who input and use the data and information used and created by HRM algorithms.

The second paper in this special issue examines algorithmic HRM where software algorithms augment HRM decision-making by humans. This paper illustrates how applying a socio-material theoretical framework can inform our understanding of how algorithmic HRM is enacted in ways that challenge technologically deterministic thinking. In a study of a large multi-divisional professional services firm implementing a digitalized talent management technology, Wiblen and Marler (this issue) highlight how the interaction between HR managers, operational managers and the algorithms that augment the identification of future talent in the organization is not deterministic or completely predictable. Despite using the same technology and algorithmic HRM in the same organization, Wiblen and Marler show how the role of HR managers, and how talent is ultimately identified, varies across divisions depending on how human actors choose to interact with algorithmic HRM and with each other. Accordingly, their study contributes by showing the different ways in which algorithmic HRM may (or may not) augment talent decision making by different organizational actors.

In the third paper, Ellmer and Reichel (this issue) illustrate how the credibility and status of HR managers is influenced by the ways they work with HRM algorithms used for HR analytical purposes. In the context of a large German corporation, the authors show how the introduction of HR analytics, and the use of HRM algorithms to augment human decision making, is a deeply socio-material process. They show how HR managers see and use HRM algorithms to demonstrate their
quantitative and business knowledge, and therefore enhance their credibility and status within the organization. Their analysis highlights the epistemic practices of boundary spanning, customizing dashboards, and speaking a language of numbers. Taken together, these practices reflect what the authors refer to as epistemic alignment, where members in an HR analytics team align algorithmic output with the way organizational decision-makers perceive business reality. Ellmer & Reichl (this issue) contribute to the literature by showing how epistemic practices – as a form of human agency – affords the augmentation of HRM-related decision making by human managers.

The final paper in this special issue provides an example of online labor platforms as a context where algorithmic HRM fully automates HRM decision-making. Waldkirch, Bucher, Schou and Grünwald (this issue) describe how algorithmic HRM is experienced by freelance gig workers using Upwork, an online labor platform that matches software projects to software contractors looking for projects. The gig workers on the Upwork platform are independent contractors and along with its completely digital business model, most of the HRM practices are automated. Using an innovative way to collect digital data, the authors analyze posted conversations on a Reddit discussion community. From these data, the authors find that HRM activities such as selection, performance management, compensation and employee relations are automated by HRM algorithms. Interestingly, training and development appear to be outsourced informally to on-line chat communities such as Reddit in which training and support are provided by a crowd of peers/co-workers who focus on building ‘platform literacy’. Gig workers who work with online labor platforms spend a lot of time trying to converse with humans as well as figuring out how to challenge, resist or game the controls and constraints built into the technology. Accordingly, the study calls for reconsideration of current thinking in the HRM literature on the design, implementation and outcomes of HRM activities to include critically evaluating the role of algorithmic HRM that is at the center of the tension between human and material agency.

**Avenues for future research into algorithmic HRM**

While almost all organizations today are part of the information technology revolution, most organizations are still in a digitalization process, albeit some at a more advanced stage than others (Strohmeier, 2020b). In contrast, some other organizations can be considered ‘digital natives’ (or ‘born digitals’), as from their inception they have always relied heavily on digital data and software algorithms for augmentation and/
or automating many aspect of their operations (Monaghan et al., 2020). The papers in this special issue highlight differences in the socio-materiality of algorithmic HRM across different types of organizations and digitalization phases. Ellmer & Reichl (this issue) and Wiblen & Marler (this issue) study organizations that are transitioning to a greater use of algorithmic HRM, while Waldkirch et al. (this issue) examine how an online labor platform (OLP) – as a ‘digital native’ – relies on algorithmic HRM from day one of operation. In fact, OLPs are an extreme example of algorithmic HRM where many (parts of) HRM processes are automated (Duggan et al., 2020). This is clearly different from organizations in a digitalization process towards digital HRM that seem to use software algorithms mostly to augment HRM decision making (Marler & Boudreau, 2017; Marler & Fisher, 2013).

Besides differing in the material agency of HRM algorithms, human agency and social processes in OLPs are likely to differ due to their business model and how they interact with (platform) workers (Gegenhuber et al., 2020; Kuhn & Maleki, 2017; Meijerink & Keegan, 2019; Wood et al., 2019). As such, we believe comparing OLPs – alongside other types of digital natives – to organizations transitioning to greater use of algorithmic HRM offers fertile ground for future research into algorithm-enabled HRM decision making. The comparison could enable a better understanding of the dynamics of how the human agency (employees, managers, gig workers, customers) and material agency (HRM algorithms) interact to shape how HRM is practiced. Although we leave it to future research to better identify, describe and analyze these differences, we take this opportunity to provide some initial potential avenues for explore these differences based on early insights from studying OLPs.

Algorithmic HRM and strategy execution

As labor market intermediaries, OLPs create online marketplaces where supply and demand for contingent labor meet electronically (Duggan et al., 2020; Kuhn & Maleki, 2017; Meijerink et al., 2021). The business model of most OLPs is based on charging a monetary fee for each match made (Prassl, 2018; Rosenblat & Stark, 2016) and thus depends on attracting and retaining a large user base on both sides of their online market (both clients and suppliers of labor). The existence of cross-side network effects, in which the value of the platform for one side of the market (e.g. clients) is positively related to the size of the other side of the market (providers) (Katz & Shapiro, 1994), further highlights the importance of operating at scale (Cennamo & Santalo, 2013; Eisenmann et al., 2006). As an example, in 2018, the online labor
platform Didi grew to the staggering number of 30 million taxi drivers who could be matched to people in need of transportation. In order to effectively match such large numbers of workers to customers, Didi is collecting as much data as possible about its market participants. To process these data, algorithms for automating HRM activities play a key role in accomplishing the fast and efficient market transactions needed for the effective organization of short-term tasks through OLPs. As an example, OLPs operate prescriptive HRM algorithms to control workers at scale (Duggan et al., 2020; Veen et al., 2020) through the automated direction, evaluation and disciplining of worker behavior (Kellogg et al., 2020). Given the size of most workforces operating on OLPs, the execution of HRM activities by human managers would simply be too time-consuming and limit platforms’ capacity to scale rapidly and perform well. Algorithmic HRM for automating HRM decision making is thus a necessary and integral part of an OLPs’ digital business strategy.

By relying on algorithmic HRM to implement a digital business strategy from their inception, OLPs seem to skip several steps (or move through them quickly) in the digitalization processes that most organizations go through, such as digitizing manual processes in HRIS (Strohmeier, 2020b) or HR analytics for improving HR-related decision making (Marler & Boudreau, 2017). The use of prescriptive HRM algorithms by ‘digital natives’ such as OLPs stands in stark contrast with organizations that are endeavoring to become digital and mostly use algorithms for augmenting HR-related decision making by human managers. For instance, a recent survey of almost 9,000 business and HR leaders shows that the majority of the organizations mostly collect worker data for descriptive purposes regarding turnover (82%), salary costs (68%) or workforce composition (53%), while predictive and prescriptive HRM algorithms are rarely used (Deloitte, 2020). It remains a question to what extent these types of algorithmic HRM add to realizing strategic organizational goals (Cheng & Hackett, 2021; Marler & Boudreau, 2017; Strohmeier, 2020b) and how this compares to algorithmic HRM for strategy execution by OLPs. Accordingly, future research could answer questions like: What characterizes the socio-materiality of algorithmic HRM of ‘digital natives’ like OLPs where algorithms that automate HRM decision making are a ‘must have’ for executing a digital business strategy? How does this compare to HRM in organizations that are in the process of becoming digital and where algorithmic HRM is not perceived as playing an essential role in overall strategy execution? How do HRM digitalization processes unfold within ‘digital natives’ compared to organizations that endeavor to ‘become’ digital? Which HRM processes and decisions are fully automated and which are not and why? How does strategic HRM differ across these two contexts and what implications
does that have for HRM strategy and the practice and relevance of HRM in organizations?

**Algorithmic HRM, worker status and employment relationships**

In contrast to most existing organizations in which work is performed by employees who exchange their labor as part of an open-ended employment relationship, OLPs work with freelancers whose alternative employment relationship is temporary and transactional (Prassl, 2018). In line with their freelance status, these workers are not employed or controlled by an employing organization, hence the description “free” (Aloisi, 2016). However, OLPs nevertheless still need to control their freelance workforce to align their behavior to strategic objectives of the OLP and clients' interests (Frenken et al., 2020; Gandini, 2019; Meijerink et al., 2021). This has implications for the design and enactment of algorithmic HRM in OLPs. For instance, rather than use organizational hierarchy to control employee behavior through physical oversight, OLPs substitute algorithmic HRM and in doing so, need to strike a balance between autonomy and control (Frenken et al., 2020; Meijerink et al., 2021; Wood et al., 2019). Moreover, OLPs rely on opaque HRM algorithms in an attempt to replace HR managers and disguise the control that is exercised over the behavior of their freelance workforce (Meijerink et al., 2021). Empirical research shows that freelance platform workers respond to algorithmic control by gaming and at times, sabotaging algorithms to (re)gain control (Gandini, 2019; Kellogg et al., 2020; Newlands, 2020; Veen et al., 2020).

In contrast, organizations that ‘become digital’ are more likely to have conventional employment contracts along with managerial oversights that serves that the primary control mechanism. As such, these organizations do not need to pay attention to balancing autonomy-control tensions that OLPs incorporate into their HRM algorithms. Moreover, employees may not be directly affected by algorithmic HRM in cases where a human manager and HRM algorithms both interact to enact HRM activities, yet where humans make the final decision. There is a need for research that examines the following questions: How does the nature of the worker-organization relationship relate to the material agency of HRM algorithms? How do workers perceive, enact and react to algorithmic HRM depending on work/employment arrangement they experience? How do interactions between managers and workers in different forms of employment relationship shape reactions to algorithmic HRM?

Although the workforce that performs tasks through OLPs generally consists of freelance workers, OLPs also have employees, for example
software engineers and data specialists, who are responsible for designing the algorithmic HRM activities that automate HRM decisions regarding platform workers (Kuhn, Meijerink & Keegan, 2021). OLPs also employ community managers and marketing specialists to manage communication within and outside of the platform (Gegenhuber et al., 2020; Meijerink & Keegan, 2019). In contrast with ‘traditional’ contexts, platform workers are not supervised by human (line) managers tasked with implementing HRM activities (Bos-Nehles et al., 2013) or HR specialists on HR analytics teams (Ellmer & Reichl, this issue; Wiblen & Marler, this issue). Put differently, in OLPs, non-managerial employees and non-HR specialists are responsible for the design and operation of algorithmic HRM systems applied to freelance workers. Accordingly, we see the need for future research that examines the implications of the exclusion of HRM specialists from algorithm-enabled HR decision making processes, and how the material agency of algorithmic HRM differs depending on whether human managers (and HR specialists) are included or excluded from the design and application of HRM algorithms. Other questions include what epistemic practices non-HR specialists perform in automated HR decisions making, and how social interactions and power dynamics within HR analytics teams play out depending on who is (not) involved in the design of algorithmic HRM activities and decision making processes.

**Ethical implications of algorithmic HRM**

The study of algorithmic HRM in OLPs opens the way for a more encompassing examination of the critical and ethical implications of HRM algorithms (Leicht-Deobald et al., 2019). As noted by Tursunbayeva et al. (2021), research on the ethical issues of HR analytics – where HRM algorithms are mostly used for augmenting decision making – is still at an early stage and focused mainly on ethical risks such as discrimination, bias, privacy concerns and excessive surveillance (Tursunbayeva et al., 2021). These issues may be the tip of the iceberg when considering the wider literature on OLPs and their use of algorithmic HRM to automate HR decisions (Gal et al., 2020; Newlands, 2020; Veen et al., 2020). Labor sociologists have shown how the use of prescriptive HRM algorithms enables employers to capture excessive economic value from workers’ labor. Automated wage theft by online labor platforms, enabled by algorithmic management, has been documented (Van Doorn, 2019). Moreover, Newlands (2020) shows how algorithms are unable to fully reflect the lived experiences of food deliverers that work for platforms including Deliveroo and Foodora. Algorithms are unable to detect and account
for obstacles (e.g. road blocks, accidents, or detours) facing food deliverers and how these negatively impact their performance metrics (e.g. delivery time) (Newlands, 2020). Business ethicists have also shown how algorithmic HRM challenges the personal integrity of workers by marginalizing human sensemaking, fostering blind trust in computer-programmed steps and limiting imagination (Leicht-Deobald et al., 2019). In this special issue, Waldkirch et al. describe how HR algorithms based on artificial intelligence and machine learning render the performance evaluation of freelancers completely opaque and prevent them from autonomously managing or marketing their capabilities. Wiblen and Marler (this issue) show how automating talent identification results in obscuring and paradoxically magnifying biases rather than eliminating them. We see a need for research into the dark(er) side of HRM algorithms and for interdisciplinary research where HRM research is enriched by insights from other streams of literature such as Sociology of Labor, Organization Studies, Business Ethics and Philosophy.

**Conclusion**

The papers in this special issue shed light on how algorithmic HRM appears to be shaping the way in which HRM is practiced and enacted within different organizational settings. From automating, to augmenting to controlling to co-opting HRM practice and decision-making, the papers in this special issue provide an insight into how digital HRM, generally, and algorithmic HRM more specifically are transforming the field of HRM. Accordingly, it recommends researchers and practitioners to take notice and learn how to assert their values and knowledge into the socio-material process that the papers in this special issue highlight is so critical to the future of HRM theory and practice.

**Note**

1. We acknowledge that human decision makers are involved in designing prescriptive algorithms and that prescriptive algorithms often rely on digital data that that is generated by humans. However, given the sheer number of decisions to be made (e.g. allocation of thousands of work assignments to food delivery riders on a single day), involvement of human decision makers during the actual algorithm-enabled decision making and execution is limited.

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