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DISCUSSION

Algorithmic Management

Bright and Dark Sides, Practical Implications, and Research Opportunities

Alexander Benlian · Martin Wiener · W. Alec Cram · Hanna Krasnova · Alexander Maedche · Mareike Möhlmann · Jan Recker · Ulrich Remus

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1 Algorithmic Management – A Key Ingredient to the Future of Work

Alexander Benlian, Martin Wiener, W. Alec Cram

The U.S.-based service company Uber offers platform-based transportation services in more than 70 countries. To this end, the company manages a global network of around 3.5 million freelance drivers who performed over 7 billion trips in 2019 alone (Statista 2020). Still, most Uber drivers never personally interact with an Uber manager. How is that possible? The answer is: through algorithmic management.

A. Benlian (✉)
TU Darmstadt, Darmstadt, Germany
e-mail: benlian@ise.tu-darmstadt.de

M. Wiener (✉)
TU Dresden, Dresden, Germany
e-mail: martin.wiener@tu-dresden.de

W. A. Cram
University of Waterloo, Waterloo, ON, Canada

H. Krasnova
University of Potsdam, Potsdam, Germany

A. Maedche
Karlsruhe Institute of Technology, Karlsruhe, Germany

M. Möhlmann
Bentley University, Waltham, MA, USA

J. Recker
University of Hamburg, Hamburg, Germany

U. Remus
University of Innsbruck, Innsbruck, Austria

Algorithmic management has become a central feature of today's platform economy in which network effects and operational scalability are enabled and fostered through the automation potential of intelligent algorithms. As the main beneficiaries of algorithmic management systems, online labor platforms (e.g., Uber, Airbnb, Upwork, and Amazon Mechanical Turk) have so far attracted over 180 million independent workers and freelancers in Europe and the U.S. alone and are among the fastest growing labor markets worldwide (Chan and Wang 2018; Manyika et al. 2016). The practices used on such platforms to orchestrate and control workers foreshadow how algorithmic management may fundamentally transform classical forms of management, and the future of work as a whole.

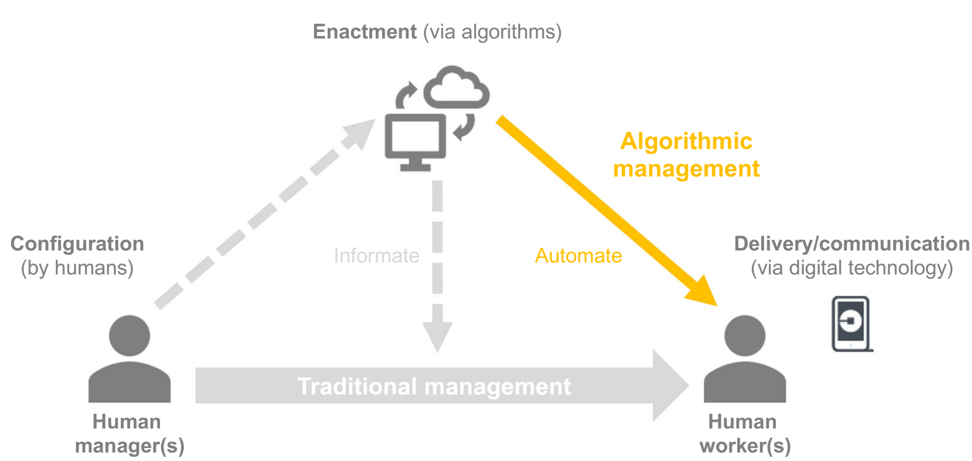
In the information systems (IS) literature, algorithmic management has been defined as "the large-scale collection and use of data on a platform to develop and improve learning algorithms that carry out coordination and control functions traditionally performed by managers" (Möhlmann et al. 2021, p. 2001). As such, a key distinguishing feature of algorithmic management (vis-à-vis traditional management approaches) is the use of increasingly intelligent algorithms in conjunction with digital technologies (e.g., mobile apps and sensors embedded in smartphones) not only to support, or "informate" (Zuboff 1985), but to automate the execution of coordination and control tasks with little to no human involvement (Cram and Wiener 2020; Möhlmann et al. 2021). The intelligence of these algorithms is largely driven by advanced technological affordances such as context-awareness, real-time responsiveness, interactivity, and (big) data availability (Kellogg et al. 2020; Schuetz and Venkatesh 2020). Here, it should be noted that the configuration of management mechanisms, including the design of the underlying algorithms, is often still the responsibility of human actors – even though artificial intelligence (AI)-based approaches that rely on data-driven learning and decision-making are playing an increasingly important role (Wiener et al. 2021; cf. Recker et al. 2021; Faraj et al. 2018). In any case, the actual enactment of relevant management mechanisms and their delivery/communication to workers is fully automated by algorithms and digital technology (see Fig. 1).

Möhlmann et al. (2021) conceptualize algorithmic management in terms of two main dimensions: algorithmic matching and algorithmic control. Uber, for example, employs AI-based algorithms for both matching drivers with customers (including dynamic pricing) and controlling (i.e., directing, evaluating, and rewarding/sanctioning) drivers' work behaviors. To do so, the firm leverages customer ratings and sensors, among other things, to collect detailed behavioral data (e.g., on driving style and service quality). These data are processed and used by algorithms to provide drivers with personalized feedback and recommendations (e.g., on how to increase service quality) and in extreme cases, to reprimand or even fire drivers (Wiener et al. 2021). In this way, companies like Uber manage to reduce the level of interpersonal interaction with workers to an absolute minimum, which favors the seemingly infinite scalability of their platform-based business models. For this reason, algorithmic management has been described as a key enabler and success factor of corresponding business models (Mateescu and Nguyen 2019).

While the use of algorithms to manage freelance workers is already an established practice in the platform economy, algorithms are also increasingly used to manage permanent employees, including full-time employed delivery drivers, parcel carriers, and warehouse workers. This applies to both traditional companies with platform-like business models (e.g., delivery services such as Gorillas and Lieferando), as well as companies with traditional business models (e.g., Amazon Fulfillment, Deutsche Post, and United Parcel Service), where algorithmic management typically has a complementary character; that is, where it does not replace human managers entirely, but instead provides a technology-enabled tool to aid managers in supervising subordinates (Wiener et al. 2021). In this context, it is also noteworthy that algorithmic management approaches are no longer limited to behavioral data (e.g., worker location), but also draw on other types of data (e.g., heart rate). One example is the MIT spin-off Humanyze, which has developed an employee ID badge equipped with several sensors enabling conclusions to be drawn about employees' stress levels via real-time speech analysis. Humanyze customers include major banks such as Bank of America, as well as leading energy and technology firms (Cram and Wiener 2020).

In terms of existing research on algorithmic management, two rather polarizing viewpoints have emerged. On the one hand, studies with a particular focus on the perspective of organizations tend to emphasize the (potential) benefits associated with the use of algorithmic management practices, including gains in decision accuracy, operational efficiency, and improved scalability of business operations (e.g., Kellogg et al. 2020). On the other hand, studies focusing on the worker perspective show a tendency toward the "dark side" of algorithmic management (e.g., Möhlmann and Henfridsson 2019; Rosenblat and Stark 2016). For example, based on an interview study with Uber drivers, Möhlmann and Henfridsson (2019) identify constant surveillance, dehumanization, and lacking transparency as three areas of consistent driver complaints about working "for" algorithms. Relatedly, other even more dystopian studies emphasize the vast power asymmetries and the looming precariousness enabled and cemented by algorithmic management (Spiekermann et al. 2022; Vallas and Schor 2020). These two contrasting standpoints reflect what Willcocks (2020) describes as the "dominant hype-and-fear narrative" (p. 286) in the broader debate on the impact of AI and related technologies on the future of work. With reference to this debate, he and other scholars

Fig. 1 Traditional vs. Algorithmic management (based on Wiener et al. 2021)



have been arguing that it is time to move beyond the hype-and-fear narrative. For example, commenting on Willcocks (2020), Huysman (2020) argues that we "need to get rid of the more general and persistent naïve anxiety and admiration of the power that we assign to AI technologies" (p. 307). In this regard, there are at least some early signs that this is exactly what is happening now with current research on algorithmic management; namely, that more recent studies start scrutinizing the arguably overly *optimistic* assessment of algorithmic management technologies from an organizational perspective, while also questioning the overly *pessimistic* assessment of such technologies from the perspective of workers. Examples include the studies by Möhlmann (2021) and Wiener et al. (2021), which conclude that algorithmic nudges do not have to be unethical, and that algorithmic control is not necessarily perceived as a "bad thing" by workers, respectively. Similarly, Cram et al. (2022) find that algorithmic control can relate to both challenge and threat technostressors for gig economy workers.

It is against this backdrop that we organized an online panel discussion, which took place at the 17th International Conference on Wirtschaftsinformatik (WI 2022) in Nuremberg, Germany, on February 22, 2022. Our panel discussion primarily revolved around three central questions:

1. What are the bright and dark sides of algorithmic management in different contexts (platform-based vs. more traditional work contexts) and from different perspectives (e.g., organizations/managers vs. workers)?
2. What are possible approaches or solutions (including the creation of appropriate framework conditions at the individual, organizational, and/or regulatory level) to realize the benefits (bright side) and mitigate the issues (dark side) associated with the use of algorithmic management practices?
3. What original research contributions can BISE scholars make in this regard?

The discussion at WI 2022 involved five panelists – namely, Hanna Krasnova, Alexander Maedche, Mareike Möhlmann, Jan Recker, and Ulrich Remus – who have been recognized for their research on algorithmic management and closely related topics. In the following sections, each panelist will elaborate on their view on algorithmic management along the three questions listed above. On this basis, the article will conclude with a summary of opportunities for BISE researchers to further explore the emerging phenomenon of algorithmic management.

2 Algorithmic Management: Opportunity or Threat to Basic Psychological Needs?

Hanna Krasnova

Algorithmic management, and in particular algorithmic decision-making, are increasingly omnipresent across multiple areas of our lives. In the private domain, algorithms increasingly determine which news we see, which products we buy, and which dates we go to. Also, the workplace witnesses an ongoing expansion in the adoption of algorithmic systems that has far-reaching implications for workers, businesses, and society. However, despite the rapid pace of workplace change, the underlying nature of these developments is still unclear. On the one hand, greater reliance on algorithmic management has been linked to greater efficiency, improved coordination, and more accuracy in decision-making (e.g., Kellogg et al. 2020). On the other hand, critics increasingly stress an array of unintended consequences that start to proliferate as algorithms conquer their place in organizational processes and structures. Especially, the impact of algorithms on workers remains ambiguous, with multiple stakeholders calling for greater organizational accountability and transparency when it comes to their use.

Self-determination theory (SDT) offers an original lens to examine the complexities of the algorithmically-driven workplace at the individual level (Deci and Ryan 2000; Jabagi et al. 2019). SDT differentiates between three basic psychological needs: the need for autonomy, competence, and relatedness (e.g., see Deci and Ryan 2000). In the workplace context, autonomy needs manifest themselves in workers' ability to make choices and initiate actions that are coherent with their inner self in the context of tasks they are assigned to perform (e.g., Van den Broeck et al. 2016; Deci et al. 2001; Deci and Ryan 2000). At the same time, competence needs reflect workers' willingness to explore new things, develop a sense of mastery, and feel capable of solving work-related tasks and challenges (e.g., Van den Broeck et al. 2016; Coxen et al. 2021). Finally, relatedness needs tap into the universal need for human connection and meaningful relationships (e.g., Van den Broeck et al. 2016; Baumeister and Leary 1995; Deci et al. 2001). A large body of research provides evidence for the critical role of satisfying basic psychological needs for workers' motivation, performance, and well-being (Deci et al. 2017). At the same time, a pervasive expansion of AI applications can influence workers' basic psychological needs in a number of (unintended) ways.

For example, a growing body of research reveals a complicated web of intricacies when it comes to understanding the impact of algorithmic management on workers' autonomy. On the one hand, workers employed in the platform economy have been shown to enjoy greater flexibility over their schedules (Möhlmann et al. 2021). On the other hand, algorithmic management has enabled organizations with unprecedented levels of control over their workforce. As reported by Levy (2015), the introduction of performance monitoring devices has resulted in greater visibility of truck drivers' daily routines and practices, making their performance more quantifiable and manageable. Armed with data, systems and managers have been shown to (try to) override drivers' decisions, resulting in drivers viewing these developments as "*confrontational and evincing a lack of trust*" (Levy 2015, p. 169). Similarly, crowdworkers find themselves constantly on alert for new tasks and feel forced to participate in activities that promote their rankings, which goes against the established narrative of greater workforce autonomy afforded by corresponding platforms (e.g., Gerber and Krzywdzinski 2019).

In a similar vein, workers' competence is being increasingly questioned by the rampant adoption of AI-based assistants. Importantly, these effects are not strictly limited to low-skilled labor. Already, a growing number of studies provide evidence for the performance of AI being on a similar level or even superior to physicians across many areas (Shen et al. 2019), including dermatology (Han et al. 2018) and radiology (Nam et al. 2019; Gonzalez-Castro et al. 2017). On the one hand, these developments promise to alleviate physicians' workload, instill more confidence when making decisions, reduce medical mistakes, and thereby improve patient care. On the other hand, this trend calls for a new and different skill- and mindset on the part of workers, including greater psychological resilience when dealing with AI. Indeed, studies show experts feeling threatened by conflicting system recommendations (Elkins et al. 2013) and physicians struggling with overriding incorrect system advice (Alberdi et al. 2004; Tsai et al. 2003). This suggests that interactions with algorithm-based decision support systems may be plagued by cognitive challenges and frustrations on the part of their users (e.g., Jussupow et al. 2021). At the same time, being forced to comply with the system advice constantly may potentially result in learned helplessness and demotivation.

Finally, algorithmic management may also interfere with the social fabric of organizations, potentially hampering the satisfaction of relatedness needs. Already, the dispersed workforce participating on ride-sharing platforms became a prime example of workers' alienation in a new platform economy (e.g., Möhlmann et al. 2021). In a similar vein, visibility of one's performance and a related scoring system may trigger competitive behaviors among workers (Levy 2015), which over time may undermine collaboration and workplace climate. Additionally, tracking and analysis of workers' communication may have chilling effects, forcing workers to be less authentic in their self-expression, which may stiffen social exchange and undermine interpersonal relationships in the long run.

Taken together, while the introduction of algorithmic decision-making may profoundly benefit human lives, the unintended implications inherent in these applications call for greater managerial sensitivity. Over time, the frustration of basic psychological needs may translate into lower performance, reduced motivation, and worsened well-being of workers (Deci et al. 1999, 2017), ultimately also affecting the organizational bottom-line. A number of preventive measures could be recommended. For example, to enable a sense of autonomy, workers should be able to negotiate which aspects of their behavior will be traced, what inferences can be made on this basis, and for which purpose. Clear guidelines might be helpful in supporting workers in a situation when recommendations of AI assistants go against their best judgment. Training that enables and promotes employee resilience when dealing with AI could be another step in this direction. Finally, the benefits and risks of scoring systems and communication tracking and analysis need to be accounted for, especially in terms of their impact on social relationships.

BISE research can support organizations on their path to an algorithmically managed workplace by delivering answers to pressing questions: What is the long-term impact of prolonged interactions with digital assistants on workers' basic psychological needs? When does surveillance and quantification of workers' practices undermine workers' perceptions of autonomy, competence, and relatedness? Does being part of a dispersed workforce in the platform economy result in alienation and loneliness, and if so, who is particularly at risk? What can be done to mitigate detrimental effects? Cross-sectional, longitudinal, and experimental designs could be helpful in exploring these pertinent research questions.

3 Toward Algorithmic Management Systems Transparency

Alexander Maedche

Managers have a central function in companies. They are responsible for crucial tasks, such as goal setting, planning, organizing, leadership, and control. Thus, the work of managers has impact on the performance outcomes on the organization level as well as on the individual level with regards to worker productivity and well-being. However, as managers are human beings with strengths and weaknesses, there are individual differences leading to good and bad management outcomes. Given the importance of management, it is not surprising that there is a long history in research and practice of providing information technology artefacts for the specific target group of managers. Prominent examples are business intelligence and analytics systems supporting decision making for operational, tactical, and strategic decisions (Chen et al. 2012). They are designed for augmenting managerial decision-making. To realize the full potential of these systems, managers must not only exploit the data-driven insights provided by these systems, but also take appropriate actions on this basis. However, especially the latter (taking appropriate actions) may be challenging for managers. These challenges are manifold, ranging from conflicts of interest, lack of responsibility, or simply the need to make unpleasant decisions. Thus, a gap between system-provided insights and managerial actions is existing.

Algorithmic management systems take the human manager out of the loop and automate managerial decision-making. By doing so, they not only close the gap between insights discovered from data and managerial decision-making and subsequent action-taking, but in addition enable efficient and effective execution of defined strategies and business models. In this regard, algorithms have several characteristics that make them an attractive alternative to humans (Schneider and Gersting 1995): They are well-ordered; they have unambiguous operations and can effectively compute operations; they are designed to produce some output for a given input in a finite amount of time. Overall, considering these advantages one may argue that algorithmic management systems represent a promising approach that in many cases should indeed lead to better outcomes for both organizations and human workers.

However, there are also manifold problems with contemporary algorithmic management systems. Here, I argue that the key problem is not the algorithmic management system itself, but rather the platform providers' exploitative strategies and business models that are encoded in non-transparent algorithmic management systems. Many providers of digital platforms target growth and profit by providing "attractive" services, where human workers are considered resources that can easily be substituted. In that sense, customers make use of the services provided by the platforms in a naïve way: They may just not be aware of the working conditions of the participating human workers (Glöss et al. 2016). For example, it is not transparent how long drivers work on Uber on a daily or weekly basis. Furthermore, the provided services are optimized towards the defined business model. Despite its feasibility, more personalized services considering trade-offs between price, convenience, and human worker conditions are currently not offered.

Operational transparency providing customers and workers with information about inner operations of an organization has shown to increase perceived value (Buell and Norton 2011). A traditional form of operational transparency is providing customers information about operational processes (process transparency). Besides, one may also provide workers information about the customers they are serving, or vice versa, provide customers information about the working conditions of human workers. A concrete example is the manufacturing of clothes in low-wage countries, which are known to be associated with negative consequences for human workers working in corresponding factories. The implementation of so-called supply chain transparency has been vigorously pursued in recent years (Montecchi et al. 2021). In the same way, accelerating transparency for the services provided by platform providers represents a promising approach to realize the benefits (bright side) and mitigate the issues (dark side) associated with the use of algorithmic management practices. Specifically, transparent algorithmic management systems should make their underlying data and logic transparent from an end-to-end perspective. This should not only cover an explanation of the inner logic – e.g., dynamic pricing (Spann and Skiera 2020) – but also make human worker conditions – e.g., working time, individual needs and preferences – explicitly visible to customers. Like in the case of the organic food and fair-trade movement, transparency of algorithmic management systems may positively impact digital platforms and their services from different perspectives: First, it may result in changes of customer behavior. With increasing transparency, customers may become aware of the underlying working conditions of the involved human workers and make more informed decisions when deciding on services offered by a digital platform. Second, transparency may be an opportunity for differentiation for digital platform providers, for example, by offering services trading off the preferences and needs of customers and human workers under consideration of price and quality in a transparent way. Third, and most importantly, changing customer behavior on the one side and offering alternative business models allowing trade-offs on the other side should result in better working conditions of human workers. Furthermore, transparency may empower human workers to make more informed decisions by themselves about how they accept and deliver their services.

BISE scholars are in a unique position to make original research contributions to the field of algorithmic management systems transparency. Besides understanding the phenomenon through well-established empirical research, design knowledge may be delivered by performing different types of design research activities (Maedche et al. 2021): First, one may manipulate existing design features of algorithmic management systems and understand their impact on the involved stakeholders. Second, design knowledge may be derived by observing and analyzing existing artifacts and their use with regard to manipulable design features. Third, new transparent algorithmic management systems may be constructed following a design science research approach. Finally, by observing and analyzing existing transparent algorithmic management systems in use outside their original development environment, new prescriptive knowledge could be derived. To summarize, I believe researching transparent algorithmic management is an interesting opportunity for the BISE community that can have a significant impact from business and societal perspectives.

4 A Call for More Ethics: Overcoming Challenges Associated with Algorithmic Opacity, Automation and Limited Human Interaction, and Algorithmic Nudging

Mareike Möhlmann

Platforms are increasingly employing algorithmic management. They are collecting data on a large scale to improve learning algorithms that carry out coordination and control functions traditionally performed by managers (Möhlmann et al. 2021). Examples such as the ride-hailing platform Uber show that, in practice, algorithmic management is often beneficial for platform companies, while it creates work environment tensions that may negatively impact workers' well-being (Gal et al. 2020; Jarrahi et al. 2021; Wiener et al. 2021; Möhlmann et al. 2022). Indeed, some of my previous research has shown that Uber drivers "*hate being managed by algorithms*" (Möhlmann and Henfridsson 2019, p.1).

Yet, I argue that, in theory, algorithmic management can be designed in a way that creates a win–win situation for all parties involved: the platform company, workers, and consumers (even if many current examples show that unfortunately we are not there yet). Indeed, algorithmic management practices such as "*algorithmic nudges don't have to be unethical*" (Möhlmann 2021, p.1). As such, I encourage future research to focus on the potential of algorithmic management to do good – and on ways of how companies can design algorithmic management more ethically, by overcoming challenges such as (1) algorithmic opacity, (2) automation and limited human interaction, as well as (3) algorithmic nudging.

The first major challenge is *algorithmic opacity*. Platform workers often face difficulties in understanding the algorithms' inner workings, given that algorithmic management is opaquer than its non-algorithmic counterpart (Kellogg et al. 2020; Möhlmann et al. 2022). On the one hand, machine-learning algorithms are incredibly complex and algorithmic instructions are subject to constant changes based on the inclusion of data points in real-time (Faraj et al. 2018). On the other hand, many platform companies feel reluctant to disclose detailed information about their algorithms to the public. Limited insight of external stakeholders into the underlying logic of algorithms allows platforms to engage in hidden nudging, intentional manipulation, and surveillance – and allows little opportunity to detect algorithmic bias (Zuboff 2019). Algorithmic opaqueness can be very frustrating to the workers exposed to algorithmic instructions, causing them to experience uncertainties about their financial compensation, job assignments, or even the accuracy and fairness of algorithmic instructions they are exposed to (Gal et al. 2020; Jarrahi et al. 2021).

In order to design algorithmic management more ethically, I encourage platforms to be more transparent about the collection and storage of their data (Kellogg et al. 2020) – here, the GDPR, which is the General Data Protection Regulation of the European Union, sets a good standard – and to explain the algorithm's logic to their workers (Möhlmann 2021). One potential approach is that platform companies engage in counterfactual explanations. These allow them to disclose what the outcome of an algorithmic decision would have been if individual workers had different attributes or characteristics. For example, in the case of Uber, the platform could share how a change in a driver's average rating by 1 star would affect the likelihood of being matched to rides, holding all other criteria constant (Möhlmann 2021). This approach may present a first step to increase the transparency of algorithmic management.

The second major challenge is *limited human interaction due to automation*. Given that under algorithmic management, the traditional manager-worker interaction is largely automated, workers often feel isolated, lonely, and even dehumanized. Often, they do not have a supervisor or team members to socialize with (Möhlmann et al. 2021; Wiener et al. 2021). Yet, social relationships are important for many workers' well-being and retention. Platforms may be able to mitigate this challenge by creating a community that allows workers to be active members of the organization and interact with co-workers even though being managed algorithmically. They may organize weekly face-to-face meetings that allow workers to socialize with like-minded people and allow them to reach out to a supervisor (not necessarily on a daily, but at least on a regular basis). It is also important to note that humans (supervisors or team members) are not always "better" than machines. Humans are certainly imperfect, and many may be prone to gender and racial bias, and some workers may prefer working in solitude. Whatever the personal preferences of individual workers are, I encourage platform companies to step up their efforts to enhance workers' well-being.

The third major challenge is *algorithmic nudging*, which is an important building block of many algorithmic management practices (Zuboff 2019). It refers to companies "*using algorithms to manage and control individuals not by force, but rather by nudging them into desirable behavior – in other words, learning from their personalized data and altering their choices in some subtle way.*" (Möhlmann et al. 2021, p. 1). For example, companies are increasingly using gamification and push-notifications to manipulate and intentionally nudge their workers into behavior that is beneficial to the company, but less so for the workers (Möhlmann et al. 2021). Yet, I would argue that algorithmic nudges can be designed ethically; increasing the well-being of workers or society at large. Indeed, Nobel Memorial Prize laureates Richard Thaler and Cass Sunstein (Thaler and Sunstein 2008) have indicated that nudging can encourage individuals to improve their own health, wealth, and happiness. Recent attempts of the United Nations to reflect on the ethical use of algorithmic nudging supports my argument. Indeed, in January 2022, I was invited to a United Nations Roundtable on "digital nudges for climate change" and discussed how these algorithmic practices can be used "for good." Let me share some examples: Behavioral approaches, such as algorithmic nudging, have been used in the context of health care (e.g., Sant'Anna et al. 2021), or in order to "trick" users into building healthier eating habits (Thaler and Sunstein 2008). I can imagine other scenarios such as personalized reminders that adjust to environmental variables in real-time, helping individuals to build climate-friendly behaviors. For example, personalized nudges sent to an Apple Watch based on their real-time location may encourage an individual to take public transportation (e.g., when walking by a train station).

In summary, I believe that we need to find ways to design algorithmic management in a way that is beneficial to both platform companies and platform workers. I call for future BISE research to focus on how companies can overcome challenges such as algorithmic opacity, automation, and limited human interaction, as well as algorithmic nudging (please note: this list is not exhaustive), in order to design algorithmic management more ethically.

5 What is the Future Frontier of Algorithmic Management?

Jan Recker

Algorithmic management is a typical example of a modern-day application of artificial intelligence (AI) and one that is likely to stay and grow in the future. While Uber provides the current go-to use case for algorithmic management, we have already seen algorithms carry out many managerial functions such as analytics (Gal et al. 2020), hiring, firing, and promotion (Ajunwa 2020), or coaching and giving performance feedback (Luo et al. 2021). These developments show how algorithmic management is following an impressive evolutionary trajectory with widening performance and scope, just like other forms of AI have done and continue to do (Berente et al. 2021). This is because algorithmic management, like other AI forms, operates on the basis of learning algorithms fueled by data to carry out coordination, control, and other managerial activities in a more or less autonomous fashion.

As such, it is worth considering algorithmic management not as a set (however large) of algorithmic systems, devices, or tools, but rather as a moving frontier of computational advances that address ever more complex managerial decision-making problems in ways that emulate or outperform human managers. And just like other forms of AI, this moving frontier is coined, bounded, and shaped by the dimensions of autonomy (the ability to act without human intervention), learning (the ability to autonomously generate models from data and experience), and inscrutability (the ability to generate algorithmic outputs that are intelligible only to a select audience) (Berente et al. 2021). In the famous example of algorithmic management at Uber, for example, we see how the algorithms have evolved alongside the frontiers of autonomy and (supervised) machine learning to carry out coordination and control in ever more performant ways, at the expense of coordination and control processes or outcomes being fully scrutinizable at scale for either controller (Uber) or controllee (millions of drivers).

This way of viewing algorithmic management brings two central questions to the fore: first, how do we want the future trajectory of the performance and scope of algorithmic management to evolve based on design decisions we take about autonomy, learning, and inscrutability; and second, in what ways can we actually design, influence, or shape the trajectory of the future frontier of algorithmic management?

The first question is primarily relevant for entities developing future versions of algorithmic management; that is, developers and firms creating and selling such solutions. These entities are responsible for the algorithms they produce (Martin 2019b). They need to consider whether the current trajectory that has led to the emergence of algorithmic management for coordination and control (much autonomy, performant learning, limited scrutability) is one that they wish to continue for the future. When acting as computational controllers, algorithmic management basically embodies a form of transactional leadership that enables contingent reward behavior (Yukl 2012): the algorithms are constructed to make sure controllees act according to preset rules and norms, just as in the case of Uber. Developing firms can continue this trajectory to increase the performance of this type of algorithmic management and increase its scope to other areas where control and coordination is needed or desired. But perhaps customers or society seek more from algorithmic management than highly performant yet increasingly inscrutinizable leadership for our transactions in ever more autonomous fashion. Perhaps we instead seek a future trajectory for algorithmic management that embraces and implements empowering leadership (Arnold et al. 2000; Seibert et al. 2004) rather than rewarding appropriate and sanctioning inappropriate behavior (Mayer et al. 2009). But algorithmic management implementing empowering leadership with a focus on participative decision-making, showing concern, interacting with the team, leading by example, informing, and coaching (Arnold et al. 2000) cannot be reached following the current trajectory of the frontiers autonomy, learning, and inscrutability. It requires a reorientation of design within these frontiers towards social rather than (un)supervised learning, less rather than more autonomy, plus the treatment of inscrutability as a motivator factor that needs careful design rather than a hygiene factor that can be compromised.

The second question is of relevance again to developers, but also managers and regulators, and brings to their attention that ongoing evolutionary processes toward new frontiers cannot be designed just like other algorithmic artefacts (such as software systems or data objects) of the past. We are able to design an ERP system or a master data record basically in the way we want to. But evolutionary processes such as ever evolving and self-learning algorithmic management cannot be designed ex ante. Ostensive aspects of algorithm design will be joined by generative changes emerging in the performance (Pentland and Feldman 2008) because the algorithms are probabilistic, not deterministic, and they are fueled by real-time data. Interventional design and endogenous evolution will continuously trigger each other (Mendling et al. 2020). Essentially, we are not really designing features or affordances of algorithmic management (e.g., Kellogg et al. 2020; Schuetz and Venkatesh 2020); instead, we are using these affordances to influence, but not to determine, the future trajectory of algorithmic management by creating possible paths (Pentland et al. 2022), as well as path dependencies (Garud et al. 2010) that shape but do not control the future frontier of algorithmic management. In turn, developers must design for emergent dynamics (Feldman et al. 2016), managers must consider effects such as lock-in, drift, or transformation (Pentland et al. 2022), and regulators must consider which possible evolutionary paths they wish to enable (through incentivization or legitimization) or disable (through penalty).

Realizing the difference between designing features of an algorithm versus influencing the future evolutionary path that algorithmic management will take might just allow us to avoid lock-in of a type of computational coordination and control that may not be societally desirable and instead enable transformation toward a frontier coined by exactly those types of machine learning that we desire, those forms of inscrutability that we find ethically responsible, and those levels of autonomy that allow us to stay in the loop to the degree and extent necessary. BISE researchers are perfectly placed to take on this challenge because they combine expertise across all phases of design, implementation, use and impact of the algorithms, and across both social and technological dimensions of this challenge. However, a shift in collective emphasis might be needed. First, understanding algorithmic management as an evolutionary trajectory with moving frontiers highlights aspects such as emergence, dynamics, and change, which are typically studied by process scholars (Mendling et al. 2020). The BISE community already connects classical IS research traditions with computationally-oriented traditions such as business process management (Mendling et al. 2021), providing them with the required conceptual and methodological toolset to take on this challenge. Second, the above discussion highlights a need for a normative, moral stance to research on algorithmic management, which is typically the domain of ethics research (Stahl 2012). We are only beginning to see BISE researchers approaching questions of accountability, ethicality, and responsibility, and much of this research is descriptive and analytical/explanatory rather than normative in nature (e.g., Wessel et al. 2022; Morse et al. 2022). We will require more BISE research on ethical questions of management and leadership (e.g., Mihale-Wilson et al. 2022), on algorithm design and use (e.g., Martin 2019a), and we will require more of this research to be both reflective and normative to create an impact.

6 Towards a More Ethical Design of Algorithmic Control

Ulrich Remus

Driven by the gig economy and platform operators, such as Uber and Lyft (Duggan et al. 2020), we see algorithmic management, and in particular algorithmic control, spilling over into other areas. Just recently, the Corona crisis triggered a spike in sales of apps used to monitor home-office performance (Wood 2020); Amazon extensively uses surveillance tools to track their staff and has recently announced an intention to sell algorithmic control tools as add-ons to companies' existing surveillance camera networks (Morse 2020); governments pushed the development of contact-tracing apps to regulate citizen behavior in an effort to interrupt chains of infection (SZ.de 2020); and in Singapore robots were used to control social gatherings in public parks (Toh 2020). Across these cases, a controversial discussion has been triggered, which sees algorithmic control either as personalized "support buddy" or as an instrument for total surveillance, in the sense of an "algorithmic panopticon" (Muldoon and Raekstad 2022).

The bright and dark side Especially in platform work, workers are portrayed as independent entrepreneurs, taking advantage of flexible work opportunities, with positive effects on efficiency, flexibility, autonomy (Wood et al. 2019), and self-improvement (Waber and Kane 2015). The use of specific apps that enable algorithmic control plays a crucial role in generating such positive effects. For example, they help workers to stay flexible in terms of a fixed work location and rigid timetables. Moreover, apps that provide real-time feedback on individual performance or behavioral nudges can softly steer workers towards "the best way" without forcing them (Möhlmann et al. 2021). In fact, they may even be perceived as motivating and guiding, providing positive challenges to workers in terms of skill development and performance opportunities (Cram et al. 2022).

However, having an inanimate, opaque system acting as boss, automatically issuing orders, and instantaneously evaluating, rewarding or sanctioning, algorithmic control is often perceived as overly controlling and intrusive and can lead to various negative effects. The often predominantly coercive control style is likely to cause emotional suffering, eventually resulting in a broad range of resistance behavior (Pregenzer et al. 2021a). This can range from mild forms, such as evading controls and finding loopholes, to moderate forms, such as active manipulation and gaming of the system, to more severe forms of algoactivism, such as protests and strikes (Kellogg et al. 2020). Due to the complex interactions between the algorithm and the human controllee, the effects of algorithmic control are thus anything but easy to explain and predict. For example, in the case of Uber, some drivers react with excitement and increased motivation to predictive messages that inform them of future supply and demand, whereas others react to such messages with frustration and resentment (Rosenblat and Stark 2016).

What are possible solutions? When it comes to mitigating negative side effects, the following interrelated aspects are repeatedly mentioned – all measures aimed at making algorithmic control more ethical.

Transparency: Opaque algorithms create insecurity and often leave workers wondering why algorithmic control directed them towards a certain behavior (Cheng and Foley 2019; Mittelstadt et al. 2016). As a result, sense-making processes take place, and all kinds of "theories" and folk stories are developed to compensate for the lack of relevant information (Pregenzer et al. 2021b). Existing research results in the area of algorithmic transparency show a divergent picture. Positive effects have been found on satisfaction (Gedikli et al. 2014), competence, and benevolence beliefs (Wang and Benbasat 2007), while adverse effects such as decreased performance (Schmidt et al. 2020) were observed as well. Moreover, people with a tendency to appreciate algorithms may find information provided by machines to be more objective (Sundar 2020). On the other hand, recent research in the field of gig work also warns of viewing transparency as a silver bullet – too divergent are the user reactions (Cram et al. 2022). Transparency might even backfire in the form of countervailing tactics (Welch 2011), and some controllees even prefer to be guided by rather vague information cues (information translucency) instead of having complete information (Zhang et al. 2022). Thus, due to the "algorithm as boss" relationship (Möhlmann et al. 2021), results from traditional control research cannot easily be transferred to algorithmic control. Instead, we need to carefully analyze the complex relationships between transparency, algorithmic control, and worker-level consequences.

Fairness: People often perceive algorithmic decisions as unpredictable, unfair, and inaccurate (Lee et al. 2015; Wiener et al. 2021), and feel manipulated and treated arbitrarily (Scheiber 2017). This is because algorithmic control mechanisms, such as incentive systems implemented in some gamified fashion, often fuel the impression of a fickle and opaque system, where decisions are by purpose not made transparent (Rosenblat and Stark 2016). In addition, the heavy use of customer ratings increase dependence on their arbitrary whims (Muldoon and Raekstad 2022). It is known that workers' well-being is strongly affected by the level of fairness they perceive from their supervisors and workplace (Zhang et al. 2022). Translating such insights to a control regime, where the boss is an algorithm, the hope is that implementing fair algorithmic control systems would create similar positive appraisals by workers.

Human in the loop: In traditional control systems, feedback cycles are at least moderated by some sort of involvement by a human controller. This is an important aspect as in algorithmic control the feedback loop becomes fully automated and detached from human controllers, providing the impression of constant real-time monitoring (Kellogg et al. 2020). Furthermore, typical human conflict resolution tactics, which are based on interaction and negotiation, are rendered ineffective. This makes "real" resistance to algorithmic control difficult as automatic responses by a non-human opaque algorithm will often lead to further frustration with feelings of helplessness and powerlessness, even reinforcing (the often futile) resistance behavior. Such power asymmetries where "*conflict itself is [made] impossible*" by "*refusing to admit the right of combat*" are what Durkheim views as the most dangerous form of inequality (Zuboff 2019, p. 179). As an important consequence, further insights into feedback loops will provide the basis for designing more social, and thus more acceptable and ethical forms of algorithmic control.

What are potential research directions? First of all, we need a broader interdisciplinary approach. For example, psychological theories on motivation and emotions may help disentangle the complex relationships between rewards and emotional outcomes, explaining why some algorithmic control mechanisms work and others don't (Deci et al. 2017; Jabagi et al. 2019). Our field can also learn from related disciplines such as organization studies, sociology, human relations, and critical management. For example, it is important not to view "transparency" simply as a matter of disclosing information. Instead, we need to acknowledge the regulatory and performative qualities of transparency, which in turn affect compliance or resistance (Weiskopf 2022). All this calls for a more ethical design of algorithmic control. For example, incorporating insights into 'broken' feedback loops of algorithmic control would help platform designers to consciously design a system that benefits (e.g., learns) from resistance rather than being disrupted by it. Likewise, there are also ideas to increasingly use algorithms for the benefit of the worker. Examples include the incorporation of features that are able to provide the right level of transparency, or the implementation of fair incentive systems or worker-centered data analytics (Zhang et al. 2022) through the use of self-tracking apps (e.g., WeClock.it, TripLog, or Hurdl). At the same time, research on algorithmic control should be long-sighted. Specifically, we still do not know enough on how we as humans will react to being exposed to algorithmic control systems on a regular basis. Our brain is used to make sense of human behavior, but not of interactions that are mediated by algorithms. So, what will happen if we become even physically integrated into control loops, by means of biohacking or cyborgs? What happens if our behavior increasingly relies on algorithmic nudges or instructions? What kind of deskilling processes take place if algorithms take over responsibility for decisions? Answers to these questions are far from being simple. But if we simply let the technical development and application of algorithmic management run their course without looking at its long-term consequences, we will not only see manifold types of "backfiring" tendencies, but also control systems spilling over into other areas we would have not wished for. The guiding principle must not be what is technically possible, but what is beneficial for us humans.

7 Algorithmic Management – What's Next?

Alexander Benlian, Martin Wiener, W. Alec Cram.

Returning to the three guiding questions posed at the outset of this discussion paper, we briefly reflect on the panelists' comments and perspectives. First, all panelists share the view that the algorithmic management phenomenon represents a double-edged sword: On the bright side, the automation potential behind algorithmic management is considered to enable tremendous efficiency and performance gains, especially to underpin the unbounded scalability requirements of platform business models. At the same time, it may also bring positive aspects to workers in the form of flexibility, skill development, and performance opportunities. On the dark side, the picture painted by the five panelists seems to be more nuanced: While a common thread is that algorithmic opacity creates feelings of uncertainty and social injustice, the areas and extent of problematic consequences for workers are multifarious. The undermining of autonomy (e.g., through surveillance or unethical digital nudging), the impairment of competence (e.g., in the form of deskilling and learned helplessness), and the social isolation of workers (e.g., in the form of algorithmic management-induced individualization and spatial dispersion) may lead to demotivation, dehumanization, and even human replacement.

Second, various approaches or solutions are proposed by the panelists to mitigate the dark sides of algorithmic management. A common denominator is a reorientation of algorithmic design toward incorporating FATE (fairness, accountability, transparency, ethics) principles throughout the entire lifecycle of algorithmic management systems, guided by regulatory frameworks and incentivization schemes. However, the panelists highlight different mechanisms to increase the transparency of algorithmic management systems ranging from providing counterfactual AI explanations and introducing mandatory reporting standards, to anticipating emergent dynamics (in terms of algorithmic autonomy, learnability, and inscrutability) associated with, or resulting from, the steadily moving frontier of algorithmic management. Last but not least, all panelists seem to agree that workers should be an integral part of the control loop and have a say in algorithmic decision-making, which can have profound implications for workers' health and livelihood.

Third, the panelists also agree that BISE scholarship – with its sociotechnical axis of cohesion (Sarker et al. 2019) – is particularly well equipped to make original research

Table 1 Research opportunities for BISE scholars to further explore algorithmic management

Research direction	Sample research questions
Conceptual nature of algorithmic management	• What are the specific technological affordances and mechanisms of intelligent algorithms in the interaction with workers that constitute and enable algorithmic management? • To what extent do existing platform-centric conceptualizations of algorithmic management translate to traditional work contexts? • How to operationalize key dimensions of algorithmic management (i.e., algorithmic coordination/matching and algorithmic control) in different work contexts?
Organizational benefits and/or challenges resulting from the adoption and use of algorithmic management	• What are key enabling and inhibiting factors in the adoption and use of algorithmic management systems? • To what degree can expected gains in operational efficiency offset the increased organizational overhead resulting from deploying, operating, and monitoring algorithmic management systems? • How do algorithmic management systems contribute to an organization's collaborative interactions and workplace climate? • What sociotechnical solutions can hold problematic aspects of algorithmic management (e.g., decision biases, unfair treatment, exclusion, power asymmetries) at bay?
Design of algorithmic management systems	• What ethical principles and values should guide the design, development, and enactment of algorithmic management systems? • How can fairness, transparency, accountability, reliability/safety, and sustainability be incorporated throughout the lifecycle of algorithmic management systems? • How do design decisions about autonomy, learning, and inscrutability of algorithmic management create possible paths or path dependencies that shape the future trajectory of such systems?
Worker reactions to algorithmic management	• How do workers interpret and make sense of the decisions and recommendations of algorithmic management systems? • How is algorithmic management related to workers' self-determination in terms of autonomy, competence, and relatedness? • How do different representational forms of intelligent algorithms (robot, virtual, and embedded) and their level of machine intelligence differentially affect worker reactions? • How do workers push back against algorithmic management and its "dark side" effects (e.g., individual resistance, platform organizing, discursive framing, legal mobilization)?
Algorithmic management as a form of leadership	• What form of leadership is implemented and exercised through algorithmic management? • What design changes are necessary to realize different forms of leadership through algorithmic management such as transactional, transformational, empowering, or participative leadership?
Future frontiers of algorithmic management	• What will be the future trajectory of algorithmic management in terms of performance and scope of such systems? • How will changes in the levels of autonomy, learning, and inscrutability influence the future trajectory of such systems? • How can BISE scholars leverage existing research on (intelligent) algorithms in other disciplines to drive innovation in algorithmic management?

contributions in the area of algorithmic management. Here, the complementary nature of behavioral and design science research provides a solid foundation to study the technical and social components, as well as the instrumental and humanistic outcomes, of algorithmic management. In this regard, a major strength of the BISE community is that its researchers are able to draw upon and combine a broad range of methodologies that help analyze various facets of the phenomenon. Still, it also becomes evident from the panelists' statements that a broader interdisciplinary approach is needed to provide comprehensive answers to often ethically problematic issues in relation to the use of algorithmic management. Collaborating with and learning from disciplines such as ethics, law, sociology, and psychology can go a long way in generating novel insights about (platform) organizations, workers, customers, and regulators on multiple levels of analysis.

Building on the thoughtful comments and suggestions of the panelists and taking them one step further, we lay out several promising research opportunities for further exploration of the algorithmic management phenomenon (see Table 1 below). Given the diverse and evolving nature of this phenomenon, the listed research directions and questions are intended to help spark an intensified scholarly debate and provide some guardrails and guidance for future inquiry into algorithmic management.

In summary, the use of algorithmic management practices in an increasingly broad range of different work contexts gives rise to numerous critical challenges and issues – not least from a data protection and ethical perspective. Nonetheless, it would be too short-sighted to simply "demonize" the trend toward algorithmic management as something fundamentally "bad". Among other things, this assertion finds support in recent studies, which have shown that the use of corresponding practices enables new forms of workplace interactions that are well received, at least by some workers, such as the possibility of receiving continuous guidance and performance feedback (Wiener et al. 2021). Moreover, algorithmic management may help extend and improve digital assistance systems in work settings, but also in health care settings (e.g., in home care). As such, we as BISE scholars should accept it as our responsibility to identify the "bright" aspects and features of algorithmic management systems and make them usable for companies and society at large, thereby making an important contribution to actively shaping the future of work for the benefit of humanity.

In conclusion, we hope that the discussion article at hand can contribute to advancing the current discourse on algorithmic management and help stimulate and inspire future research on this topic in our field.

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