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Between control and participation: The politics of algorithmic management

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Abstract

Understanding the role of human management is crucial for the debate over algorithmic management—to date limited to studies on the platform economy. This qualitative case study in logistics reconstructs the actor constellations (managers, engineers, data scientists and workers) and negotiation processes in different phases of algorithmic management. It offers two major contributions to the literature: (1) a process model distinguishing three phases: goal formation, data production and data analysis, which is used to analyse (2) the politics of algorithmic management in conventional workplaces, which differ significantly from platform companies. The article goes beyond surveillance to elucidate the role of the regulatory framework, various actors' knowledge contributions to the algorithmic management system, and the power relations resulting therefrom. While the managerial goals in the examined case were not oriented towards a surveillance regime, the outcome was nevertheless a centralisation of knowledge and disempowerment of workers.

KEYWORDS

algorithmic management, engineers, industrial relations, labour control, labour process, logistics, manufacturing

INTRODUCTION

Algorithmic management is a core topic in current debates about the digital transformation of work. Researchers emphasise that algorithmic systems are increasingly used for tasks such as direction, performance evaluation and worker discipline (Galière, 2020; Kellogg et al., 2020; Lee et al., 2015). The discussion has made significant contributions to the analysis of contemporary transformation of work, but it has two important shortcomings. First, the analyses have examined primarily gig-work platforms (Cini, 2023; Huang, 2023). While some studies have extended the notion of algorithmic management beyond the platform economy to conventional enterprises (Jarrahi et al., 2021; Lippert et al., 2023; Wood, 2021), researchers are only just beginning to reflect on the particularities of these contexts. Second, the focus to date has mainly been on how new technical infrastructures function, while the role of human management and the process of negotiating algorithmic management has been undertheorised. For the most part, management is assumed to be using these technologies primarily for monitoring and disciplining workers (De Stefano & Taes, 2023; Mateescu & Nguyen, 2019). As Meijerink and Bondarouk (2023) and Noponen et al. (2023) rightly criticised, its implementation has been conceptualised mainly in a control-resistance paradigm, with management and workers being the only two actors taken into consideration (Kellogg et al., 2020).

In our contribution, we tackle these two shortcomings and argue that we have to open the black box of algorithmic management to develop a more sophisticated notion for it than control-resist. Our first and major contribution has been to develop a process perspective on algorithmic management by following the different phases of introduction and deployment. Building on older (Zuboff, 1988) and more recent (Alaimo & Kallinikos, 2021, 2022) work, we distinguish three phases: goal formation, data production and data usage. The analysis of these phases allows us to look at the intense exchanges and negotiations between a range of actors in firms, a process we call the politics of algorithmic management. We analyse the role of managers, process engineers, data scientists as well as workers and their representatives and go beyond the dualistic focus on management and workers alone. Thus, our findings speak for narrow limits to the automation of management decisions in conventional companies vis-à-vis platforms, which have fewer bargaining parties.

Our second contribution is to examine the deployment of an algorithmic system in a conventional workplace, which differs significantly from platform work. The system used in this workplace (a logistics company) records workers' movements and is deployed for optimising work processes. At first glance, it resembles a panopticon, which creates information asymmetries and amplifies managerial control of the labour process (Rosenblat & Stark, 2016). However, we show that this system relies on mobilising the knowledge of various actors to be effective, especially workers themselves. Building on labour process and power resources theories (Schmalz et al., 2018), we argue that actors can use their knowledge as a power resource in the negotiations about the algorithmic management system. We use the term negotiations to describe the process in which organisational actors adapt their work practices and interdependent work roles to the introduction of new technologies (Bailey & Barley, 2020; Barley, 2020). Negotiations can include explicit bargaining about tasks and roles, but also implicit strategies of enforcing or undermining new role contents (organisational misbehaviour as per Ackroyd and Thompson (2022)). We draw on the discussion of managerial strategies (Child, 1985; Thompson & McHugh, 2009; Vidal, 2022) in labour process theory to show how specific regulatory contexts (Doellgast & Wagner, 2022; Thompson & Laaser, 2021) influence negotiations and lead management follow a process- or workforce-oriented strategy.

Our central questions are as follows:

RQ1. *What knowledge do different actors have to contribute to the implementation of algorithmic management system?*

RQ2. *What power relations between the actors result from their different knowledge?*

RQ3. *What impact does the introduction of the algorithmic management system have on working conditions?*

Our case study is embedded in a particular regulatory context, namely Germany. German law offers favourable conditions for the articulation of worker voice (Krzywdzinski, Pfeiffer, et al., 2022). One might expect German workers to have more influence on management than in the case of a platform company operating in New York or Nairobi, for example, given the legal and organisational framework. The aim of our differentiated approach and choice of case is to investigate this aspect of algorithmic management. Therefore, our case study focuses on potential for worker participation and the impact on worker voice that algorithmic management can have.

After discussing the state of research and developing our analytical approach in 'State of the research and analytical approach' section, we introduce the case study and its methods in 'Data and methods' section. In 'Algorithmic management in practice' section presents the empirical analysis. The article ends with a discussion and conclusions.

STATE OF THE RESEARCH AND ANALYTICAL APPROACH

Algorithmic management in conventional workplaces

The concept of algorithmic management has been developed in the wake of the platform economy (Duggan et al., 2020; Jarrahi et al., 2021; Lee et al., 2015; Wood et al., 2019), where work tasks are performed online or with the help of apps, leaving permanent digital traces. Maatescu and Nguyen have outlined several characteristics of algorithmic management on platforms that consist in 'prolific data collection and surveillance of workers through technology; real-time responsiveness to data that informs management decisions; automated or semi-automated decision-making; transfer of performance evaluations to rating systems or other metrics; and the use of "nudges" and penalties to indirectly incentivize worker behaviours' (2019, p. 3). Kellogg et al. (2020, p. 371) have argued that algorithmic management encompasses three key dimensions: direction, performance evaluation and disciplining.

In past years, a growing body of literature started discussing the gradual implementation of algorithmic management tools in more conventional settings such as warehouses, marketing, manufacturing or consultancies (Brynjolfsson & McElheran, 2016; Evans & Kitchin, 2018; Gal et al., 2020; Leicht-Deobald et al., 2019; Pignot, 2021; Wood, 2021). Schaupp (2022b) has argued that algorithmic management is spreading in conventional companies, as it can build on long-established Taylorist practices and existing enterprise resource planning (ERP) systems. While we agree on the longstanding traditions of Taylorist performance management in conventional companies, we want to emphasise considerable differences between those workplaces and platform work. The result is specific conditions that arise for the implementation of algorithmic management.

First, digital traces are produced in the work process of conventional companies only to a limited extent, which means that a data-based infrastructure must first be established which requires new competences in relation to algorithmic systems (Barro & Davenport, 2019). Alaimo and Kallinikos (2021, 2022), in particular, have recently pointed out the growing importance of management of and by data for organisations. In particular, Alaimo and Kallinikos considered the data production phase to be crucial, as this is the phase in which core concepts are defined and measured. Existing ERP systems provide only aggregate output indicators based on orders and material flows. Unlike apps, ERPs cannot be easily used for micromonitoring and analysis of individual work processes. Productivity management in the blue-collar field has relied mainly on traditional concepts like methods-time measurement (MTM), which work with predetermined times to design processes and calculate staffing levels. In the strongly influential lean production concept, process optimisation has been seen as a shop-floor activity involving workers and using hands-on tools like stopwatches (Adler & Borys, 1996; Macduffie, 1995). The core field for more technically enabled performance management has been not blue-collar work, but rather call centre work, in which constant employee monitoring creates a tightly meshed control regime (Bain & Taylor, 2000; Bain et al., 2002).

The second difference between conventional and platform workplaces is that attempts to implement algorithmic management run up against pre-existing forms of organisation, workplace bargaining and regulation. In conventional companies, management often has to negotiate with employee representatives to implement new technology. In addition, labour regulation—at least in European countries—often limits managerial prerogative regarding the use of technology for monitoring, evaluation and sanctioning of work performance. Accordingly, studies on call centre work have found that digital monitoring of work processes is accompanied by a 'range of normative, bureaucratic and other managerial practices' (Bain et al., 2002, p. 184; see also Vallas et al., 2022). An overview study by Lippert et al. (2023, p., 5289) showed that traditional workplaces generally introduce only some elements of algorithmic management, but not the most widely criticised ones such as restricting worker behaviour, sanctions and dismissal.

The implementation process of an algorithmic system itself, however, can transform power relations between the affected actors (Jarrahi et al., 2021). To address this more systematically, we propose to distinguish between the following phases in the analysis of algorithmic management systems in traditional workplaces:

- The process of goal formation in which negotiations revolve around defining shared objectives in the implementation of the technology.
- The data production process in which the measurement instruments are installed and the measurement takes place, constituting the data objects.
- The use, analysis and interpretation of the vast amount of data produced, which successively lead to optimisation recommendations.

Politics of algorithmic management

Zuboff (1988) had already elaborated that the turn to data-based algorithmic control raises the dilemma of knowledge and authority for management: management might need other actors to make sense of data. Zuboff (1988) described two scenarios of dealing with this dilemma (cf. Butollo et al., 2019). On the one hand, management can try to involve employees in developing knowledge from algorithmic systems. On the other hand, management can use digital tools to centralise knowledge. In any case, the implementation of algorithmic management changes the importance of different forms of knowledge and influences the power relations in the company.

We refer to the exchange and negotiation between actors controlling different types of knowledge as the politics of algorithmic management. We define negotiation as the process of aligning work practices and roles with the newly implemented technologies (Barley, 2020). This alignment hews to existing power relations in the company (Bailey & Barley, 2020). It is generally accomplished through explicit bargaining. However, implicit adaptation also takes place in which some actors (e.g. management) try to enforce new rules, while other actors (e.g. workers) can use their knowledge to undermine these rules. Knowledge is a central power resource in these negotiation processes (Schmalz et al., 2018). The algorithmic management systems increase process transparency for management and can reinforce the information asymmetries between management and actors on the shop floor (Rosenblat & Stark, 2016). However, algorithmic management depends on knowledge contributions from different actors, as we will show in our analysis, and thereby creates spaces for resistance and agency (Wood, 2020).

The set of relevant actors does not merely include management and workers. Recent theoretical contributions by Meijerink and Bondarouk (2023) and Noponen et al. (2023) expand the list of relevant actors to include developers, and we suggest to consider several further actors:

First, external data producers and data analytics service providers are key: organisations increasingly use data generated by outside actors, and thus the managerial control over data production might be dissolving. Alaimo & Kallinikos (2022, p. 32) have called this an epochal shift in the sense of 'decentring of organisations'.

Second, workers' representatives and works councils: when introducing algorithmic tools, management has to negotiate with these actors. The analysis has to consider the rules and processes in these negotiations and that they differ strongly between countries (Doellgast & Wagner, 2022; Krzywdzinski, Gerst, et al., 2022).

Third, management is not a single actor. There are various levels of management in a given company. Central management does not necessarily share the perceptions of shop floor management. This point was also made by Jarrahi et al. (2021), who emphasised that algorithmic management particularly challenges the power of middle management.

Fourth, new employee groups, especially data scientists, are becoming increasingly important (Avnoon, 2021; Dorschel, 2021): this may be accompanied by a further disempowerment of middle management in particular, but top management is also faced with the question of whether it still has sufficient knowledge to be able to control the new technologies.

Finally, industrial and process engineers: the role of these actors in companies is also being called into question (Torstendahl, 2022). These engineers were the classic bearers of the Taylorist scientific management revolution and mastered the design and optimisation of processes in companies (Merkle, 1980). For the internal organisation of companies, the relationship between classic engineering roles and the data scientists will be of central importance.

To our knowledge, the relations between these different actors have not received any attention in empirical research on algorithmic management so far. We will try to fill this research gap in our analysis.

Managerial goals and the outcomes of algorithmic management

It is striking that, in the now extensive literature on algorithmic management, the goals and interests of management itself are rarely analysed. Some contributions have identified the central interest of management (in a tradition reaching back to Braverman (1974) and Edwards (1979)) with the control of workers and the automation of this control (De Stefano & Taes, 2023; Kellogg et al., 2020; Veen et al., 2020). As a consequence, work intensification is emphasised (Green et al., 2022). We do not intend to cast doubt on the fact that control of workers plays an important role and that certain aspects of management are automated by platforms (Wood et al., 2019), even if there are limits to automation (Griesbach et al., 2019; Krzywdzinski & Gerber, 2021; Schaupp, 2022b). In our analysis, however, we will question whether management strategies must always be geared towards control and work intensification.

We agree with Meijerink and Bondarouk (2023) and Noponen et al. (2023) that a more differentiated understanding of the role of human management is needed in the debate over algorithmic management. In the labour process theory context, Thompson and McHugh (2009) emphasised that managers often have to formulate their goals under conditions of limited information and time pressure, which is why they invest a lot of time in exchange with other actors in the organisation. Vidal (2022) argued that management makes its decisions under contradictory influences. On the one hand, it must ensure a sufficient labour effort, and it therefore has an interest in controlling workers. On the other hand, management must also ensure that capital is valorised. A competitive product must be produced, which in turn might require that workers, engineers and other groups in the company participate in ensuring quality, solving problems and optimising processes. While management often settles with 'lean enough' solutions, which focus primarily on standardisation and control, particularly high productivity can be achieved with high involvement strategies that dispense with monitoring and surveillance—such a strategy contradicts the sole focus on work intensification.

Vidal's concept fits well with recent contributions from management research. Meijerink and Bondarouk (2023) as well as Noponen et al. (2023) have argued that algorithmic management can restrain workers but also enable them. Which approach prevails depends on recursive loops of negotiations between workers and managers as well as their adaptation to system implementation. Menz et al. (2019) proposed distinguishing process-oriented and workforce-oriented goals of using algorithmic control. In the latter case, the management focus is on the increased process transparency to unlock unused portions of working time (i.e. work intensification) or to identify opportunities for replacing labour with technology. Process-oriented goals, by contrast, focus on the use of data-based process transparency for the elimination of systematic problems: typical issues are machine breakdowns and process bottlenecks. The distinction between workforce-oriented and process-oriented strategies is, of course, a simplification (see Attewell, 1987); for our purposes, however, it offers a good starting point.

The choice of strategies has been shown to be strongly influenced by the regulatory context (Doellgast & Wagner, 2022; Krzywdzinski, Pfeiffer, et al., 2022; Thompson & Laaser, 2021). German law makes the introduction of technical systems that can be used to monitor performance subject to approval by the company works council. In addition, the works council has the right to review new technologies with regard to the resulting physical and mental stress as well as risks for employee data protection (Krzywdzinski, Gerst, et al., 2022; Krzywdzinski, Pfeiffer, et al., 2022). Regulation in Germany strengthens labour voice, which means greater opportunities for the development of more process-oriented approaches.

The distinction between workforce- and process-oriented strategies contradicts the argument that algorithmic management necessarily leads to work intensification and stress (Baiocco et al., 2022; De Stefano & Taes, 2023; Green et al., 2022). However, the work-intensification argument is not the only way to develop a critical perspective on algorithmic management. In our analysis of actor constellations and knowledge contributions, we will focus on how algorithmic management affects the work roles and work contents of actors. Following the argument of increased information asymmetries (Rosenblat & Stark, 2016), we will show that a potential danger of the system lies in the centralisation of knowledge that renders workers' optimisation and problem-solving activities superfluous and thus reduces work content Butollo, Jürgens, et al., 2019.

DATA AND METHODS

Our analysis was based on an in-depth case study (Priya, 2021) of an algorithmic management system used for process optimisation on the shop floor. Our case study approach allowed for a reconstruction of the knowledge practices, negotiations and power relations and the consideration of the contextual conditions (Yin, 2014).

The choice of our case study was based on our own prior research projects. These examined a larger sample of algorithmic management systems (Krzywdzinski, Pfeiffer, et al., 2022) and assessed further studies (Menz et al., 2019; Wood, 2021) revealing that algorithmic management technologies are still in a relatively early stage. Our major goal was to find a company on the brink of implementing a highly developed algorithmic system within a conventional workplace setting, which might then lead to a fundamental reshaping of the work organisation and processes in the company. Indeed, we found two companies acting as supplier/consultant and client implementing an algorithmic management tool. Taken together, our case (at the time of the analysis in 2022) represented a highly advanced technology of datafication of the shop floor in terms of penetration of work processes and accuracy of data collection.

The first company, which we call AnalyticsTech, is a software developer and describes itself as a leading provider of automated analysis of manual processes. The company has around 50 employees. Its approach differs from traditional concepts such as MTM (Karger & Bayha, 1987) or even the approaches to process monitoring developed in the Taylorisation of white-collar work in call centres (Bain et al., 2002). MTM analyses are based on predetermined times for basic movements (such as grasp, move, release) used by engineers to define the standard work operations and to calculate the standard duration for completing tasks. Until recently, industrial engineers did not have data and systems with which detailed work process data could be accurately collected and analysed on a regular basis.

Compared to these traditional practices, AnalyticsTech's software generates data at unprecedented depth and speed. The approach is based on using wearables as well as immobile sensors to take a comprehensive measurement of manual work processes. Based on the immense amount of data, the artificial intelligence (AI)-based algorithm automatically detects types of motion (walking, bending, lifting, hammering, assembling, overhead work, etc.), which we call *basic* data objects. In a second step, the software calculates different kinds of indicators for the distribution of tasks, length of different processes, usage of tools, bottlenecks, waiting times and many more. We call these indicators *composed* data objects.

The software is specialised for manual activities in the areas of goods logistics (storage, picking), in industrial production or in control and inspection processes. It is designed as a platform to enable companies to perform process analysis on their own. However, AnalyticsTech also offers to perform the measurements and analysis for the customers, acting as a kind of consulting company.

We call the second company in our case study LogisticsCorp. It is a logistics company with headquarters in Germany and operates throughout Europe with more than 10,000 employees. The company has recently deployed AnalyticsTech's software at its sites. The collaboration between AnalyticsTech and LogisticsCorp represents a case of decentring data production, in Alaimo and Kallinikos' (2022) terms. Initially, LogisticsCorp was completely dependent on AnalyticsTech for operating the software. In our case study, however, we analysed how LogisticsCorp worked to internalise the required knowledge and recentralise control over its data.

As Table 1 shows, our data collection included (a) semistructured interviews, (b) field notes from observation of the implementation of the algorithmic management system, (c) field notes from the participation in two workshops with company actors and (d) document analysis of workshop and information materials including process maps and protocols created in the course of the implementation process.

We conducted 16 interviews in total of one to two hours in length with AnalyticsTech management as well as the management, process engineers and data scientists of

TABLE 1 Data.

Data collection strategy	Collected data	Participants
(1) Semistructured interviews	16 qualitative interviews	Management of AnalyticsTech, central and local management of LogisticsCorp, process engineers, data scientists, management of other companies working with AnalyticsTech
(2) Field observation	Two-day field observation of the system's implementation on the shop floor – Participation in formal and informal meetings – Observation of the work of design, setup and execution of the measurements – Observation of the work in the course of the measurement	Local management, process engineers, data scientists, shop-floor workers
(3) Participative, technographic workshops	Participation in two workshops conducted by AnalyticsTech focusing on the in-depth presentation of the software structure, functions and use	Management, process engineers and data scientists of AnalyticsTech
(4) Document analysis	Workshop materials, information documents for works councils and shop-floor workers, process maps and protocols, analysis outputs	

Source: Authors.

LogisticsCorp. We also conducted four interviews with managers from other companies using the AnalyticsTech software to validate the findings from our case study. All interviews were recorded and transcribed. In addition, we were able to participate in two workshops conducted by AnalyticsTech that gave an in-depth introduction to the design and use of the software.

The second important part of our empirical analysis was field observation. During a two-day field trip, we observed the implementation of the algorithmic management system in one location of LogisticsCorp, focusing on the data production cycle described in the analysis below. We took detailed field notes about all observations that included inspection of the shop floor by the process engineers, discussions with workers and shop floor supervisors, meetings between the process engineers, local management and shift leaders. In the course of this observation, we were also able to speak with workers informally about their perceptions of problems in the data production process, and we were granted access to several information meetings between workers, management and works councils regarding the plans and implementation of the work-process data analysis.

Finally, we analysed the training materials that LogisticCorps received from AnalyticsTech about the use and application of its software. This included specific materials for the works councils and workers as well as the process maps and protocols that were created during the data production process. These materials contained software and process descriptions, layouts, measurement designs and the analysis results for the plant we studied. After our field observation, we discussed our findings in a workshop with the company actors to subject our interpretations to respondent validation (Maxwell, 2004).

We coded the interview transcripts, field notes and company documents using a mix of deductive and inductive procedures based on qualitative content analysis (Mayring, 2004) in MAXQDA. After a first inductive coding round in which we detected central claims and informative passages out of the material, we developed four thematical main categories, including several subcategories, addressing our research questions on (a) different actors and organisational roles, (b) knowledge and information distribution about the algorithmic system, (c) bargaining conflicts and managerial goals as well as (d) working conditions.

These main categories helped us to outline the different actors involved, the information in their possession, tasks they were occupied with and the negotiation process in which they were involved. During our analysis, the procedural character became clear as the tasks and information differed significantly depending on different steps in the implementation process.

Therefore, in a last coding step, we used our existing main categories to think about the different process steps that were crucial in the deployment of the algorithmic system. The conceptual framework we developed was then, finally, used deductively to integrate the findings of the main categories. This is further described in the following section and also reflected in Table 2.

ALGORITHMIC MANAGEMENT IN PRACTICE

Negotiating goals

The primary actor in our case study is LogisticsCorp's Central Production Management (CPM). CPM is responsible for overarching standards of production organisation as well as location-based performance analyses and benchmarking. Traditionally, CPM has worked with the classic methods of industrial engineering, mainly MTM analyses. The company also has other

TABLE 2 Phases of implementing algorithmic management.

Process	Actors	Negotiation	Knowledge
Goal formation	– CPM LogisticsCorp – Local management – Management AnalyticsTech – Works council LogisticsCorp	– Definition of objectives – Acceptance of the technology – Implementation process – Data protection	Technical feasibility Domain knowledge about process Regulatory framework
Data production	– Process engineers CPM – Data scientists AnalyticsTech – Local management LogisticsCorp – Workers	– Specification of goals on plant level – Installation and measurement	Domain knowledge about shop-floor tasks Process knowledge Technical know-how
Data usage	– Process engineers CPM – Data scientists AnalyticsTech – Local management	– Data interpretation and sense-making – Optimisation goals	Data literacy and analysis Process transfer

Abbreviation: CPM, Central Production Management.

Source: Authors.

indicators at its disposal, such as the number of deliveries or the total time required for deliveries at a site. However, these figures have not allowed for an in-depth analysis of the work processes or an understanding of the causes of problems or variations in the speed of processes.

To explore the use of digital tools for an in-depth understanding of work processes, the CPM initiated the cooperation with AnalyticsTech. At first, LogisticsCorp used an external platform and external data expertise to better understand its own processes. It was thus relinquishing power over data production. However, the goal of the CPM at LogisticsCorp from the beginning was to learn from the collaboration with AnalyticsTech, first to use the consulting services but later to license the software itself and use it independently. The specific knowledge of AnalyticsTech created in the first phase a dependency on the side of LogisticsCorp and the learning process required to reduce this dependency took several years as CPM's process engineers had to be trained in data analysis and the use of AnalyticsTech software.

The politics of algorithmic management in the phase of goal formation are thus characterised by negotiations between LogisticsCorp's CPM, AnalyticsTech and—as we will see shortly—between different management levels and the employee representatives of LogisticsCorp. At the beginning, CPM did not develop specific rationalisation targets but was driven rather by the desire to generate better data about the production sites and to make the processes more transparent—a situation which, according to AnalyticsTech, is quite typical for many companies. The head of CPM argues as follows:

> The issue was three years ago that a lot came from gut feeling, and a lot was evaluated subjectively. And through AnalyticsTech, we have gained valuable insights and will hopefully continue to gain valuable insights, which we can then use to perhaps review the standards again to some extent and then also improve them. (IV3_Production_Management_LogisticsCorp)

From the point of view of CPM, it was important to reach an understanding about the use of the software with the management of all affected business units and locations as well as with the works councils. The head of CPM explains:

> I then organised the whole thing in terms of project management, ... starting with the branch manager, works council, other managers. Then we also planned, for example, employee information events, where really all the industrial employees came into the room and I stood in front and informed them of our goal. (IV4_Production_Management_LogisticsCorp)

To avoid creating resistance from local management, it was crucial for CPM to show that the software had a benefit for local management; that is, it not only facilitated control and benchmarking but also produced concrete suggestions for improvement. Creating this joint understanding was an important element of the politics of algorithmic management to defuse potential resistance from local management and to mobilise its knowledge. Local management was considered an important actor for 'algorithmic brokerage' (Kellogg et al., 2020, p. 389), that is, for convincing workers on the shop floor to work with the new system.

> On the one hand, we needed support in process optimisation, on the other hand, our plants must test the [analysis results] for plausibility, for applicability, for meaningfulness. (IV4_Production_Management_LogisticsCorp)

It was clear that the metrics achieved by the best sites would finally be used to define targets for other sites. However, the strength of the AnalyticsTech concept was that it also provided the microdata on how the respective numbers were achieved, so that sites could learn from one another.

The negotiation with the works council also significantly influenced how goals for the use of the AnalyticsTech software were defined. The importance of this negotiation in the politics of algorithmic management is typical for the German regulatory context. The first step was to present the project to the Central Works Council, which is made up of representatives of the works councils at all locations. The IT Committee of the Central Works Council examined AnalyticsTech's software and the planned measurement and analysis for compliance with data protection legislation. To facilitate this, AnalyticsTech commissioned a report by an independent data protection officer for its software.

CPM and the Central Works Council at LogisticsCorp agreed to test the project at four sites upon consent of the respective locations' works councils. The pilot project was important for management and the works council to generate knowledge about how the software functions. After this pilot project, an agreement was concluded between management and the works councils regulating the use of the AnalyticsTech software. Important points were that participation is voluntary (employees may refuse to participate); the data are only used anonymously, that is, not for individual performance monitoring; and the recording is only done for optimisation goals in the work process and not for monitoring employees (e.g. no measurements during breaks). Technically, the AnalyticsTech software could be used for real-time monitoring of workers, but such use is unauthorised by the agreement between management and the works council:

> We also issued data protection declarations for the employees, where we as LogisticsCorp ultimately assure them that the whole thing will remain anonymous....

> The most important thing is voluntary participation.... If you feel like it, you take part. If you don't, it doesn't matter.... In the information rounds with the employees, we also strategically integrated the branch manager and the works council to show that they are behind it. (IV4_Production_Management_LogisticsCorp)

The process of negotiating managerial goals thus involved several actors. The CPM had to enter into cooperation with AnalyticsTech and decide whether it wanted to have external support on a permanent basis or build up its own competencies. It also had to develop an implementation concept that would convince the works council and the management of the various plants. The exchange with local management and the negotiations with the works council convinced CPM to adopt 'a process-oriented strategy', using Menz et al.'s (2019) term, which foregrounds the generation of process transparency with the goal of developing optimisation ideas. CPM did not try to push for workforce-oriented rationalisation measures (e.g. individualised performance monitoring, predefined targets of performance increase or even employment reductions). Instead, it emphasised that benchmarking does not involve automatic decisions:

> AnalyticsTech is certainly not there to... immediately make a decision based on the insights we get... But it simply enriches our processes with valuable information. (IV3_Production_Management_LogisticsCorp)

Data production

Although AnalyticsTech advertises its software as highly automated, it quickly became apparent in our study that the process of data production constituted an independent phase in the politics of algorithmic management. It required specific knowledge of different actors and involved the negotiation of the implementation of technology. Four steps could be distinguished: (1) definition and negotiation of data production goals, (2) development of a design for data production, (3) data collection and (4) production of data objects. The core actors in this stage were the process engineers responsible for implementing the software, the local management and the workers.

First, process engineers from AnalyticsTech and LogisticsCorp's CPM held detailed discussions with the local managers to define and negotiate the specific goals for each wave of data collection. This involved developing an initial definition of strengths and weaknesses of the processes: what is working well and which areas require recommendations for improvement. A survey of the workers was also carried out to capture their knowledge about problematic process steps (unergonomic workplaces, machine problems, waiting times, etc.).

Second, the development of a measurement design started. The CPM process engineers developed a so-called process profile in which all work processes were described in detail so as to subsequently decide which employees should be equipped with wearables and where immobile sensors should be installed. The development of the process profile required thorough negotiations with the plant management and local shift leaders, on-site visits to see the process and gather the knowledge of workers, as described by a process engineer:

> So, what we never do is that we measure the process and then, when we have the data, we start to analyse and to think about what can be done better.... It is actually

> the other way around. We see the process, we talk and quite often already see something, form initial assumptions. (IV7_Process_Engineer)

The measurement itself was the third step. To ensure a meaningful analysis and also anonymisation of the data, the measurements were taken for two weeks. The sensors generated approximately 3000–4000 data points per second and sensor. Based on these data, the AI algorithm identified the type of position or movement, that is, the basic data objects. Based on the digital map of the shop floor, the composed data objects were generated, which included heat maps and indicators (walking distances, hours required, proportion of unergonomic movements, proportion of waiting times, etc.).

Consistent with practices of undermining managerial control reported in other studies (Ackroyd & Thompson, 2022), process engineers reported that practices of disrupting or undermining measurement occur repeatedly when workers had not been informed or when they distrusted the measurement. When workers suspected that they were being controlled by the technology, they did not put on the wearables, removed the sensors from the measurement points or purposefully worked slower and deviated from their everyday work practices. Thus, to assure a valid measurement, management considered it paramount to credibly assure that there would be no individual performance monitoring nor layoffs or cutbacks. Despite their efforts, the communication processes on the shop floor showed only partial success. The information conveyed to workers remained technical and difficult to understand. Workers repeatedly referred to themselves as 'lab rats' and expressed doubts that the technology would not be used for monitoring. Plant management, CPM and the works council tried to allay these concerns and were eventually able to calm the criticism. It was clear, however, that the workers' acceptance was mainly based on their trust in the works council and their shift leaders, and not on any actual understanding of why the measurement was needed.

This overview shows that data production constitutes a crucial phase of the politics of algorithmic management. The core ideas for the benchmarking and optimisation concepts were already developed in this phase. The process engineers and the local management were the most powerful actors due to their domain knowledge. While the former represented the headquarters' interest in benchmarking, the latter brought in knowledge needed to align the outputs of algorithmic management with the interests of the local plant. Data production is also the phase where workers have an important power position: their knowledge proved important to identify process weaknesses. This resulted in a variety of negotiation and algorithmic brokerage efforts on the side of management and engineers to ensure worker acceptance at least to the extent that the latter did not undermine the data production process.

Data analysis and sense-making

The data analysis represented the last phase of the politics of algorithmic management. The core actors in this phase were the process engineers, data scientists and the local management—three groups with different types of knowledge. The core outcomes were optimisation suggestions that focused on the following issues: redesign of the process layout to avoid unnecessary walking; decisions to purchase new machinery (e.g. packaging machines) for use where heat maps and waiting time indicated bottlenecks; decisions to install new racking systems where excessive bending or overhead work was noted. It was clear that such changes could have an impact on work contents, but management assured the workers that there would be no staff cuts.

The data analysis process was directed by process engineers, who have been intensively trained in data science and the use of the AnalyticsTech software. They emphasised that the AnalyticsTech's software allows for detailed analysis but cannot automatically generate any recommendations or decisions.

> The algorithm doesn't tell you what's bad in the process or what's good in the process, but it basically presents the process transparently first. And then, with the help of process know-how and experience, you have to be able to interpret this data and derive… optimisation measures. (IV6_Process_Engineer)

To underline the value of their domain knowledge, process engineers pointed out the danger of the overreliance on the outputs, as there are always incorrect measurements which can lead to outliers and implausible results. The process of sense making was hence based on a close exchange between process engineers and data analysts:

> The data analysis team takes over in the step from the recorded raw data to developing KPIs or to certain analyses…. Where I [as a process engineer] come in is… to derive optimisation from these representations. What is done in the analysis team is not to say 'we can save 20% of the time by doing this and that'. Rather, they give me a basis of, let's say, 500 charts in such a project…, and I work my way through them systematically and of course have to recognise the special features, the anomalies in the process and make my optimisation proposals. (IV7_Process_Engineer)

While the data production phase involved negotiations on the shop floor, the data analysis phase represented the centralisation of knowledge. The most powerful actors in this last phase proved to be the process engineers of CPM. The data scientists now took on more of a service function to help CPM developing the key figures that can be used for comparison and benchmarking between sites.

The only other actor to influence the outcomes was the local management, who worked together with the engineers to identify problems and develop improvement suggestions. The local actors did not need expertise in data science; instead, they to acquire general data literacy.

It is remarkable that the workers were not involved in these optimisation processes. Systematic improvement workshops, in which management works together with workers on improvement ideas, did not exist in the company. During our field observation, it was clear that the workers did not feel involved in problem solving and thought of themselves primarily as objects of measurement. The implementation of AnalyticsTech's software reinforced information asymmetries in the company.

DISCUSSION

Actors and their knowledge contributions

Our RQ1 focused on the central actors of the politics of algorithmic management and the knowledge they contribute to the implementation and use of the system. A central contribution of our analysis is a differentiated understanding of the actor constellations in different phases.

With our approach, we build on Jarrahi et al.'s (2021) understanding of algorithmic management as a 'sociotechnical process' and suggest a new path to further develop the process perspective. The frequently cited conceptualisation by Kellogg et al. (2020) as well as, for instance, the recent approaches by Meijerink and Bondarouk (2023) and Noponen et al. (2023) have focused thus far on a classification of the *functions* of algorithmic management. Meanwhile, we follow the conceptual work done by Alaimo and Kallinikos (2021, 2022) to distinguish different *phases* of algorithmic management. Such an approach allows for a differentiated analysis of the role and power relations between actors.

Our process-oriented approach distinguishes three phases: goal formation, data production and data analysis (see following table). The central actors and the core knowledge contributions change in each phase. Central management guides the goal formation phase, but it is highly dependent on the technological knowledge of AnalyticsTech and on the domain knowledge of local management. It also needs an agreement with local management and the employee representatives (works council) as both actors must take over algorithmic brokerage functions.

In the second phase of data production, the core actors are process engineers and data scientists (from AnalyticsTech), but they must also involve local management and gain acceptance from the workers. The domain knowledge of workers and engineers constitutes an important power resource in this phase.

In the third and final data usage phase, the process engineers take the lead and work on the optimisation concepts with the data scientists and local management. We can consider this phase of politics of management to be the centralisation phase: this phase creates process transparency for management and information asymmetries between management and workers.

Our process perspective on algorithmic management sheds new light on the discussion about the potential to automate managerial practices such as decision-making, oversight or task allocation (Jarrahi et al., 2021; Newlands, 2021; Noponen et al., 2023). Our study shows that there are huge differences between platform companies and conventional firms and that these must be taken into consideration. Past studies on managerial-practice automation have focused on platforms (Newlands, 2021). Unlike platform labour, however, there is no digital tracking of work processes and no automated data production in most conventional companies. If detailed data about the work process is needed, it must be produced in a laborious procedure with clear limits to automation. When we look at the phase of data usage, the ability to automate is related to complexity. Simple analyses can be automated, but identifying problems or developing optimisation concepts and other more complex analyses require interpretation by domain experts. Overall, our findings speak for narrow limits to the automation of management decisions in conventional companies.

Shifting power relations

Reconstructing the knowledge that different actors need to contribute to implementing algorithmic management allows us to answer our RQ2 by analysing the changes in power relations. The first important relation is between the management of LogisticsCorp and the external service provider AnalyticsTech. Following Alaimo and Kallinikos (2022), we show that collaboration with an external service provider was necessary for LogisticsCorp to implement algorithmic management at all. We can expect similar developments in many conventional companies. Unlike Alaimo and Kallinikos, however, we do not see a necessary trend toward loss of power over data to external platforms and thus a 'decentring' of organisations. While the initial phase of our case corresponded to a decentring process, LogisticsCorp strived to develop the competence it needed itself. After some time, it licensed the software from AnalyticsTech, but it no longer needed to contract out the analysis; the company's own process engineers used their acquired knowledge to gather and analyse new data. This shows that, depending on the managerial strategy, decentring and recentring scenarios are equally possible.

Our findings remain ambivalent regarding the power relations between central and local management. Jarrahi et al. (2021) have emphasised that the role of lower level managerial ranks in particular might be weakened due to the implementation of algorithmic management. Our study shows, however, that central management needs the support of local management in implementing algorithmic management and ensuring worker acceptance. Local management is needed for what Kellogg et al. (2020, p. 389) call ‘algorithmic brokerage’, which means communicating ‘the logic and value of the algorithmic systems to various groups’. Central management must therefore take care to implement a system that is useful from the perspective of local management. Once the system is in place, algorithmic management increases the transparency of the processes in the plants and strengthens the centralisation of knowledge in the hands of the headquarters.

Our study emphasises the importance of process engineers and data scientists in data production and data usage—a topic that has been neglected in research on algorithmic management. Our study offers interesting insights here that shed new light on discussions about the power relations between engineers and data scientists, about the demise of engineers (Torstendahl, 2022) and the rise of data scientists in organisations (Dorschel, 2021). In our case, the process engineers took the lead in data production, and data analysis and the data scientists operated more in the role of a service provider. The domain knowledge of the process engineers represented a crucial power resource, while the data scientists mainly contributed their methodological knowledge. Certainly, the process engineers had to develop digital literacy with regard to the new systems, but this was not an insurmountable hurdle. We expect that this relationship between the two organisational roles does not just apply to our case, but this hypothesis has to be verified in further studies.

Our empirical findings are ambivalent with regard to the position of workers and the power relations between workers, engineers and management. On the one hand, our case was embedded in the German regulatory framework, which offers the works council, as the representative of the workers, far-reaching possibilities to prevent the use of algorithmic management for individual monitoring and increasing the pressure to perform. Accordingly, the negotiations between management and works council led, in our case, to a process-oriented strategy that explicitly refrained from rationalising employment and increasing performance targets. We consider the creation of institutional arrangements similar to German co-determination to be a necessary prerequisite for promoting worker-friendly approaches to algorithmic management.

We have also shown that workers have their own power resources, especially in the data production phase in which management invested heavily to gain workers' acceptance. However, our case also shows that once the data was collected, management no longer relied on workers' involvement at all. We did not find practices such as quality circles or team improvement workshops that are otherwise a core element of lean production concepts (Adler & Borys, 1996; Macduffie, 1995; Vidal, 2022). We see evidence here for the possibility that AI-based data analysis, combined with the domain knowledge of the process engineers and local management, may make the development of optimisation concepts achievable without the workers' involvement. While management must make compromises to assure worker cooperation in the data production phase, the information asymmetries created by the algorithmic management system overall reduce the need for worker involvement practices.

The impact on working conditions

Our RQ3 focused on the impact on working conditions. At first glance, our findings seem to contradict a number of studies on algorithmic management in the tradition of labour process theory. In these studies—concisely in Kellogg et al. (2020), but similarly in Duggan et al. (2020) and Schaupp (2022a)—the primary outcomes of algorithmic management were assumed to be work intensification and stress. This is matched by arguments made by Green et al. (2022), who characterised the current digitalisation processes as an 'effort-biased technological change'. Labour agency is seen primarily in resistance to these management concepts.

In contrast, we show, first, that labour agency can also consist in negotiating the implementation conditions of algorithmic management. This type of agency requires institutional participation rights and data protection rules. Second, we follow Vidal's (2022) reconsideration of labour process theory in arguing for a differentiated understanding of management goals and practices. We distinguish workforce-oriented strategies as well as process-oriented strategies in the use of algorithmic management. This approach is compatible with recent contributions from management research (Meijerink & Bondarouk, 2023; Noponen et al., 2023). Third, we do identify potential for workers' agency and resistance, especially in the data production phase.

Our major contribution lies in refocusing the critical analysis of algorithmic management. We argue that the dangers of algorithmic management lurk not just in increasing surveillance and work intensity but rather in its impact on companies' employee involvement policies. Our study suggests that algorithmic management leads to centralisation of knowledge and the development of an expertocracy in companies that could lead to a weakening of high-involvement approaches (see also Butollo et al., 2019). The new digital tools might provide such in-depth process transparency that quality circles and improvement workshops with workers become less relevant—with the further dangers of disillusionment, nonacceptance, resistance and backlash on the workers' side. In our interviews with AnalyticsTech managers, we could not identify a single company which would use AnalyticsTech's technology to empower workers. While existing studies suggest that the proportion of companies implementing high-involvement practices has been slowly increasing since the 2010s (Gallie & Zhou, 2013, 2020), the diffusion of algorithmic management could change this trend. We see the testing of this hypothesis as an important task for future research.

LIMITATIONS

The limitations of our approach lie in the methodological characteristics of an in-depth case study. Despite having developed a unique analytical framework and painstakingly reconstructed the interactions and power relations in our case which led to testable hypotheses, we cannot draw conclusions about how common the constellation we describe is actually represented in the overall population of companies. This will be an important question for future research.

CONCLUSION

The starting point for our argumentation was the observation that the discussion on algorithmic management is dominated by a narrow perspective based on the control-resistance paradigm and overestimating the potential of digital technologies for the automation of control.

Our motivation and aim was to open the black box of management processes, as recommended in recent contributions to labour process theory (Vidal, 2022).

Based on Alaimo and Kallinikos (2022), we have proposed an analytical framework that differentiates the phases of goal formation, data production and data usage. We see this process perspective on algorithmic management as a new and important tool to analyse interactions and bargaining between actors.

Our first core finding is that the actors' domain knowledge represents an important power resource—not simply top management and employees' know-how, but also that of process engineers and local management. With regard to management, or second core finding is how the regulatory context in Germany led to the development of a process-oriented strategy. This strategy dispensed with individual monitoring and focused on the elaboration of optimisation ideas that relate to process design, the use of machines and also ergonomic issues. This differs from studies from the US and UK contexts which have often shown the dominance of workforce-related strategies that focus on rationalisation and performance pressure. We conclude that a regulatory framework along the lines of German co-determination is an important prerequisite to promote worker-friendly implementation of algorithmic management. At the same time, however, our third core finding is that even in this context there is the danger that practices of algorithmic management could weaken the previous role of high-involvement practices for the elaboration of optimisation proposals and lead to degrading of work.

Our major contribution to the research literature is the process model of algorithmic management and the empirical analysis of the politics of algorithmic management in conventional workplaces, which differ significantly from platform companies. We argue that research has to elucidate the role of the regulatory frameworks, various actors' knowledge contributions to the algorithmic management system, and the power relations resulting therefrom.

Our research also has practical implications. For management actors, it shows firstly the importance of cross-functional collaboration between process engineers, data scientists and workers, and secondly the possibilities of a cooperative design of algorithmic management systems with employee representatives. For employee representatives, on the other hand, it illustrates the importance of pushing for forms of worker involvement in the use of algorithmic management systems, in addition to issues of data protection and performance monitoring.

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