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How Algorithmic Direction Affects Work Autonomy Within Varying Control Configurations: A Fuzzy-Set Qualitative Comparative Analysis**

Abstract

Employers are increasingly using algorithmic directions to instruct employees. Algorithmic direction controls work through instructions and recommendations based on algorithms, either substituting or complementing traditional control mechanisms, such as formal input and output control or informal clan control. However, it is unclear how the combination of algorithmic direction and other control mechanisms influences employees' perceived work autonomy. This empirical study analyses which combinations of algorithmic direction and other control mechanisms ensure employees continue to perceive work autonomy. A fuzzy-set qualitative comparative analysis was applied to a linked employer-employee dataset of 559 employees in large German workplaces. Results suggest that control configurations that combine algorithmic direction and informal clan control through personal interaction with supervisors or colleagues facilitate method autonomy, provided that organisations refrain from algorithmic monitoring and devaluation of prior skills. To ensure criteria autonomy, employees should also get to develop new skills and interact personally with both supervisors and colleagues.

Keywords: algorithmic control, algorithmic monitoring, configurational perspective, fsQCA, work autonomy
(JEL: M12, M54, J81, O33)

Introduction

Based on rapid technological advances, algorithmic direction has become prevalent in many industries and constitutes a new form of control through which organisations aim to efficiently align employee behaviour and performance (Baiocco et al., 2022; Kellogg et al., 2020). Being an integral part of algorithmic management, organisations use software programs to automatically generate algorithmic direction that provides work instructions, suggestions or further information to employees (Lee et al., 2015; Leicht-Deobald et al., 2019; Wood et al., 2019). Therefore, the algorithmic direction is expected to influence employees' work autonomy, i.e., the

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degree of freedom that employees perceive in deciding how to perform tasks and what work goals to accomplish (Breaugh, 1985; Humphrey et al., 2007). Work autonomy is a key job characteristic that relates to job quality because it is positively associated with employee motivation, well-being, and performance (Backhaus & Steidelmüller, 2021; Gallie, 2012; Muecke & Iseke, 2019). Employees strive for control over their work, which makes them feel needed, and work autonomy is a valuable job characteristic (Hattrup et al., 2020). If employees perceive algorithmic direction as limiting their work autonomy, they are likely to resist the new technology; however, if they feel empowered by algorithmic direction, they are more likely to embrace it (Blazejewski & Walter, 2018; Kellogg et al., 2020; Ruiner & Klumpp, 2022).

Yet, there has been little cross-industry research so far examining how employees in traditional employment perceive algorithmic direction as it relates to their work autonomy (Baiocco et al., 2022; Gagné et al., 2022). In particular, empirical evidence regarding how algorithmic direction influences the degree to which employees perceive work autonomy remains inconclusive (Bader & Kaiser, 2017; Meijerink & Bondarouk, 2023; Noponen et al., 2023; Ruiner & Klumpp, 2022). Some researchers suggest that algorithmic direction may foster work autonomy, as digital technologies support employees' ability to make complex decisions and enhance their flexibility (Ahlstrom et al., 2020; Grønsund & Aanestad, 2020; Nurski & Hoffmann, 2022). However, work organisations typically implement algorithmic management in ways that undermine employees' work autonomy by standardising, deskilling, and decomposing jobs, resulting in digital Taylorism (Gagné et al., 2022; Noponen et al., 2023). Using a dataset of employees working in traditional employment, Gensler and Abendroth (2021) show that employees perceive significantly less work autonomy when they receive algorithmic direction every day compared to employees who never receive algorithmic direction.

In this paper, we seek to find out how algorithmic direction is implemented as part of an organisation's control system (Cardinal et al., 2017; Duggan et al., 2020; Kalleberg & Reve, 1993) and which implementation is associated with high levels of work autonomy. The concept of a control system denotes that algorithmic direction co-occurs with other control mechanisms, resulting in specific control configurations (Cardinal et al., 2010; Lebas & Weigenstein, 1986; Sitkin et al., 2020). Research on organisational control has identified four different prototypical control mechanisms: input, behavioural, outcome and clan control (Ouchi, 1979; Sihag & Rijsdijk, 2019; Sitkin et al., 2020). These control mechanisms can be formal or informal (Kreutzer et al., 2016). In addition to algorithmic direction as a form of formal behavioural control, we consider algorithmic monitoring as a formal output control mechanism and changes in skill requirements (i.e., the devaluation of prior skills and the need to acquire new skills) as input control. We also consider personal interaction with supervisors and colleagues as indicators of informal clan control (Cardinal et al., 2010; Kirsch, 1996; Turner & Makhija, 2006).

In order to study how algorithmic direction is combined with these control practices and how they jointly influence employees' perceived work autonomy, we analyse a sample of 559 employees in large German workplaces who receive daily algorithmic direction, using fuzzy-set Qualitative Comparative Analysis (fsQCA; Misangyi et al., 2017; Park et al., 2017; Ragin, 2008). The method allows us to explore how different control mechanisms combine for employees to experience work autonomy. It also accounts for the fact that multiple combinations of control mechanisms may be associated with work autonomy. Thus, fsQCA shows which control mechanisms are relevant for employees to experience work autonomy, and it indicates whether control mechanisms are complementary or substitutive in explaining work autonomy.

In sum, we seek to make three contributions to the literature on algorithmic management in work organisations. First, we add to the sparse knowledge of the algorithmic management of traditional work. This study covers algorithmic direction as applied in conventional jobs from both public and private sectors across different industries, while prior research has largely investigated platform-based work (H. Huang, 2023; Parent-Rocheleau & Parker, 2022; Wood, 2021). Furthermore, most studies to date have analysed whether or not algorithmic direction has been applied, but little is known about how algorithmic direction is implemented in conventional work settings. We seek to provide a more nuanced understanding of algorithmic management by studying the implementation of algorithmic direction as part of organisational control systems following recent calls (Noponen et al., 2023; Parker & Grote, 2022a, 2022b).

Second, we contribute to organisational theory by applying a configurational approach to better understand how algorithmic direction influences employees' perceptions (Cardinal et al., 2017; Sihag & Rijsdijk, 2019; Sitkin et al., 2020). We argue that configurations of control mechanisms rather than individual control practices influence employee perceptions. So far, scholars have rarely applied a configurational approach when studying the digitalisation of work (for recent exceptions, see Lyngstadaas & Berg, 2022; Meier et al., 2023), but it promises to enrich knowledge about algorithmic management and its implications for work autonomy (Monteiro & Adler, 2022; Parker & Grote, 2022a; Schafheitle et al., 2020). Prior research has often assumed that formal behavioural and output control practices, such as algorithmic direction and monitoring, restrict work autonomy, while informal clan control, such as personal interaction with supervisors and peers, has been characterised as empowering (Cardinal et al., 2018; Sitkin et al., 2020). Yet, empirical evidence indicates that these assumptions may be overly simplistic (Adler & Borys, 1996; Monteiro & Adler, 2022). Instead, researchers have suggested that employee perceptions are influenced by the interaction of several controls (Cardinal et al., 2018; Long & Sitkin, 2018; Sihag & Rijsdijk, 2019). Therefore, we argue that it depends on the configuration of control practices and whether employees experience work autonomy. Even though we find that employees receiving algorithmic direction tend to experience less work autonomy, we identify specific combinations of algorithmic direction with other control mechanisms that are associated with high levels of work autonomy, using fsQCA as a configurational method.

Third, we contribute to research on work autonomy by distinguishing between method autonomy and criteria autonomy to explore whether they require distinct control configurations to occur. Method autonomy describes the latitude of employees to decide how to execute their work, while criteria autonomy refers to the extent to which employees can select or change criteria to assess work outcomes closely linked to previously set work objectives (Breaugh, 1985). We focus on method and criteria autonomy because they are most likely influenced by algorithmic direction (Ruiner & Klumpp, 2022; Schafheitle et al., 2020). Method autonomy and criteria autonomy differ in their impact on employee attitudes, well-being, and performance (Humphrey et al., 2007; Muecke & Iseke, 2019). Yet prior research has not considered that algorithmic management may influence method and criteria autonomy in distinct ways (Möhlmann & Zalmanson, 2017; Noponen et al., 2023). Therefore, this study refines our understanding of work autonomy in a context that is subject to significant changes in work autonomy due to the digital transformation of work (De Spiegelaere et al., 2016; Schafheitle et al., 2020).

Overall, the findings promise to advance the discussion on how to implement algorithmic direction without compromising work autonomy and, eventually, employee motivation and well-being, thus helping organisations preserve job quality in light of the digital transformation of work.

Literature Review

Organisations exercise control to ensure that work processes are coordinated so that organisations meet their objectives (Cardinal et al., 2010; Ouchi, 1979). Organisational control systems consist of various control mechanisms that serve to direct, evaluate, and discipline employees (Cardinal et al., 2018; Edwards, 1979; Ouchi, 1979). Control mechanisms are any individual formal (i.e., written institutional rules, job descriptions, skill requirements, and work instructions) and informal (i.e., values, norms, beliefs, and information on organisational priorities) control procedures that organisations apply to control the input, behaviour, or output parts of the labour process (Cardinal et al., 2010; Ouchi, 1979; Schafheitle et al., 2020). To exercise formal input control, work organisations define skill requirements for performing a job (Cardinal et al., 2018; Schafheitle et al., 2020). Formal mechanisms focusing on behaviour control intend to control how employees perform work, while formal output control aims at measuring and assessing whether and to what extent a work target has been achieved (Cardinal et al., 2010; Ouchi, 1979). In contrast, clan control is informal in nature, relying on face-to-face interactions among employees, supervisors, and peers to foster collaboration and the adoption of shared work values (Cardinal et al., 2018; Eisenhardt, 1985; Ouchi, 1979). Supervisors and peers shape and monitor employee behaviour through frequent personal interaction (M.-P. Huang et al., 2005; Huber & Gärtner, 2018; Kirsch et al., 2010).

Algorithmic direction serves as a formal behaviour control mechanism by providing work instructions and recommendations to direct employees and guide them in making work-related decisions (Kellogg et al., 2020; Lee et al., 2015; Wood, 2021). Algorithms link, consider and evaluate large amounts of data about organisational processes, personnel, capacities, priorities, supply and demands in order to efficiently solve work-related problems and support complex decisions, such as those related to recruitment (Leicht-Deobald et al., 2019), loan approvals (Terry et al., 2022), and logistics (Delfanti, 2021). Employees receive algorithmic direction on how to perform tasks via computer programs, apps, tablets or wearables in the form of suggestions or direct orders (Elliott & Long, 2016; Ruiner & Klumpp, 2022).

Organisations can implement algorithmic direction as a formal behaviour control mechanism, along with other forms of organisational control, thereby creating distinct control systems. The digital transformation of work may imply that organisations use algorithmic monitoring as a formal output control mechanism in addition to algorithmic direction. Algorithmic monitoring relies on sensors, cameras, and further input devices (e.g., keyboards or touchscreens) to automatically gather, store and evaluate data on work processes and outcomes (European Commission [EC] & Ball, 2021). Based on these large amounts of data, algorithms monitor work processes and evaluate work outcomes (Parent-Rocheleau & Parker, 2022). Organisations use algorithmic monitoring to compare work outcomes with standards and automatically adjust organisational resources and work targets or sanction and reward employees (EC & Ball, 2021).

Additionally, algorithmic direction may be associated with a shift in formal input control, as previously necessary skills become obsolete or employees must develop new skills (Delfanti, 2021; Grønsund & Aanestad, 2020; Johansson et al., 2017). Skill requirements serve as an input control mechanism because they define what skills and abilities organisations consider relevant and are willing to reward (Cardinal et al., 2017; Schafheitle et al., 2020). Organisations may devalue some skills because, for example, technology replaces human skills (H. Huang, 2023). On the other hand, organisations that use algorithmic direction can also redesign jobs to include novel or more complex tasks that require employees to develop new skills (Meijerink & Bondarouk, 2023; Noponen et al., 2023).

Finally, organisations using algorithmic direction may also rely on personal interaction with supervisors or peers as informal clan control to direct and monitor employees. Even though algorithmic direction may replace managerial functions, such as directing and coordinating work (Kellogg et al., 2020; Schwarzmüller et al., 2018), supervisors are still essential in the context of platform-based work (Cram & Wiener, 2020; Ruiner & Klumpp, 2022) and in conventional work settings (Elliott & Long, 2016). Similarly, while employees may increasingly interact with sociotechnical systems, colleagues are still likely to influence how their peers act and perform work (De Jong et al., 2014; Elliott & Long, 2016). Through frequent personal interactions, supervisors control employees by giving directions, motivating employees to achieve organisational goals and providing feedback (Cardinal et al., 2018; Kreutzer et al., 2016). Likewise, personal interaction with peers helps to instil shared values, norms and perspectives and fosters coordination and collaboration (Walter et al., 2021).

To date, little is known about how organisations combine algorithmic direction with algorithmic monitoring, changing skill requirements and personal interactions with supervisors and peers. Therefore, we seek to explore organisational control systems entailing algorithmic direction.

Algorithmic Direction and Work Autonomy: A Configurational Perspective

Employees may perceive organisational control as coercive, thereby limiting work autonomy, or as enabling, i.e., facilitating work autonomy (Adler & Borys, 1996; Crowley, 2012). Similarly, the autonomy-control paradox suggests that algorithmic control can simultaneously enhance and restrict work autonomy (Bader & Kaiser, 2017; Ruiner & Klumpp, 2022). Accordingly, the association between algorithmic direction and perceived work autonomy remains ambiguous. Some studies indicate that algorithmic direction supports work autonomy (Meijerink & Bondarouk, 2023; Ruiner & Klumpp, 2022; Wood et al., 2019), while others show that algorithmic direction undermines work autonomy (Delfanti, 2021; Kinowska & Sienkiewicz, 2023; Nurski & Hoffmann, 2022; Wood, 2021). In a cross-sectional study on employees in traditional jobs, Gensler and Abendroth (2021) find that employees who receive algorithmic direction daily perceive significantly less work autonomy than employees who receive no algorithmic direction.

Yet research shows that it is inadequate to characterise individual control mechanisms as either coercive or enabling (Sitkin et al., 2020). Therefore, we argue that employees' perceptions of algorithmic direction can vary greatly, depending on how algorithmic direction is combined with algorithmic monitoring, changing skill requirements and personal interactions with supervisors and peers. Thereby, we follow a configurational approach that has gained a lot of attention in organisation theory (Furnari et al., 2021; Park et al., 2017). The configurational approach emphasises that specific combinations of conditions (i.e., a configuration) jointly produce an outcome of interest and that different configurations may lead to the same outcome (Fiss et al., 2013; Misangyi et al., 2017; Ragin, 2008). Recent research on organisational control suggests studying organisational control as configurations of control practices that jointly influence employee perceptions (Parker & Grote, 2022b; Sitkin et al., 2020). The configurational perspective takes into account the multifaceted nature of organisational control, providing a more nuanced picture of the complex control systems in organisations (Cardinal et al., 2017).

Employees perceive configurations of control mechanisms, i.e., control systems, as coercive or enabling, thus affecting their work autonomy (Adler & Borys, 1996; Crowley, 2012). As control systems differ in their emphasis on controlling behaviour, output and/or input (Cardinal et al., 2018), they provide more or less discretion for employees to decide how to work (method autonomy) and what to focus on (criteria autonomy). For example, control systems with a strong emphasis on controlling employee behaviour permit less method autonomy than control systems focusing on controlling the output. Control systems emphasising both formal behaviour and formal output control tend to be perceived as more coercive than control systems that rely on input control or informal clan control (Cram & Wiener, 2020; Meijerink & Bondarouk, 2023; Schafheitle et al., 2020; Wesche & Sonderegger, 2019).

Output Control: Algorithmic Monitoring

If algorithms are not only used to direct employees but also to monitor their work performance and outcomes, thereby combining formal behaviour and output control, then employees are expected to have less work autonomy. Algorithmic monitoring enables the continuous, invasive, immediate, and extensive capturing and evaluation of work performance (EC & Ball, 2021), including information on employees' tacit knowledge, actions, thoughts, feelings, physiology, relationships and reputation (Ravid et al., 2020), as well as their movements and location within and beyond work establishments (Elliott & Long, 2016; H. Huang, 2023). Some employees perceive quick and specific feedback as helpful, particularly insofar as it can encourage them to learn and acquire new skills (Tomczak et al., 2018). However, if algorithmic monitoring complements algorithmic direction, employees have little room to evaluate their own performance and revise it accordingly. Moreover, giving employees immediate feedback on their performance creates an atmosphere in which they feel as if they are constantly being judged or even disciplined. Hence, the combination of algorithmic direction and monitoring likely restricts work autonomy because it impedes independent thinking and increases the pressure on employees to act in 'anticipatory conformity' (Zuboff, 1988) with the work organisation.

Input Control: Devaluation of Prior Skills and New Skill Requirements

Skills are important for work autonomy because employees draw upon their skills and knowledge to address problems and cope with job demands. The more employees understand their work context, procedures, and how to achieve work goals, the better their ability to take control and work autonomously (Wu et al., 2015).

Therefore, changing skill requirements as formal input control in combination with algorithmic direction is expected to influence employees' perceived work autonomy (Cardinal et al., 2010).

If algorithmic direction is implemented in a way that renders prior skills obsolete, employees tend to experience less work autonomy, as this implies that jobs become more standardised and underutilise employees' prior skills (Noponen et al., 2023). This is particularly likely if algorithmic direction is combined with algorithmic monitoring and a devaluation of prior skills. Yet if prior skills remain valued, employees may view algorithmic direction as a tool that complements their skills or as guidance to base their decisions on, thereby increasing work autonomy (Noponen et al., 2023; Schildt, 2017).

Algorithmic direction may also be associated with the need for employees to learn new skills (Grønsund & Aanestad, 2020), with ambiguous effects on perceived work autonomy. On the one hand, employees may perceive a mismatch between their current skills and the skills required to understand, interpret and cope with algorithmic direction, thereby threatening their self-efficacy and leading them to perceive less work autonomy (Grønsund & Aanestad, 2020). On the contrary, the need to develop skills due to the implementation of algorithmic direction may also imply that jobs become more challenging and complex, thereby enhancing work autonomy. Receiving augmented information on work processes by algorithmic direction serves to reduce information asymmetries and may enable new forms of coordination and self-directed teamwork (Hirsch-Kreinsen, 2016; Schildt, 2017), resulting in employees gaining decision-making competencies (Wood et al., 2019).

Informal Clan Control: Personal Interaction with Supervisors and Peers

In general, employees consider good communication and relationships with supervisors and colleagues to be important work characteristics (Hattrup et al., 2020). Algorithmic direction can complement or substitute personal interactions with supervisors and peers as informal mechanisms of clan control. If algorithmic direction is used to give employees instructions, information and feedback, it is reasonable to assume that the role of human managers shifts accordingly (Jarrahi et al., 2021; Wesche & Sonderegger, 2019). Current research on algorithmic direction suggests that supervisors increasingly take on the role of an advisor and interpreter of algorithmically generated decisions (Ruiner & Klumpp, 2022; Terry et al., 2022). Moreover, algorithmic direction cannot replace the strengths of human managers, such as insight into human nature, instinctive feelings, or the ability to appreciate employees' performance and motivate them when necessary. This is why supervisors have proven essential in supporting employees' work autonomy (Jungert et al., 2021). Supervisors who frequently communicate with employees may mitigate potential problems employees face when working with algorithmic direction, thereby reducing insecurity and strain (Cram & Wiener, 2020; Kreutzer et al., 2016). In general, respectful and supportive leadership is positively correlated with employee decision autonomy (Backhaus & Steidelmüller, 2021). Therefore, employees working in algorithmic directions may perceive frequent personal interaction with supervisors as supportive, creating leeway for them to decide how to work or what to work on. Yet, informal control through supervisors may add to the strain-enhancing effects of algorithmic direction, for example, if employees perceive the personal interaction with supervisors as coercive rather than supportive.

Similarly, the interaction with co-workers serves as a clan control mechanism by creating cohesion and structuring work processes through team organisation and peer supervision owing to task interdependence (Hodson, 2008; Loughry, 2010). Employees exchange information, support one another, and show appreciation and motivation, thus countervailing the potentially negative effects of algorithmic direction. Hence, joint action and increased cooperation of colleagues can mitigate the counterproductive effects of algorithmic direction and help employees conserve work autonomy (Kellogg et al., 2020; Lammi, 2021). However, case studies show that close integration into social relationships with colleagues, joined by algorithmic direction and monitoring, evokes competitive work behaviour due to the chance to evaluate behaviour and performance in real time (Elliott & Long, 2016; Payne, 2018). Therefore, close personal interaction with colleagues may also curtail employees' work autonomy. Following these considerations, for the control system in which algorithmic direction is present, it is possible that clan control by supervisors and peers results in restricting *or* enabling work autonomy.

In sum, we assume that the effect of algorithmic direction on work autonomy depends on how it is implemented in joint interaction with other formal and informal control mechanisms. So far, little is known about these configurations or the joint effects of the various control systems in which algorithmic direction as behavioural control is implemented. Therefore, we use an exploratory approach to identify configurations of control systems, including algorithmic direction, that allow for high levels of work autonomy.

Methodology

Sample

This study analysed the third wave of a linked employer-employee panel dataset (LEEP-B3[1]) of employees of large-scale work organisations (i.e., 500 or more employees) in Germany. Work organisations were from both the public and non-public sectors, as well as from various industries. Data were collected between April 2018 and January 2019 and based on administrative data from the German Federal Employment Agency provided by the Research Institute for Employment Research (IAB) and a survey conducted by Bielefeld University, Germany (Diewald et al.,

1 https://doi.org/10.4119/unibi/sfb882.2014.12.

2014; Marx et al., 2020; Peters et al., 2020). Employers were drawn from a random sample based on all work organisations with 500 or more employees in Germany operating at the time of reporting. Interviewed employees were randomly selected from the population of all employees of the employer sample who were born in 1960 or later and were subject to social insurance contributions (Marx et al., 2020; Peters et al., 2020). The complete sample of the third wave comprised 6,287 cases from 160 different work organisations. The sample used for the present analyses comprised 559 cases.[2] Namely, those who worked under algorithmic direction daily or several times a day for which other relevant information was available.

Method

To examine which combinations of organisational control mechanisms lead to high work autonomy for algorithmically directed employees, this study applied fsQCA (Ragin, 2008). Although this approach is popular in organisation and management science (Greckhamer et al., 2018; Lyngstadaas & Berg, 2022), it has rarely been applied in research on job design (for exceptions, see Kalleberg & Vaisey, 2005; Ong & Johnson, 2023). FsQCA allows researchers to analyse 'multiple conjunctural causation' (Rihoux, 2006). Holding that combinations of conditions—rather than one condition alone—are related to an outcome, 'conjunctural causation' implies that algorithmic direction may be linked to high work autonomy (only) if it is combined with other specific work conditions. 'Multiple' causation or equifinality refers to the idea that more than one of these combinations of conditions may serve as a causal path to an outcome. This implies that several configurations of control mechanisms may lead to work autonomy if algorithmic direction is applied.

The fsQCA approach expresses causal links in set-theoretic language. First, the conditions and outcomes are calibrated into set membership values ranging from 0 (the observation is fully out of the set) to 1 (the observation is fully in the set), with a crossover point at which a case is either in or out of the set (Ragin, 2008). Second, the intermediate set membership values for all cases are defined by applying the log odds method (Ragin, 2008). Third, based on the membership values, fsQCA implements algorithms that explore how the membership of cases in causal conditions is linked to membership in the outcome.

This study defined a frequency threshold (Greckhamer et al., 2018) whereby only configurations with at least five cases were considered for further analysis. In doing so, 96.6 % of all the cases were retained. The remaining cases below the frequency threshold are classified as logical remainders. To analyse sufficiency, fsQCA assesses

2 Of 6,287 cases, 85.7 % gave consent to have their data to be linked to administrative data relevant for the analyses, and they still worked for the same company of which the sample was drawn and were currently employed. Of the remaining 5,387 cases, 10.7 % worked with algorithmic direction daily. A share of 2.8 % of the remaining 575 cases were not included due to missing information.

configurations displaying the outcome based on consistency scores, with high consistency scores inferring that a configuration almost always leads to the outcome (Ragin, 2008). Following recent recommendations (Greckhamer et al., 2018), this study applied a minimum raw consistency score of. 80 and a minimum PRI consistency[3] (i.e., proportional reduction in inconsistency) score of .60 for method autonomy and .51 for criteria autonomy. Configurations with consistency scores below the cut-off values were not considered sufficient. Combinations of causal conditions found to be sufficient were then subjected to the truth table algorithm, thereby reducing the number of expressions needed to describe the sufficient combinations of conditions (Ragin, 2008). All analyses were conducted using the statistics program R and applying the 'SetMethods' (Oana et al., 2021) and 'QCA' (Duşa, 2019) packages.

Measures and Calibration

Outcomes: Method and Criteria Autonomy

The outcomes of work autonomy were measured according to Breaugh (1985). Respondents rated each autonomy dimension on a Likert scale ranging from 1 to 5 in terms of how much autonomy they perceive (see Appendix Table A1 for details on the measurements of the outcomes and conditions). Both method autonomy and criteria autonomy were calibrated using the logic behind the five-point Likert scales as external criteria (Fiss et al., 2013). Accordingly, a score of 1 corresponded to fully out of the respective set (set membership value of 0), while a score of 5 corresponded to fully in the respective set (set membership value of 1). The thresholds for the crossover points of each work autonomy dimension set corresponded to their respective mean levels in the member sets of employees who were not members of the algorithm direction set. This study opted for this route because its primary objective was to identify control systems compensating for possible forms of implementation of algorithmic directions that restrict work autonomy. A score of 3.9 marked the point of maximum indifference about the set membership of method autonomy (set membership score of .5), and a score of 3.1 marked the point of maximum indifference to criteria autonomy.

Conditions

Following the underlying theoretical assumptions of the original five-point Likert scales, algorithmic monitoring was calibrated using 1 and 5 as anchors and 3.1 as crossover point. Clan control in the form of personal interaction with colleagues was considered high (set membership value of 1) if employees communicated

3 To ensure that the identified solutions are consistent despite the PRI consistency levels being below .75, this study included robustness checks analysing the negation of the outcome (see Table A2 in the appendix). The results of the negation analyses confirmed the consistency of the relevant solutions.

several times a day (score 5) and low (set membership value of 0) if employees communicated rarely or never (score 2.1). A value of 4.1 (daily communication) marked the crossover point. Clan control in the form of personal interaction with supervisors occurred less frequently, as indicated by a mean of 3.54 (s.d. 1.07) compared to a mean of 4.57 (s.d. 0.70) for personal interaction with colleagues. To account for these distinct communication patterns, a value of 3.1 (weekly communication) was chosen as the crossover point for personal interaction with the supervisor. Formal input control in the form of changes in skill requirements was represented by two original crisp sets, which differ between 0 and 1. The 'need to learn new skills' and 'a devaluation of prior skills in the course of the digital transformation' were calibrated by 0 for a full non-membership of the respective set, .51 as POI[4], and 1 for full membership. Table 1 presents descriptive statistics, the calibration of all sets and the share of cases that experience both algorithmic direction and the respective control mechanism.

Table 1. Descriptive Statistics, Calibration and Co-occurrence with Algorithmic Direction

Control Mechanisms			Mean/ %	St. Dev.	Qualitative Anchors: Full Non-Membership	Point of Indifference	Full Membership	Combined with Algorithmic Direction in x % of Cases
Formal	Output Control	Algorithmic Monitoring	3.90	1.38	1	3.1	5	69 %
	Input Control	Devaluation of Prior Skills	15.03	-	0	.51	1	15 %
		Need for New Skills	66.91	-	0	.51	1	67 %
Informal	Clan Control	Personal Interaction with Supervisor	3.54	1.07	1	3.1	5	51 %
		Personal Interaction with Colleagues	4.57	0.70	1	4.1	5	66 %
Work Autonomy								
		Method Autonomy	3.57	1.28	1	3.9	5	
		Criteria Autonomy	2.78	1.23	1	3.1	5	

Note. Descriptive statistics and calibrated fuzzy sets of the sample of employees receiving algorithmic direction daily.
N = 559; corresponds to 9 % of the raw data sample (N = 6,287) of LEEP-B3 data 2018/19, wave 3.

Results

Prevalence of Control Systems, Including Algorithmic Direction

About 10 % of employees in the secondary data sample (N = 5,387) reported receiving algorithmic directions at least daily. Most of them (69 %) indicated that al-

4 For technical reasons, the point of indifference is set at.51 instead of.50.

gorithmic direction was combined with algorithmic monitoring, implying that algorithms are frequently used to combine formal behaviour and output control. In 15 % of the cases, algorithmic direction was associated with a devaluation of prior skills, while 67 % of employees receiving algorithmic direction reported that they had to learn new skills. About half of the employees (51 %) indicated that they had daily personal interactions with their supervisor, and 67 % reported that they closely interacted with their colleagues in addition to receiving algorithmic direction.

As expected, control systems varied considerably, indicating that organisations implement algorithmic directions in various ways. The most common control system in our sample, representing 18 % of the cases, entailed a combination of algorithmic direction with algorithmic monitoring, upskilling (i.e., no devaluation of prior skills but a need to learn new skills) and informal clan control (i.e., personal interaction with both supervisors and peers). Another 18 % of the cases pertained to control systems that included algorithmic direction and monitoring, upskilling and no frequent personal interaction with supervisors. These control systems were associated with low levels of method and criteria autonomy. Overall, about 25 % of algorithmically directed employees reported experiencing method autonomy. Only 7 % of the algorithmically directed employees indicated to have criteria autonomy.

Sufficient Combinations of Control Mechanisms for Method and Criteria Autonomy

For each dimension of work autonomy, this study conducted a separate fsQCA to identify organisational control configurations that result in method or criteria autonomy. Control configurations are intermediate solutions that take the presented theoretical considerations and empirical evidence into account. The results of the sufficiency analyses are depicted in Table 2.

Six of the 32 possible configurations are consistently associated with method autonomy (cf. Table A3), while the other 26 configurations are not. The six configurations can be summarised, resulting in three solution paths sufficient to explain method autonomy (cf. Table 2). In addition to the joint absence of a devaluation of prior skills and algorithmic monitoring, there should be no need to learn new skills (M1; CONS:.801; COV: 21.4 %), or there should be additional personal supervisor interaction (M2; CONS:.835; COV: 34.3 %) or close personal interaction with colleagues (M3; CONS:.798; COV: 36.8 %). Together, all configurations sufficient for method autonomy had a consistency rate of .776 and covered 39.0 % of the cases (cf. Table 2).

Table 2. Results of Sufficiency Analyses

Control Mechanisms Combined with Algorithmic Direction	Method Autonomy			Criteria Autonomy
	M1	M2	M3	C1
Algorithmic Monitoring	×	×	×	×
Devaluation of Prior Skills	×	×	×	×
New Skills Required	×			■
Personal Interaction with Supervisor		■		■
Personal Interaction with Colleagues			■	■
Mean Autonomy	*3.82*	*3.84*	*3.92*	*3.27*
n *(% of Cases with Algorithmic Direction)*	61 *(11 %)*	76 *(14 %)*	108 *(19 %)*	37 *(7 %)*
Raw Consistency	.801	.835	.798	.848
PRI Consistency	.550	.624	.590	.536
Raw Coverage	.214	.343	.368	.284
Unique Coverage	.008	.009	.019	
Overall Solution Consistency		.776		-
Overall Solution Coverage		.390		-

Note. The results table shows three solution paths for method autonomy and one solution path for criteria autonomy. ■ = Condition must be present; × = Condition must be absent; [] = Condition may be absent or present.
Source: LEEP-B3 data 2018/19, wave 3; own calculation.

As it was more difficult to explain how employees achieved criteria autonomy than method autonomy, this study instituted a lower PRI cut-off in order to obtain any solution with a positive outcome. The truth table analysis (cf. Table A4) for criteria autonomy suggested only one configuration that met the criteria of a minimum consistency score of .80 and a PRI score of .51. Sufficiency analyses suggested that, in addition to no devaluation of prior skills and no algorithmic monitoring, employees with algorithmic direction should experience the need to learn new skills, personal interaction with supervisors and peers in order to experience criteria autonomy (C1: CONS: .848; COV: 28.4 %). Thus, requirements to perceive criteria autonomy under algorithmic direction were high because all workplace conditions investigated were part of the only solution path.

Discussion

This study investigated which systems of organisational control, including algorithmic direction, result in employees perceiving work autonomy. The digital transformation of work has led to the implementation of algorithmic direction in work organisations, which has raised concerns about employees' work autonomy (Gagné et al., 2022; Möhlmann & Zalmanson, 2017). However, there has been limited research on the co-occurrence of algorithmic direction and varying control mechanisms, which form control systems that differ in their impact on work autonomy (for an exception, see Ruiner & Klumpp, 2022). Therefore, this study follows a configurational approach (Cardinal et al., 2017; Furnari et al., 2021; Misangyi et al., 2017; Ong & Johnson, 2023). The aim of this study was to enhance our understanding of how work organisations implement algorithmic direction as part of their control system (Cardinal et al., 2017) and which implementation results in high levels of work autonomy.

The analyses suggest that the configuration of control mechanisms determines whether employees experience work autonomy when organisations use algorithmic direction. These results are in line with the assumption that it is the configuration of multiple control mechanisms that influences how employees perceive work autonomy (Cardinal et al., 2018; Long & Sitkin, 2018; Sihag & Rijsdijk, 2019). Thus, the study's findings provide a better understanding of how distinct control systems including algorithmic direction influence employees' perceptions of work autonomy.

By applying fsQCA as a configurational method, our findings help to understand previous inconsistent findings by showing that the combination of algorithmic direction with other control mechanisms determines whether employees experience work autonomy. Furthermore, the results indicate that algorithmic direction does not undermine employees' work autonomy per se. In fact, the results suggest that when algorithmic direction is not combined with other formal output control in the form of algorithmic monitoring and changes in skill utilisation, employees still perceive high levels of work autonomy. In line with this finding, Delfanti (2021) assumes that when skills become obsolete, perceived competence may decrease, making employees even more dependent on algorithmic direction on how to perform work. However, in contrast to formal control, informal controls can partly offset the constraints on work autonomy that may arise from algorithmic direction. Informal control in the form of leadership correlates with higher decision autonomy. This finding is consistent with the overall appreciation of employees for beneficial mutual interaction and feedback from supervisors. (Hattrup et al., 2020). Moreover, employees may seek the assistance of supervisors and colleagues to manage or work around algorithmic direction, which helps them improve their work autonomy and achieve their work goals (Kellogg et al., 2020; Petrakaki & Kornelakis, 2016). These results imply that the opportunity to consult supervisors for suggestions, interpretations or negotiation is crucial for attaining method autonomy when algorithms are used to control work, confirming previous findings (Cram & Wiener, 2020; Ruiner & Klumpp, 2022; Terry et al., 2022).

Prior research indicates that informal clan control exerted by colleagues promotes competitive behaviour in workplaces utilising algorithmic management, limiting employees' ability to choose how to work (Elliott & Long, 2016; Payne, 2018). Our findings suggest that organisations can limit negative consequences of informal peer control in case of employees receiving algorithmic direction by refraining from combining algorithmic direction with algorithmic monitoring and a devaluation of prior skills.

Our research has practical implications for the implementation of algorithmic management in work organisations. It is important for employees to have work autonomy as it allows them to stay alert and train and develop their skills. Therefore, organisations should pay attention to different control configurations involving algorithmic direction and their specific implications for different dimensions of work autonomy. Yet, none of the control mechanisms studied can compensate for the limitations on work autonomy caused by formal output control through algorithmic monitoring and formal input control by devaluing prior skills. As algorithmic monitoring is typically important in algorithmic management, previous research suggests it is important to provide employees with access to and control over their monitoring. When implementing algorithmic direction and algorithmic monitoring in work procedures, it is advisable to do so in a transparent and controllable way so that employees can maintain their autonomy.

There are several limitations of this study that should be considered in future research. While the fsQCA of large German workplaces provides new insights into the configuration of different implementations of algorithmic direction and how they relate to work autonomy, analyses of smaller workplaces or workplaces in other countries could produce different results. In addition, further investigations considering group differences between different sectors or occupational status groups may provide additional knowledge that work organisations could consider when planning to implement algorithmic direction.

Conclusion

This study makes several contributions to the understanding of how algorithmic direction is related to employees' work autonomy. It is one of the first studies to focus on how conventional workplaces implement algorithmic direction as part of their control system. The study is based on a representative dataset of 559 employees working in large German organisations. The findings indicate that algorithmic direction is implemented in various distinct ways in traditional workplaces. We found that a significant share of control systems exhibits features of digital Taylorism (Noponen et al., 2023), often as a combination of algorithmic direction and algorithmic monitoring or, less commonly, as a combination of algorithmic direction and employee deskilling.

Other configurations show characteristics of digital empowerment (Cardinal et al., 2018; Sitkin et al., 2020), as algorithmic direction is combined with an upskilling of employees or close personal interactions with supervisors and peers. The findings also indicate that algorithmic direction does not replace informal clan control but rather complements personal interactions with supervisors and peers in most cases. Additionally, the results suggest that a combination of algorithmic direction and informal clan control through personal interaction with supervisors or colleagues allows for high levels of method autonomy if organisations avoid algorithmic monitoring and devaluing prior skills.

Moreover, the study shows that granting method autonomy can be achieved through a wider range of control configurations that incorporate algorithmic direction, as opposed to enabling criteria autonomy. Employees experience criteria autonomy only in those control systems that avoid algorithmic monitoring and a devaluation of employees' prior skills but require them to develop new skills *and* provide informal controls through personal interaction with supervisors *and* colleagues. The requirements for criteria autonomy are higher than for method autonomy, making it more difficult for organisations that use algorithmic direction to preserve criteria autonomy. Furthermore, if algorithmic direction does not require employee retraining for new skills, then employees may have method autonomy, but this configuration precludes criteria autonomy.

Overall, the results suggest that algorithmic direction does not necessarily lead to digital Taylorism, where employees are restricted in their work autonomy *per se.* Algorithmic direction can be used as a control mechanism while still allowing employees to perceive method and criteria autonomy. The configurational perspective highlights that employees' perception of work autonomy depends on the configuration of algorithmic direction with other control mechanisms.

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Appendix

Table A1. Original Measurement and Scales of the Outcomes and Conditions

	Original Item/Question	Original Scales				
Outcomes		Completely Applicable				Completely Unapplicable
		1	2	3	4	5
Method Autonomy	I am allowed to decide how to go about getting my job done.	❒	❒	❒	❒	❒
Criteria Autonomy	I am able to define my job objectives.	❒	❒	❒	❒	❒
Conditions		Completely Applicable				Completely Unapplicable
Algorithmic Monitoring	Information or data about my operations are automatically stored; for example, via an app, machines or a computer program.	1 ❒	2 ❒	3 ❒	4 ❒	5 ❒
			Yes		No	
			1		2	
New Skills Required	In the last three years, additional qualifications were required because of changes in my work in the course of digitalisation.		❒		❒	
Devaluation of Prior Skills	In the last three years, my professional expertise has become less important in the course of digitalisation.		❒		❒	
		Several times per day	Daily	Weekly	Rarely	Never
		1	2	3	4	5
Personal Interaction with Supervisor	How often do you communicate/interact face to face with your supervisor about your work?	❒	❒	❒	❒	❒
Personal Interaction with Colleagues	How often do you communicate face to face with your colleagues about your work?	❒	❒	❒	❒	❒

Table A2. Necessary Analyses

Autonomy Dimension	Method Autonomy			Criteria Autonomy		
Conditions	Cons. Nec	Cov. Nec	RoN	Cons. Nec	Cov. Nec	RoN
AM	.772	.571	.494	.791	.492	.452
DOWNG	.209	.587	.914	.211	.498	.898
UPG	.696	.556	.545	.709	.476	.504
IS	.772	.653	.643	.824	.586	.601
IC	.876	.599	.438	.896	.515	.392
~AM	.421	.742	.902	.455	.675	.880
~DOWNG	.887	.567	.344	.903	.486	.307
~UPG	.400	.600	.824	.405	.510	.793
~IS	.507	.688	.837	.532	.606	.803
~IC	.333	.729	.922	.348	.640	.899

Note. '~' denotes the negation of a condition. 'AM' = Algorithmic Monitoring, 'DOWNG' = Devaluation of Prior Skills, 'UPG' = New Skills Required, 'IS' = Interaction with Supervisor, 'IC' = Interaction with Colleagues; 'Cons. Nec.' = Consistency Parameter of Necessity; 'Cov. Nec' = Coverage Parameter of Necessity; 'RoN' = Relevance of Necessity.

Table A3. Truth Table Analysis of Method Autonomy

#	AM	DOWNG	UPG	IS	IC	Outcome	n	Incl	PRI
7	0	0	1	1	0	1	14	.956	.708
1	0	0	0	0	0	1	15	.954	.665
6	0	0	1	0	1	1	25	.948	.775
2	0	0	0	0	1	1	21	.919	.664
4	0	0	0	1	1	1	25	.885	.646
8	0	0	1	1	1	1	37	.869	.627
13	0	1	1	0	0	0	8	.957	.403
5	0	0	1	0	0	0	16	.946	.590
25	1	1	0	0	0	0	6	.946	.173
29	1	1	1	0	0	0	13	.931	.575
19	1	0	0	1	0	0	11	.924	.580
31	1	1	1	1	0	0	5	.922	.436
17	1	0	0	0	0	0	23	.888	.507
28	1	1	0	1	1	0	7	.877	.249
23	1	0	1	1	0	0	24	.865	.510
18	1	0	0	0	1	0	24	.842	.537
32	1	1	1	1	1	0	14	.829	.462
30	1	1	1	0	1	0	16	.824	.398
21	1	0	1	0	0	0	47	.820	.406
22	1	0	1	0	1	0	52	.777	.453
20	1	0	0	1	1	0	39	.764	.505
24	1	0	1	1	1	0	98	.720	.494
9	0	1	0	0	0	?	1	1	1
11	0	1	0	1	0	?	1	.991	0
27	1	1	0	1	0	?	1	.988	.697
3	0	0	0	1	0	?	4	.972	.678
10	0	1	0	0	1	?	2	.970	.034
15	0	1	1	1	0	?	1	.962	.194
12	0	1	0	1	1	?	1	.956	0
14	0	1	1	0	1	?	2	947	.381
16	0	1	1	1	1	?	2	.942	.291
26	1	1	0	0	1	?	4	.923	.311

Note. 'incl' = Parameter of Fit Consistency/ Inclusion Score; 'PRI' = Proportional Reduction in Inconsistency; 'AM' = Algorithmic Monitoring, 'DOWNG' = Devaluation of Prior Skills, 'UPG' = New Skills Required, 'IS' = Interaction with Supervisor, 'IC' = Interaction with Colleagues.

Table A4. Truth Table Analysis of Criteria Autonomy

#	AM	DOWNG	UPG	IS	IC	Outcome	n	incl	PRI
8	0	0	1	1	1	1	37	.848	.536
7	0	0	1	1	0	0	14	.939	.485
13	0	1	1	0	0	0	8	.932	.132
1	0	0	0	0	0	0	15	.929	.449
25	1	1	0	0	0	0	6	.919	0
5	0	0	1	0	0	0	16	.917	.367
29	1	1	1	0	0	0	13	.906	.335
2	0	0	0	0	1	0	21	.901	.473
31	1	1	1	1	0	0	5	.901	.255
19	1	0	0	1	0	0	11	.897	.437
6	0	0	1	0	1	0	25	.888	.491
4	0	0	0	1	1	0	25	.864	.449
17	1	0	0	0	0	0	23	.841	.336
28	1	1	0	1	1	0	7	.828	0
18	1	0	0	0	1	0	24	.820	.432
23	1	0	1	1	0	0	24	.819	.339
32	1	1	1	1	1	0	14	.814	.388
30	1	1	1	0	1	0	16	.793	.193
21	1	0	1	0	0	0	47	.781	.250
22	1	0	1	0	1	0	52	.734	.317
20	1	0	0	1	1	0	39	.716	.383
24	1	0	1	1	1	0	98	.641	.352
3	0	0	0	1	0	?	4	.991	.866
11	0	1	0	1	0	?	1	.983	0
9	0	1	0	0	0	?	1	.982	0
15	0	1	1	1	0	?	1	.961	0
27	1	1	0	1	0	?	1	.957	0
10	0	1	0	0	1	?	2	.953	0
12	0	1	0	1	1	?	1	.951	0
16	0	1	1	1	1	?	2	.950	.173
14	0	1	1	0	1	?	2	.910	.082
26	1	1	0	0	1	?	4	.862	0

Note. 'incl' = Parameter of Fit Consistency/ Inclusion Score; 'PRI' = Proportional Reduction in Inconsistency; 'AM' = Algorithmic Monitoring, 'DOWNG' = Devaluation of Prior Skills, 'UPG' = New Skills Required, 'IS' = Interaction with Supervisor, 'IC' = Interaction with Colleagues.