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Understanding Algorithmic Management in the Traditional Work Context: A Quantitative Analysis

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Research Paper

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Abstract. Algorithmic management (AM) is increasingly transferred to the traditional work context (TWC) and is applied to support the management of permanent workers. AM only partially replaces human managers here, but the core elements of AM remain similar. Hence, AM is implemented into pre-existing organizational structures to enhance processes and performance. AM in the platform-based context is already well-researched, its implications for the TWC from a managerial perspective remain unclear. To enhance our understanding, we conduct a quantitative study analyzing the utilization of AM at an international automotive supplier. Using linear mixed modeling, we examine a data set of 12743 error records and reveal that AM has performance advantages in the TWC as it reduces the error resolving time of workers. Furthermore, the impact of influencing factors such as workforce involvement, task complexity, time of work, and experience with AM are considered, evaluated, and discussed.

Keywords: Algorithmic management, traditional work context, manufacuturing data.

1 Introduction

The introduction of intelligent algorithms at the workplace heavily influences various aspects of work, such as the interaction among workers and managers. If algorithms are utilized to assume workforce management practices and increasingly take on managerial roles, it is also described as algorithmic management (AM) (Lee et al., 2015). Its characteristics are mainly rooted in the gig economy, where well-known platforms such as Uber or Upwork are the key players (Cameron et al., 2023). AM can scale such platform-based businesses, enabling them to react to fluctuating demands. Since the workforce is structured and managed by AM, it can be considered a critical success factor for their business models, significantly increasing their value contribution (Benlian et al., 2022; Möhlmann et al., 2021).

Even outside the platform-based work context, AM gains more and more importance in the traditional work context (TWC) (Benlian et al., 2022). Well-established firms (e.g., in manufacturing, hospitality, or warehouses) envision how the AM approach can be integrated into their existing organizational structures and improve their processes and performance (Cameron et al., 2023). In this context, AM is perceived as a “sociotechnical process emerging from the continuous interaction of organizational members and the algorithms that mediate their work” (Jarrahi et al., 2021). Hence, managers of established organizations must consider minor adaptations before transferring AM from the platform-based work context to the TWC. For example, AM in the traditional work setting coexists with human managers. It results in a complementary character of the algorithm, as the human-to-human interaction is supported by AM (Benlian et al., 2022; Wiener et al., 2021). Moreover, the organizational logic in traditional work should still follow an organizational hierarchy and not a platform logic (Ashford et al., 2018; Cappelli and Keller, 2013; Lippert et al., 2023). Despite these adaptations, the core elements of AM remain the same as AM in the TWC still includes the analysis of the massive amounts of data in real-time to improve learning algorithms that coordinate workers and inform automated managerial decision-making (Mateescu and Nguyen, 2019; Möhlmann et al., 2021). Besides, AM in the TWC also increases managerial power by mediating the pre-existing relationship between managers and workers (Jarrahi et al., 2021). Finally, for managers in established organizations, using AM to manage their available workforce efficiently is highly relevant (Cameron et al., 2023; Veen et al., 2020).

While these performance advantages of platform companies are well noted (Benlian et al., 2022), a validation of the impact of AM in the TWC is needed (Parent-Rocheleau and Parker, 2022). From this managerial perspective, further research on relevant moderators that influence the outcome of AM in the TWC is of high interest. Hence, we raise the following research question: *What performance impact does AM have in the TWC, and what are the relevant influencing factors?*

We anticipate the recent call of Cameron et al. (2023) for more quantitative approaches in this research area. Thus, we conducted a quantitative analysis within an international automotive supplier. We collected data on 15297 manufacturing errors at a German manufacturing plant between January and September 2023. Analyzing the data with linear mixed modeling, we find that AM significantly reduces error resolving time. Further moderating aspects such as workforce involvement, task complexity, time of work, and experience with AM are investigated and discussed.

2 Theoretical Background

AM can take over coordination and control activities traditionally performed by human managers (Möhlmann et al., 2021). As a result, an ongoing interaction occurs between workers and the algorithms that facilitate their work (Jarrahi et al., 2021). In the platform-based context, these interactions are facilitated via digital interfaces such as mobile apps managed by hidden data processes. Thus, a real co-working environment between employees and managers does not exist, and the algorithm is considered as co-worker asking to conduct a specific task (Tarafdar et al., 2022). In the platform-based work context, algorithmic matching and algorithmic control represent the two key dimensions. Algorithmic matching refers to the coordination of demand (customers) and supply (workers) and, e.g., serves as a marketplace. The platform aims to achieve the highest possible level of economic efficiency by, e.g., dynamic pricing strategies (Möhlmann et al., 2021). Algorithmic control makes use of algorithms capable of reviewing and controlling the actions of workers to ensure that their behaviour aligns with the overall goals of the organization (Cram et al., 2022; Kellogg et al., 2020). This alignment can be realized, e.g., by implicit or explicit recommendations via the algorithm, restricting workers' access to complete information or targeting to reward high-performing workers with non-monetary or monetary incentives (Kellogg et al., 2020). Based on this logic, algorithms create power asymmetries and constrain the actions of workers in the platform-based context (Kinder et al., 2019; Wood, 2021).

Whereas the utilization of algorithms for supervising freelance workers is well-established within the platform economy, there is an increase in AM usage in the TWC (Benlian et al., 2022). This increase holds for companies with traditional business models, such as Amazon or Deutsche Post (Benlian et al., 2022; Lippert et al., 2023). For managers in such organizations, using AM to manage workers is relevant for enhancing processes and performance (Cameron et al., 2023). It must be noted that traditional organizations must consider some adaptations for transferring the AM approach from the platform-based work context toward the TWC (Table 1). A vital adaptation is that AM only partially substitutes managers in the TWC, and the organizational logic still follows the organizational hierarchy as compared to the platform-based work context (Lippert et al., 2023). Besides, AM complements existing organizational structures, strengthens established operations, or is attached to existent processes (Cameron et al., 2023; Wiener et al., 2021). In addition, traditional companies organize work with AM around the established team structures of separate work units, while platform-based businesses are predominately task-centric (Karanović et al., 2021). Hence, the individual output within work units of traditional companies is more complex to optimize due to organizational intersections since work unit relevant outcomes might be preferred over organizationally preferred results (Olkkonen and Lipponen, 2006). Nevertheless, the fundamental elements of AM also apply to the TWC. For example, the existing hierarchical power dynamics between managers and workers are strengthened by AM (Jarrahi et al., 2021). Besides, the collected data enhances the algorithms that manage workers and improves automated decision-making of management (Mateescu and Nguyen, 2019; Möhlmann et al., 2021).

However, studies analyzing AM in the TWC are rare or predominantly focus on the workers' perspective. For example, Kellogg et al. (2020) investigates literature-based the role of AM for reshaping established manager-worker relationships, especially when workers resist to its implementation. In the field of human resource management, Meijerink and Bondarouk (2023) show the effects of AM on workers' autonomy and value creation. In sales organizations, the salespeople are instructed to follow algorithmic recommendations made by AM, which often leads to a defensive attitude. Finally, Lee (2018) analyzes the perceived fairness and trustworthiness of algorithmic decisions in the TWC. Especially with tasks that are attributed to humans, algorithms were recognized as less fair and trustworthy.

Table 1. From platform-based towards the traditional work context

Elements to consider	**Platform-based work context**	**Traditional work context**	**Sources**
Role of management	Substituted by AM	Co-exists with AM	(Lippert et al., 2023)
Role of AM	Foundation of any processes	Attached to pre-existing processes	(Cameron et al., 2023; Kinder et al., 2019)
Communication	Via AM	Via AM & people	(Benlian et al., 2022)
Form of organization	Task-centric	Team and work unit centric	(Karanović et al., 2021; Olkkonen and Lipponen, 2006)
Optimization of output	Individual observation and tracking	Overall observation, tracking	(Möhlmann and Henfridsson, 2019)
Employment	Self-employed, no permanent contract	Direct employment, permanent contract	(Ashford et al., 2018; Lippert et al., 2023)
Work environment	Isolated, AM as co-worker	Colleagues & AM as co-workers	(Lippert et al., 2023; Tarafdar et al., 2022)

Overall, studies on AM in the TWC need to consider the managerial perspective for utilizing AM. For managers of established organizations, the validation of the performance effects of AM in the TWC, as well as possible influencing factors, are of high relevance (Parent-Rocheleau and Parker, 2022).

3 Model and Hypotheses

It is well known that AM has an enormous efficiency potential and performance advantage in platform-based businesses (Jarrahi et al., 2023). Uber uses AM, e.g., to monitor the productivity and performance of its workers (Möhlmann et al., 2021). Besides, AM on platforms provides employees performance metrics. These metrics allow a comparison among employees and an overall performance evaluation of each individual to increase the productivity (Healy et al., 2017; van Doorn, 2017). Within the context of platforms, workers, therefore, aim to receive above-average ratings to avoid automatically sanctioning by the platforms' AM. Hence, sanctioning AM increases platform performance (Kuhn and Maleki, 2017; Wood et al., 2019). Outside of the platform-based work context, it is generally acknowledged that algorithmic technologies benefit to employers, e.g., through improved efficiency in decision-making or coordination activities (Kellogg et al., 2020). First researchers already show in a simulation study that AM can reduce the average duration of tasks in the TWC (Kandemir and Handley, 2019). Hence, we suppose:

Hypothesis 1: AM decreases the error resolving time.

In the TWC, AM is implemented in a pre-existing work environment with an established manager-worker relationship (Lippert et al., 2023). Thus, managers must actively involve workers in the implementation process to ensure successful outcomes (Jarrahi et al., 2021; Zink et al., 2008). Enhanced algorithmic transparency, understandability, or explanations, e.g., regarding the general process and outcomes, can lead to better reactions and improve usability (Kordzadeh and Ghasemaghaei, 2022; Langer and Landers, 2021). Hence, managers need to empower workers to provide feedback to the algorithmic work and raise questions when encountering confusion in the new setting (Tarafdar et al., 2022). Based on these reasons, the following hypothesis is proposed:

Hypothesis 2: Workforce involvement positively moderates the relationship between AM and the error resolving time.

For successful AM utilization, managers within the TWC need to understand the role of task characteristics which directly influence the application of the algorithm at its outcomes. Kordzadeh and Ghasemaghaei (2022) argue that for tasks with a high impact workers are more sensitive to algorithmic biases and might react unfairly to algorithmic processes. This reaction contrasts low-impact tasks, which are less prone to workers' concerns. In the field for automation, Vimalkumar et al. (2021) show that variances in task complexity lead to distinctions in their potential of automation. Whereas simple tasks with a low complexity have a higher automation potential, complex tasks are much more challenging to automate. Based on these arguments, we propose to analyze the effects regarding differing complexity levels of tasks, which describe how demanding a specific task is for the worker (Efatmaneshnik and Handley, 2021). Thus, we hypothesize the following:

Hypothesis 3: Task complexity negativly moderats the relationship between AM and the error resolving time.

Employees' well-being at the workplace is of high relevance for managers in the TWC, as workers are directly employed with a permanent contract (Ashford et al., 2018). However, working at nighttime is associated with increased health risks like sleep disturbances or disruption of the circadian rhythms (Boivin and Boudreau, 2014). Besides, the severe issues regarding workers' well-being, an excessive sleepiness during night shifts can also harm performance (Cordova et al., 2016). First researchers show that AM can positively impact the overall work environment, e.g., by avoiding overwork or enhancing decision-making (Kandemir and Handley, 2019; Kellogg et al., 2020; Parent-Rocheleau and Parker, 2022). To analyze whether managers can use AM in the TWC to enhance the working conditions during the nighttime we posit:

Hypothesis 4: Time of work (nighttime) positivly moderates the relationship between AM and the error resolving time compared to daytime.

Previous studies show that more experience within a particular role or with a specific task enhances workers' knowledge or job performance (Di Pasquale et al., 2020). According to the law of practice, performance within a job increases as workers practice a task more frequently (Newell and Rosenbloom, 1982). The reasons lay in the fact that workers undergo a learning curve and enhance their performance based on task repetitions and training (Glock et al., 2019). In the gig economy, recent results show that same-day experience increases workers' productivity (Guha and Corsten, 2023). Based on these assertions, the following hypothesis is proposed:

Hypothesis 5: Experience with AM positively moderates the relationship between AM and the error resolving time.

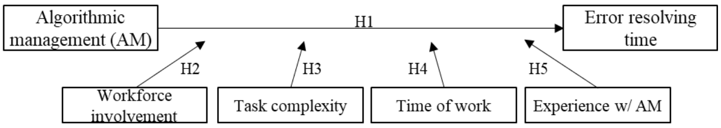


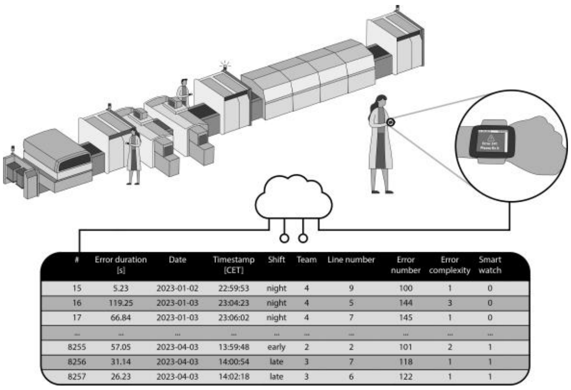
Figure 1. Research model.

4 Methodology

4.1 Research Setting, Data and Sample

We analyse the production data of an international automotive supplier to answer our research question. Our research object is using smart watches as an AM approach at a German manufacturing plant. The workers in our setting are responsible for ensuring the continuous operation of nine production lines, e.g., by maintaining equipment, promptly resolving any occurring errors, proactively preventing interruptions, and reducing downtime. They are split into four teams with similar backgrounds and demographics, working in a three-shift model. On average, two workers are responsible for three manufacturing lines representing a confusing working atmosphere. Moreover, the work environment is characterized by a high task fluctuation, which requires different skills and equipment. Hence, managers have the responsibility for overseeing and coordinating their employees' work efforst. Starting from April 1st 2023, AM is installed to optimize the communication on the shop floor and to deliver the right information at the right time to the right worker. AM informs the responsible worker in real time about machine alarms or events, also described as algorithmic recommending (Kellogg et al., 2020). In addition, AM provides detailed information related to the error type, position of error and how to fix it. Besides, it collects data on error resolving to predict patterns and to proactively identify upcoming errors. Finally AM learns from workers' responses, enabling managers to adjust the work processes accordingly. An illustrative example of the error report is shown in Figure 2.

We collect production data between January 2023 and September 2023. The uncorrected dataset contains 15297 data points, and each data point represents one occurring error at a production line. The following information is linked for each error: error duration in seconds [s], date, timestamp [CET], line number, and error number. We match additional descriptive data to each record, e.g., the shift, processing team, error complexity, and whether the error is processed with or without AM (smart watch). Based on process expert review, we removed all errors with an error duration below 5 s and above 300 s to enhance data quality. In addition, we clear out all errors with missing or wrong information. This results in the final data set of 12743 errors.



#	Error duration [s]	Date	Timestamp [CET]	Shift	Team	Line number	Error number	Error complexity	Smart watch
15	5.23	2023-01-02	22:59:53	night	4	9	100	1	0
16	119.25	2023-01-03	23:04:23	night	4	5	144	3	0
17	66.84	2023-01-03	23:06:02	night	4	7	145	1	0
...	...	...	...	...	...	...	...	...	...
8255	57.05	2023-04-03	13:59:48	early	2	2	101	2	1
8256	31.14	2023-04-03	14:00:54	late	3	7	118	1	1
8257	26.23	2023-04-03	14:02:18	late	3	6	122	1	1

Figure 2. Research setting with table illustrating sample data.

4.2 Measures

Dependent variable. We want to quantify the error resolving time as our dependent variable. Generally, minimizing error resolving time is essential for cycle time, which is fundamental for overall production performance (Ayabakan et al., 2017; Banker et al., 2006). For that purpose, we use the specific indicator variable *error duration* in order to measure error resolving time. The definition of error duration is as follows: it refers to the time interval between the occurrence of an error and its resolution by an operator or expert. The primary goal is to reduce the error duration since therewith production downtime can be decreased and thus overall plant performance can be increased. Accordingly, we are able to collect the error duration of 22 different error types, resulting in an overall 12743 errors.

Independent variables. Starting from the 1st of April 2023, 8902 errors were processed by the operators using AM, resulting in a binary measure for AM (1=w/ AM; 0=w/o AM), which can be identified based on the error type. Besides, we included four independent variables in our model (H2-H5), namely workforce involvement, task complexity, time of work, and experience w/ AM. These independent variables will be defined in the following. The variable *workforce involvement* (H2) refers to the fact that the affected workers of a team were involved in the use case development of the AM approach at their workplace or not. In our case, the employees of team 4 were actively involved by providing feedback and brining in own ideas, whereas the employees of teams 1-3 were not involved. Thus, we measure workforce involvement by comparing team 4 with team 1-3. In order to measure *task complexity* (H3), we use the variable error complexity. Error complexity is ordinally scaled and takes on values between 1 (low error complexity, can be easily solved by the worker) and 4 (high error complexity, workers cannot solve the error on their own). Process experts have categorized the complexity of the different error types according to a pre-defined scheme. Moreover, we considered the respective shift during which the errors were observed in order to measure the *time of work* (H4). The shift model includes the early shift (6:00 am – 2:00 pm), late shift (2:00 pm – 10:00 pm), and night shift (10:00 pm – 6:00 am). As nighttime refers to the period between sunset and sunrise, we consider the night shift as nighttime and the early and late shifts as daytime. As the last dependent variable, we measure the experience effect of the workers with the AM by the variable *experience w/ AM* (H5). To measure it, we counted the amount of days AM is in place and used by the workers, starting from 1st of April 2023 onwards.

4.3 Data Analysis

We use linear mixed modeling for our data analysis. Longitudinal data from repeated observations of 22 different error numbers at nine manufacturing lines provides evidence for the verification of this kind of modeling (Fahrmeir et al., 2013). It must be noted that linear mixed models (LMMs) are generally robust to violations of the model assumptions such as data not following a normal distribution (Schielzeth et al., 2020). The LMM is an extension of the general linear regression, allowing to model and estimate fixed and random effects. Thus, the LMM is also called the random effects model (Fahrmeir et al., 2013). In contrast to the fixed effects (unknown population parameters), random effects refer to subject-specific effects and can be described as grouping factors (McCulloch and Searle, 2000; Schielzeth et al., 2020). The overall goal of including subject-specific effects is to enhance the estimation of the fixed effects (Fahrmeir et al., 2013). We modeled two random effects: (i) manufacturing line and (ii) error number. The variable manufacturing line indicates which of the nine lines the error occurred. This is included as a random effect to avoid overlooking any bias coming from any line. Moreover, the error number was modeled as a random effect to consider modifications based on specific error types.

5 Results

5.1 Descriptive Statistics

Between January 2023 and September 2023, around 2/3 of the errors (8902) are processed with AM and around 1/3 (3841) errors without. In our sample – as a baseline – the average error duration without AM is 77.55 s. With AM, the error duration significantly decreases by 11.14 s (14.36 %) to 66.41 s. The error processing is distributed across the four teams almost equally. While team 1 processed 2856 errors (22.4 %), team 2 processed most errors (3381; 26.5 %). Team 3 & 4 processed 3249 errors (25.5 %) and 3257 errors (25.6 %). The errors occur in three different shifts in which all teams rotate. 3864 errors occurred during the early shift, representing 30.3 %, the smallest amount. 4057 errors (31.8 %) occurred in the late shift and 4822 (37.8 %) in the night shift. A total of 22 different error numbers are included in our sample, appearing on one of the nine production lines. Each error type occurs with varying frequency, between 3 and 4666 times within the nine months. Most occurring errors (11257) are attributed to complexity level 1. Besides, 1096 errors are categorized as complexity level 2, 194 as complexity level 3, and 196 as complexity level 4.

5.2 Linear Mixed Model

Table 2 summarizes the descriptive statistical values such as estimate, standard deviation (SD), p-value of the dependent variable *error duration w/ AM,* and all independent variables. *Manufacturing line* and *error number* are modeled as random effects.

Table 2: Results of the linear mixed model

Parameter	**Estimate**	**Standard deviation**	**p-value**	**95 % conf. interval**	
				Lower	**Upper**
Intercept	3.787	0.105	<0.001	3.578	3.905
Algorithmic management	-0.310	0.048	<0.001	-0.404	-0.217
Team (team 4)					
Team 1	-0.102	0.046	0.025	-0.192	-0.013
Team 2	-0.082	0.050	0.102	-0.180	-0.016
Team 3	-0.168	0.044	<0.001	-0.254	-0.081
Complexity (complexity = 1)					
Complexity = 2	-0.224	0.193	0.247	-0.605	0.157
Complexity = 3	-0.107	0.212	0.613	-0.523	0.309
Complexity = 4	0.142	0.255	0.578	-0.361	0.654
Shift (night)					
Shift (early)	-0.123	0.042	0.004	-0.205	-0.040
Shift (late)	0.019	0.042	0.650	-0.063	0.102
Workforce involvement (team 4)					
Workforce involve. (team 1)	0.123	0.055	0.025	0.015	0.231
Workforce involve. (team 2)	-0.028	0.054	0.606	-0.134	0.078
Workforce involve. (team 3)	0.163	0.053	0.002	0.059	0.267
Error complexity (compl.= 1)					
Error complexity (compl. = 2)	0.082	0.076	0.285	-0.068	0.232
Error complexity (compl. = 3)	0.438	0.189	0.021	0.067	0.808
Error complexity (compl. = 4)	0.224	0.195	0.250	-0.158	0.606
Nighttime (shift = night)					
Daytime (shift = early)	0.133	0.050	0.008	0.034	0.231
Daytime (shift = late)	-0.203	0.051	<0.001	-0.304	-0.103
Experience w/ AM (days)	0.002	0.000	<0.001	0.001	0.002

Dependent variable: Error duration [ln]

N = 12743; R^2 (marginal) = 0.015; R^2 (conditional) = 0.329; SD of random effects: 0.070

The coefficient of determination R^2 represents an essential indicator for the amount of variance explained by any linear model (Fahrmeir et al., 2013). For LMMs, reporting R^2 has become increasingly relevant. In this specific case, R^2 can be categorized into two types: *marginal* R^2 (= variance explained by the fixed factors) and *conditional* R^2 (= variance explained by both fixed and random factors) (Nakagawa and Schielzeth, 2013). Whereas the marginal R^2 can be reported with 0.015, the conditional R^2 reveals that 0.329 of variance can be explained by the entire model. It is acceptable, as most of our explanatory variables are statistically significant (Ozili, 2022). We start our analysis by examining the effect of AM on workers' performance. In particular, we consider the error resolving time (= error duration) as a relevant performance outcome. Our results show that AM has a significant negative effect on the *error duration* (exp(b) = 0.310; $p < 0.001$). Thus, it can be confirmed that AM significantly reduces the error resolving time (H1) and thus enhances work performance. For *workforce involvement* (H2), we found mixed effects. We can support that team 4 is significantly faster than team 1 (exp(b) = 0.013; p = 0.025) if both teams apply AM. However, we do not find this effect of team 4 compared to team 2 (exp(b) = -0.069; p = 0.606) and team 3 (exp(b) = -0.024; p = 0.002). Analyzing the level of *error complexity* (H3) reveals that AM does not work for all error levels the same way. The error duration of errors with complexity level 3 (medium level) is significantly higher with AM compared to errors with complexity level 1 (exp(b) = 0.263; p = 0.021). In contrast, we cannot identify significant effects for errors with a complexity of 4 (exp(b) = 0.631; p = 0,250) and complexity of 2 (exp(b) = -0.138; p = 0.285). Thus, we can only partially confirm *error complexity* as the assumed negative moderator (H3). The results concerning the *time of work* (H4) show that the early shift is significantly slower with AM compared to the night shift (exp(b) = 0.010; p = 0.008), whereas late shift is significantly faster (exp(b) = -0.184; $p < 0.001$) compared to the night shift. Hence, the hypothesized positive moderation effect of *nighttime* (H3) can only be confirmed for the early shift. Finally, we cannot support H5, as the error duration with AM is slightly increased with increasing *experience w/AM* (exp(b) = 0.002; $p < 0.001$).

We check the robustness of our results by analyzing the error duration of two error types that are not processed with AM starting April 1st, 2023. The robustness check reveals that the error duration without AM does not significantly decrease.

6 Discussion

As the first distinct contribution, we demonstrate with our study utilizing a quantitative analysis that the performance enhancements of workers observed in the platform business can also be recognized in the TWC. Interestingly, the performance increase is not based on individual tracking or related to penalties and sanctions in case of bad performance (Möhlmann, 2021; Wood et al., 2019). Instead, it is based on the enhanced coordination of workers within the complex work environment and an increased decision-making efficiency related to the error resolving (Kellogg et al., 2020). It is an important finding, as it can serve as a confirmation for traditional companies to implement AM to improve performance while respecting legal obligations and further encourage platform-based businesses to use AM ethically (Möhlmann, 2021).

In addition, four relevant moderators are examined that influence the outcome of AM in the TWC. From a managerial perspective the impact of (i) workforce involvement, (ii) task complexity, (iii) time of work, and (iv) experience w/ AM is considered. Strikingly, we find out that missing workforce involvement does not negatively affect performance outcomes. This clearly contradicts to general studies on technology implementation, which promote a participatory approach as a relevant success factor (Gagné et al., 2022; Jarrahi et al., 2021; Zink et al., 2008). Most probably, the reason is that we are dealing with a highly standardized work, which generally eases automation (Goel et al., 2021). Hence, AM is not considered disruptive in the TWC and represents a rather competence-enhancing than a competence-destroying technology (Ghawe and Chan, 2022; Tushman and Anderson, 1986). This can be explained by the fact that AM is attached to the pre-exisitng organizational environment. Hence, it augments a few managerial activities (Jarrahi et al., 2021). In the platform context, work is broken down into small parts (gigs), which disrupt the work identity, as the purpose of the work is more challenging to recognize due to this transience of work (Ashford et al., 2018). Besides, employees can hardly control the AM in the platform context, which means that autonomy is reduced (Kinder et al., 2019). The lack of autonomy leads to a classification of AM as a disruptive system since the algorithm replaces human roles step-by-step (Jabagi et al., 2019; Jarrahi and Sutherland, 2019).

On a generic level, it is recommended to structure tasks at varying degrees of complexity on a labor platform to attract the most suitable worker (Taylor and Joshi, 2018). We advance the discussion by showing a U-shape relationship for the moderation effect of task complexity in the TWC. Whereas AM has limited functionality for easy and complex tasks, AM significantly impacts tasks with medium complexity. Consequently, managers need to to look at the type of task before implementing AM in the TWC. Tasks with high complexity are more difficult to automate, since there are multiple possibilities to achieve a desired outcome, and further expert knowledge is needed (Efatmaneshnik and Handley, 2021; Vimalkumar et al., 2021). This finding proves that AM does not enhance workers' performance for highly complex tasks. In contrast, work performance for relatively simple tasks is also not improved by AM. One reason might be that such tasks are too simple (Parent-Rocheleau and Parker, 2022). Hence, the support of AM is not relevant for the workers. Instead, AM is highly meaningful for tasks with medium complexity. Generally, medium complex tasks indicate that not all complexity contribution elements such as the goal, input factors or process components are applying (Liu and Li, 2012). Here, AM reduces perceived task complexity and enables workers to enhance their work performance (Chan et al., 2015; Kyndt et al., 2011).

Furthermore, we can show that AM eases the working environment, e.g. during night shifts. In warehouses, AM is considered to enhance working conditions by simplifying workers' jobs or by solving problems (Parent-Rocheleau and Parker, 2022). We contribute to these findings and display that AM can level out performance fluctuation during nighttime. Studies in the medical domain indicate that shifts at nighttime are linked to disturbed circadian rhythms and inadequate sleep (Boivin and Boudreau, 2014). Such conditions frequently result in psychosomatic stress, manifesting as depression, burnout, cognitive impairment, and an elevated risk of work-related errors (Cordova et al., 2016; Maltese et al., 2016). This compensating effect of AM during nighttime emphasizes that AM can be introduced by managers as a a supportive IS in the TWC. Such supportive systems have already been proven to reduce perceived stress (Eisel et al., 2014).

Finally, our results do not show an influence of experience w/ AM on performance in the TWC. The reasons might be that the workers are familiar with the existing processes and can thus immediately exploit the full potential of AM (Jarrahi and Sutherland, 2019). The role of increasing knowledge and experience with the algorithm is also highly debated within the platform-based work business. On the one hand, gig workers use their increasing algorithmic competency to work around or manipulate the algorithm. This effect is also called "algoactivism" and refers to the individual or collective resistance towards AM (Jarrahi and Sutherland, 2019; Kellogg et al., 2020). On the other hand, Guha and Corsten (2023) show that same-day experience can also benefit gig workers' productivity up to a certain threshold.

Overall, our study contributes to research on AM as it validates the positive performance impact of AM in the TWC. Besides, we highlight the managerial perspective and show relevant moderating aspects that influence the success of transferring the AM approach to the TWC.

6.1 Pracitcal Implications

AM has great potential for established companies. However, selecting the right application areas with distinct carefulness is essential. While AM has a considerable impact related to tasks with medium complexity.it is not reasonable to implement AM for every single task. Nonetheless, we can recommend further integrating relevant aspects from the platform-based work context within the TWC, e.g., adding competency profiles and considering task complexity. With this approach, the tasks could be deployed even more precisely to a specific worker, which leads to performance enhancement. Additional contributions, such as recommendations or instructions, could further increase the value contribution of AM in practice.

6.2 Limitations and Further Research

Characteristics of AM in different work contexts The present study is subject to some limitations. First, we acknowledge that work performance is a multidimensional concept that includes various additional dimensions besides error resolving time. Thus, further research could also consider soft aspects such as the leadership style (Li and Hung, 2009). Second, the analyzed sample is limited to a time period of 9 months. It might lead to the fact that the effect of experience w/ AM (H5) could not be confirmed. However, while experience w/ AM might cause enhanced performance, it can also stimulate workarounds and a manipulation of AM (Jarrahi and Sutherland, 2019). As a future work, it would be reasonable to collect further data to analyze such consequences. Third, the data set was limited to error types that were subjected to the usage of AM. Nevertheless, most of the collected error types have not been processed using AM since 1st of April. Hence, these error types were excluded from the analysis, which might bias our results. Effort was taken to consider these errors in the robustness check. Nevertheless, further analysis might be needed as soon as AM is implemented for a more extensive range of errors.

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