Employee Affective Reactions to Algorithmic Management: How Does Context and Algorithm Transparency Matter?

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Abstract

The use of algorithmic management (AM) expands continuously, whereas knowledge about the influence of context and algorithm transparency on employee affective reactions to AM is still underdeveloped. To fill these voids, this study draws on the affective response model (Zhang, 2013) and examines the role of different contexts (i.e., work allocation, training allocation, performance evaluation) and levels of algorithm transparency (i.e., high vs. low) for the relationship between the decision-entity (human vs. algorithm) and employee reactions. Results of a vignette study with German employees (N = 354) showed that employees had more positive reactions to AM in training allocation compared to work allocation, whereas both levels of algorithm transparency had similar effects on reactions in the AM condition. Our results shed light into the intricacies of AM reactions, guiding future research directions. Practitioners can leverage these insights to determine contextual nuances of AM and refine consequent communication strategies.

Keywords: Algorithmic Decision-Making, Employee Reactions, Algorithm Transparency, Algorithmic Management

1. Introduction

Organizations are adapting to a transformative landscape, as the rise of algorithmic management (AM) sparks innovation (Jarrahi et al., 2021; Schulze et al., 2023). AM includes delegating managerial functions, specifically decision-making, to algorithms (Jarrahi et al., 2021). In this case, algorithms can be used to simply assisting human decision-makers in their decision-making (i.e., augmentation) or to fully automate decision-making procedures without human intervention (i.e., automation), applied across diverse contexts (Langer & Landers, 2021). AM promises to increase objectivity, speed, and efficiency of human management (HM) by processing comprehensive amounts of data in a short time span (Lee, 2018).

Besides these advantages, research and practice showed that the implementation of AM might replicate inherent biases rather than reducing or eliminating them (Langer & Landers, 2021). Previous research mainly focused on analyzing employee reactions towards AM in the field of recruitment because organizations tend to adopt algorithms in this area more frequently compared to other management functions (Koch-Bayram et al., 2023). The results show that applicants are rather context-sensitive in their reactions, for example, when the algorithm is the sole decision-entity or when it is used in asynchronous interviews rather than for CV screening (Koch-Bayram et al., 2023; Köchling et al., 2023). However, studies reveal that algorithm aversion, meaning the preference of human decision-makers, prevails (Dietvorst et al., 2014). As the application areas for AM are expanding, the question arises whether previous insights concerning applicant reactions can be transferred to other contexts of managerial decisions.

In this study, we distinguish the management contexts of work allocation, training allocation, and performance evaluation. Individuals prefer humans over algorithms in decisions that involve subjective and emotional evaluations, so-called human skills (Lee, 2018). Furthermore, the degree of interpersonal interaction in the context is critical for whether AM is accepted or perceived negatively (Köchling & Wehner, 2023; Köchling et al., 2024). Consequently, individuals tend to accept AM in contexts that include processing data for objective outcomes, that is, mechanical skills (Lee, 2018). Work allocation, a context adapted from Lee (2018), includes rather mechanical tasks due to the more objective measurements. Conversely, training allocation and performance evaluation have more profound effects on the employee's career, a high degree of interpersonal interactions, and involve emotional evaluations (i.e., human skills; Köchling et al., 2024).

URI: https://hdl.handle.net/10125/108856
978-0-9981331-8-8

In addition to context, previous research showed that increased transparency during the implementation of artificial intelligence (AI) leads to more positive applicant and employee reactions (Friedrich et al., 2022). During the introduction of AI, transparency can appear either focused on the algorithm, meaning to explain the functionalities and decision criteria of the algorithm, or focused on the decision process itself, meaning the role of the algorithmic decision within the decision process (Park et al., 2021). Previous studies focused on process transparency as they analyzed perception changes of AI when the algorithmic decision is reviewed by a human compared to AI as a sole decision-entity (Köchling & Wehner, 2023). Jabagi and colleagues (2024) added that the level of transparency influences employee reactions to AI, such as fairness and trust, as they get a deeper understanding of the interplay between human and algorithm.

However, current knowledge about employee reactions towards algorithm transparency is still limited. Thus, we aim to determine whether and how additional information about the algorithm's functionalities change employee reactions to AM. One reason why employees might react positively is that they could get insights into the functionalities of the system, thereby partially opening the black box and enabling them to detect flaws in the decision-making process (Park et al., 2021). Conversely, employees do not have detailed knowledge about mathematical functionalities of algorithms. Hence, giving them information about AI might lead to confusion and information overflow, which could yield into negative perceptions of algorithm transparency.

To fill these research voids, the aim of this paper is threefold. First, drawing on the affective response model (ARM; Zhang, 2013), we offer new insights on how affective reactions by employees might change depending on the managerial context in which AI is applied. By focusing on the management context as important boundary condition, we deepen our understanding on how employees evaluate situations that include the use of novel technologies and how these employee reactions affect turnover intention. In the spirit of extending the work by Lee (2018), we adapt her scenario descriptions to find further supporting evidence of the proposed influence of human skills over AI acceptance. Second, we question whether algorithm transparency might create adverse effects on employee reactions, extending previous research on positive implications of process transparency. Lastly, this study provides useful practical insights for businesses to understand how to implement AM in a way that works best for employees and managers.

2. Theoretical background and hypotheses development

2.1. Affective response model

According to Zhang (2013), the ARM describes the concept of affective reactions and places it in the context of communication and information technology. The author describes affect as a result of mainly unconscious evaluation processes towards a stimulus that helps individuals with orientation. When interacting with stimuli, individuals always display a core affect that is relatively stable throughout their life (Russell, 2009). A stimulus can be anything that a person reacts to, meaning that it does not always have to be real or manifest (Zhang, 2013). Affect can either reside within a person or a stimulus or between a person and a stimulus (Russell, 2009). One person can react differently to various stimuli as well as that several individuals can have different responses to the same stimuli, meaning that the reaction resides within the person and the stimulus (Zhang, 2013). This includes for example emotions, attitudes, or affective reactions. Affective reactions are a "broader term to include both a person's emotions induced by a stimulus and affective evaluations of the stimulus" (Zhang, 2013, p. 254).

The connection of both emotions and affective evaluations makes it perfectly suited to be used for analyzing relationships in human-AI interaction. In addition, the ARM has been adopted by previous literature in the realm of human-AI interaction, which further strengthens the inclusion of this theoretical model (Cui & Kankanhalli, 2023; Köchling et al., 2023).

2.2. Employee affective reactions to algorithmic management

Previous literature has established that AM elicits certain reactions in employees as its introduction still posits a new phenomenon in today's organizations (Langer & Landers, 2021). Algorithms function as an additional decision mechanism in AM which employees perceive as rather negative, as they lack understanding or insights into how the decision is formed and which role the algorithm plays (Benlian et al., 2022; Dietvorst et al., 2014). In particular, employees feel that the introduced algorithm is less fair, creepier, and that it invades their privacy more compared to the human equivalent (Jarrahi et al., 2021; Köchling & Wehner, 2023; Langer & König, 2018). After investigating current literature in terms of employee reactions to AM, we include the concepts of privacy concerns, emotional creepiness, and opportunity to perform as conceptualization of affective reactions in our study. This approach aligns with Zhang's (2013) theoretical basis, which proposed that affective responses should be directly linked to the technology in question.

Concerns about privacy occur in the area of AM implementation as employees feel that the AI system saves and uses highly personal data to come to a decision (Zhou et al., 2023). In particular, the data gathered in these practices is highly sensitive, revolving around past performance of an employee, the salary or the strengths and weaknesses of the person. Therefore, an imbalance of available information might occur in such a way that the employee feels that the employer has much more information available about them than vice versa (van Berkel et al., 2020). These imbalances might affect their reactions to AM, as the underlying algorithms make use of the gathered data, leading to a feeling of privacy concern. Therefore, we hypothesize the following:

H1 Compared to human management (HM), algorithmic management (AM) increases privacy concerns.

According to Langer and König (2018), emotional creepiness describes the emotional reaction to a creepy situation. Individuals display this intense emotional reaction when the predictability in the behavior of situations is reduced as well as when the situation is unknown (Langer & König, 2018). In line with this, individuals can perceive AI in AM to show unpredictable and unusual behavioral patterns as most algorithms are seen as a black box (Nordström, 2020).

Previous literature has found that decisions made by algorithms are attributed an inhuman and artificial component, which can make them seem creepy (Köchling et al., 2023; Köchling & Wehner, 2023; Langer & König, 2018). Previous literature has already established that introducing AI leads to higher emotional creepiness (Köchling et al., 2023; Langer & König, 2018). However, most of the studies in question were conducted in recruiting scenarios, that is, during screening or interviews. We therefore want to understand if AI is perceived with higher emotional creepiness in other managerial contexts as well. In conclusion, we hypothesize the following:

H2 Compared to human management (HM), algorithmic management (AM) increases emotional creepiness.

Opportunity to perform describes the possibility of being able to satisfactorily demonstrate one's own knowledge, skills and abilities (Köchling et al., 2023). Opportunity to perform can be used as a concept to address the affective evaluation aspect within affective reactions (Zhang, 2013). This way, we ensure that both aspects of affective reactions, that is, the aspect of emotions (i.e., privacy concerns, emotional creepiness) and affective evaluations (i.e., opportunity to perform) according to the ARM (Zhang, 2013), are covered. Previous research has already confirmed that opportunity to perform is a consistent predictor of perceived fairness and is implemented in this study to infer the level of fairness in different managerial decisions (Köchling et al., 2023). Low opportunity to perform can lead to candidates leaving the recruiting process prematurely because they do not feel they can present themselves sufficiently. In asynchronous videos there are no opportunities for personal feedback, hence, applicants perceive their possibilities to show what they can rather low (Köchling & Wehner, 2023). However, we see that previous studies mostly found place in recruiting scenarios, which is why it is unclear if those results can be directly transferred to other managerial contexts. We claim that the concept of opportunity to perform is relevant in other areas of management and maybe even more so as the outcome of low opportunity to perform can be much more severe than applicants leaving a recruiting process. Hence, we hypothesize the following:

H3 Compared to human management (HM), algorithmic management (AM) decreases opportunity to perform.

2.3. Context-specific employee affective reactions

Research has shown that the type of decision strongly influences employee reactions to AI (Lee, 2018). More precisely, this perception builds on different expectations towards certain decision tasks. Lee (2018) explains that in tasks that are based on explicit knowledge, people tend to assume that these tasks can be transferred into an algorithm. In contrast, she states that tasks that require experience and practical knowledge from the decision-entity are less likely to be trusted when they are made by an algorithm. Included in this rationale are tasks that involve making subjective and intuitive judgements as well as understanding emotions. With this in mind, this study assumes that individuals distinguish between decisions that have a higher possibility to be attributed to a human (i.e., subjective judgement, emotional skills) and decisions that are more likely to be attributed to an algorithm (i.e., analyzing quantitative data). Lee (2018) already confirmed this assumption in the tasks of work assignment and scheduling, recruiting, and performance evaluation. Work assignment and scheduling were presented as objective and mechanical types of decisions, which were perceived as similarly fair when being made by humans or algorithms. In the contexts of performance evaluation, however, AM was rated less fair.

Previous research has analyzed the proposed context specificities in employee reactions to AI mostly in the recruiting context (Hunkenschroer & Luetge, 2022). Only few studies tried to transfer this notion onto other management practices, such as promotional decisions (Höddinghaus et al., 2021), assigning training tasks (Höddinghaus et al., 2021), or evaluating performance (Zhang & Amos, 2023). These studies deployed only one or two different contexts, which complicates inferences between contexts. Furthermore, researchers used various scenario descriptions, which makes it difficult to synthesize the results. Accordingly, we focused on three different typical managerial contexts—work allocation, training allocation, performance evaluation—to challenge these limitations. For better comparison with previous literature, we adopt the context of work allocation from Lee (2018), which includes rather objective and mechanical decision components. Decisions made in training allocation, a context which was self-developed, and performance evaluation, also adapted from Lee (2018), require a higher degree of emotional and subjective skills. When allocating work tasks, the decision on who receives which tasks can be made rather objectively, for example, distributing the tasks equally between employees. The underlying knowledge needed to translate this decision into an algorithm seems rather explicit; therefore, employees might feel that an algorithm could perform the job just as well as a human (Lee, 2018). However, decisions about who receives a training or on how employees are evaluated require more complex knowledge from the decision-making entity, and might not be as easily transferable to an algorithm. In addition, previous relationships with managers and other colleagues come into play in these decisions, hence, employees might react more negatively when they are made by an algorithm. Therefore, we hypothesize:

H4 Compared to work allocation, algorithmic management (AM) in training allocation is positively associated with (a) privacy concerns, (b) emotional creepiness, and negatively associated with (c) opportunity to perform.

H5 Compared to work allocation, algorithmic management (AM) in performance evaluation is positively associated with (a) privacy concerns, (b) emotional creepiness, and negatively associated with (c) opportunity to perform.

2.4 Effects of algorithm transparency on employee affective reactions

During the introduction of AM, the disclosure of information regarding an algorithm's functionalities is referred to as algorithm transparency (Park et al., 2021). These functionalities encompass mathematical principles underlying the algorithm, explicit decision criteria guiding its decisions, and the nature of data utilized for decision derivation (Park et al., 2021). Previous research has emphasized that employees tend to perceive higher process transparency positively, such as revealing which role the algorithm plays in the decision-process (Friedrich et al., 2022). However, the literature on algorithm transparency presents a nuanced perspective. Park and colleagues (2021) delineate a phenomenon known as the "transparency paradox", which states that there is an optimal level of algorithm transparency that is perceived favorably. However, beyond a certain threshold, excessive information provision can lead to negative perceptions (Schmitt et al., 2021). Notably, as most employees lack expertise in algorithmic functionalities, confronting them with mathematical details of the algorithm may induce confusion rather than clarity (Park et al., 2021). This shows that emotional mechanisms play an important role in the assessment of algorithm transparency, as these reactions help to understand in detail how employees think about AM introduction. In particular, excessive information disclosure might be perceived as intrusive into their own privacy, as it reveals the specific types of data used for decision-making, hence, leading to increased privacy concerns and feelings of emotional creepiness (Zhou et al., 2023). When employees feel this type of surveillance, their ability to show what they are actually able to do could be reduced, leading to reduced opportunity to perform. To date, scholarly investigations have primarily focused on the positive ramifications of transparency, without delving extensively into the tipping point where transparency becomes counterproductive (Schmitt et al., 2021). This study seeks to address this gap by examining affective reactions to increased algorithm transparency, hence, we propose the following:

H6 Compared to low algorithm transparency, algorithmic management (AM) with high algorithm transparency is positively associated with (a) privacy concerns, (b) emotional creepiness, and negatively associated with (c) opportunity to perform.

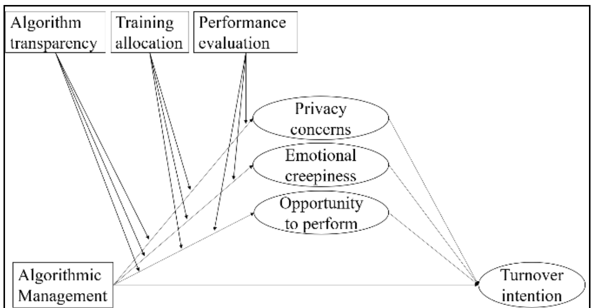
2.5. Turnover intention

Negative employee affective reactions significantly impact the entire organization (Zhang, 2013). Turnover intention, the employee's intention to leave the organization, is a crucial predictor of general turnover (Mobley et al., 1978), resulting in high recruitment costs and reduced efficiency in the long run. Previous research has demonstrated that negative employee affective reactions can increase turnover intention as these reactions can reduce trust and loyalty to the organization (Langer & König, 2018). Lastly, we hypothesize that our affective reactions mediate the relationship between AM and turnover intention.

H7 (a) Privacy concerns and (b) emotional creepiness are positively associated and (c) opportunity to perform is negatively associated with turnover intention.

H8 (a) Privacy concerns, (b) emotional creepiness, and (c) opportunity to perform mediate the relationship between AM and turnover intention.

The hypothetical research model is depicted in Figure 1.



Note. Reference category of algorithmic management: human management. Reference category of training allocation and performance evaluation: work allocation. Algorithm transparency: high vs. low (reference).

Figure 1. Hypothetical research model.

3. Methodology

3.1 Sample

We utilized an ISO 20252:19 certified online sample provider to obtain a quota-based sample. A G*Power analysis was conducted for MANOVA global effects, determining a required sample size of 324 participants to achieve statistical power (Faul et al., 2007). We slightly oversampled and recruited 393 participants based on this analysis. We excluded 39 participants who did not answer the implementation checks accordingly, resulting in a final sample of 354 participants, with 49.40% females and 50.60% males. The mean age was 45.33 years (*SD* = 12.14). Participants had to be at least 18 years old and currently employed.

3.2. Scenarios

In our experimental vignette study, we designed a between-subject approach with twelve hypothetical scenarios based on a 3 x 2 x 2 structure (3 contexts, 2 levels of transparency, 2 decision-entities) to allow realistic manipulation (Aguinis & Bradley, 2014). Participants were randomly assigned to one of the scenarios and answered identical questions about their scenario. We adapted two contexts from Lee (2018) for work allocation and performance evaluation. We developed the third context for training allocation. These fictional scenarios covered everyday work experiences in the three contexts. For the manipulation of algorithm transparency, we created the low transparency scenarios according to previous literature (Köchling et al., 2023). For the high transparency scenarios, we explained more in detail which parameters the algorithm or human used in the decision-making (e.g., data on speech rate, voice intensity, eye/body movements). These descriptions were also adopted from previous literature (Bader & Kaiser, 2019). We conducted a balance check to confirm the effectiveness of the random assignment of the service provider.

3.3. Measures

All questionnaire items were measured on a 5-point Likert scale, where 1 indicated "strongly disagree" and 5 "strongly agree". We performed a pre-test with 35 participants to enhance scenario and instrument clarity. Participants in the experiment failing to answer two attention checks correctly or three comprehension questions about the independent variable (AM vs. HM) were excluded to ensure attentiveness. We provided a brief definition of AI in the AM scenarios to make sure participants shared a common understanding of AI.

We created one dummy variable for training allocation (work allocation = 0, training allocation = 1) and one for performance evaluation (work allocation = 0, performance evaluation = 1). For algorithm transparency, we coded another dummy variable, where 0 = low and 1 = high transparency. Lastly, we created one dummy variable to compare the two decision-entities (HM = 0, AM = 1).

Privacy concerns were measured with two items from the organizational justice scale by Roch and Shanock (2006). Cronbach's Alpha was .63. Emotional creepiness was measured with two items from Langer and König (2018). Cronbach's Alpha for these items was .90. Opportunity to perform was measured with two items from Bauer et al. (2001). Cronbach's Alpha of this measure was .89. Turnover intention was measured with two items by Mobley et al. (1978). Cronbach's Alpha of this scale was .85.

4. Results

4.1. Descriptive statistics

All means, standard deviations and correlations are depicted in Table 1. The correlations ranged from small to moderate and the variance inflation factors ranged from 1 to 4.32, showing that multicollinearity is not apparent in this study.

Table 1. Correlations and descriptive statistics.

	Variables	*M*	*SD*	1	2	3	4	5	6	7
1	PC	3.47	0.86	(.63)						
2	EC	2.92	1.10	.36*	(.90)					
3	OP	3.35	0.96	.17*	-.36*	(.89)				
4	TI	2.93	1.12	.42*	.64*	-.40*	(.85)			
5	AM	0.49	0.50	.10	.18*	-.31*	.22*			
6	TA	0.34	0.47	-.07	.16*	.06	.05	.00		
7	PE	0.33	0.47	-.12*	.40*	-.12*	.32*	.00	-.50*	
8	AT	0.48	0.50	-.05	.08	-.16*	.07	.03	-.04	.02

Note. M = mean, *SD* = standard deviation. PC = privacy concerns, EC = emotional creepiness, OP = opportunity to perform, TI = turnover intention. Algorithmic management (AM): 0 = HM, 1 = AM. Training allocation (TA): 0 = work allocation, 1 = training allocation. Performance evaluation (PE): 0 = work allocation, 1 = performance evaluation. Algorithm transparency (AT): 0 = low transparency, 1 = high transparency. Cronbach's Alpha is reported on the diagonal in parentheses. * $p < .05$; $N = 354$.

4.2. Hypotheses testing

We conducted several multiple linear regressions as well as a mediation analysis in R with the mediation package to test our hypotheses. We investigated the interaction effects of training allocation, performance evaluation, and algorithm transparency as well as AM for each proposed mediator as dependent variable. Lastly, we conducted regression analyses to test the direct and indirect effects on turnover intention.

All models were significant and could be used for further interpretation (privacy concerns: $F(7, 346) = 3.26$, $p < .001$, $R^2 = .06$; emotional creepiness: $F(7, 346) = 29.12$, $p < .001$, $R^2 = .37$; opportunity to perform: $F(7, 346) = 10.90$, $p < .001$, $R^2 = .18$). Table 2 displays our regression results in detail. Regarding the direct effects of AM on our mediators, we found a significant relationship between AM and emotional creepiness ($\beta = .21$; $p = .016$) and between AM and opportunity to perform ($\beta = -.65$; $p < .001$); hence, we confirm H2 and H3. For H1, the relationship between AM and privacy concerns was not significant ($\beta = .01$; $p = .932$).

Table 2. Regression results.

Variable	*B*	*SE*	*β*	*p*
Treatment effects				
AM → privacy concerns	0.02	.18	.01	.932
AM → emotional creepiness	0.45*	.19	.21	.016
AM → opportunity to perform	-1.24***	.19	-.65	< .001
TA → privacy concerns	-0.15	.15	-.08	.326
TA → emotional creepiness	1.21***	.16	.52	< .001
TA → opportunity to perform	-0.48**	.16	-.24	.003
PE → privacy concerns	-0.22	.15	-.12	.148
PE → emotional creepiness	1.43***	.16	.61	< .001
PE → opportunity to perform	-0.47**	.16	-.23	.004
AT → privacy concerns	0.09	.13	.08	.305
AT → emotional creepiness	0.22	.13	.10	.090
AT → opportunity to perform	-0.47***	.13	-.25	< .001
Two-way interactions for moderators				
Privacy concerns				
AM x TA	-0.36	.22	-.20	.103
AM x PE	-0.33	.22	-.19	.132
AM x AT	0.09	.18	.50	.633
Emotional creepiness				
AM x TA	-0.18	.23	-.08	.441
AM x PE	0.12	.23	.05	.617
AM x AT	-0.10	.19	-.05	.594
Opportunity to perform				
AM x TA	0.94***	.23	.46	< .001
AM x PE	0.45*	.23	.24	.049
AM x AT	0.39*	.19	.20	.037
Effects of the mediators				
Privacy concerns → Turnover intention	-0.26***	.05	-.20	< .001
Emotional creepiness → Turnover intention	0.50***	.04	.49	< .001
Opportunity to perform → Turnover intention	-0.21***	.05	-.18	< .001
Direct effect				
AM → Turnover intention	0.14	.09	.06	.122

Note. B = unstandardized effect, *SE* = standard error, *β* = standardized effect, Algorithmic management (AM): 0 = HM, 1 = AM. Training allocation (TA): 0 = work allocation, 1 = training allocation. Performance evaluation (PE): 0 = work allocation, 1 = performance evaluation. Algorithm transparency (AT): 0 = low transparency, 1 = high transparency. Number of bootstrap samples = 1,000. * $p < .05$; ** $p < .01$; *** $p < .001$; $N = 354$.

We found significant moderating effects of training allocation ($\beta = -.65$; $p < .001$) and performance evaluation ($\beta = -.65$; $p < .001$) between AM and opportunity to perform, supporting H4c and H5c. We did not find any moderating effects of training allocation and performance evaluation for emotional creepiness and privacy concerns; hence, we reject H4a, H4b, H5a, and H5b. For our moderator algorithm transparency, results showed that the relationship between AM and opportunity to perform was significant ($\beta = -.65$; $p < .001$), confirming H6c. However, there was no association for emotional creepiness and privacy concerns; thus, we reject H6a and H6b.

Regarding the mediation effects, we conducted one multiple linear regression including all mediators and turnover intention as a dependent variable. The regression model was significant ($F(4, 349) = 80.13$, $p < .001$, $R^2 = .48$). We were able to confirm H7, as our proposed mediators all had a significant relationship with turnover intention (privacy concerns: $\beta = -.65$; $p < .001$; emotional creepiness: $\beta = -.65$; $p < .001$; opportunity to perform: $\beta = -.65$; $p < .001$).

Lastly, the results of our causal mediation analysis are depicted in Table 3. We calculated the average causal mediation effect (ACME), the average direct effect (ADE), the total effect, and the proportion of the data for which the mediator is truly mediating (Imai et al., 2010). We found that emotional creepiness and opportunity to perform are full mediators, as the ACME, total effect, and proportion mediated were significant while the ADE was not. Hence, we can confirm H8b and H8c. However, we reject H8a because the proportion mediated was not significant in the analysis for privacy concerns.

Table 3. Mediation results.

Variable	Estimate	95%-CI	*p*-value
Privacy concerns			
ACME	.05*	0.00; 0.10	.050
ADE	.14	-0.02; 0.33	.122
Total effect	.19*	0.01; 0.38	.038
Proportion mediated	.23	-0.07; 1.29	.072
Emotional creepiness			
ACME	.19***	0.07; 0.32	< .001
ADE	.14	-0.04; 0.31	.110
Total effect	.33***	0.12; 0.55	< .001
Proportion mediated	.57***	0.28; 1.32	< .001
Opportunity to perform			
ACME	.12***	0.05; 0.20	< .001
ADE	.14	-0.03; 0.31	.104
Total effect	.27**	0.09; 0.43	.008
Proportion mediated	.46**	0.18; 1.20	.008

Note. ACME = average causal mediation effect, ADE = average direct effect, CI = confidence interval; $N = 354$, * $p < .05$; ** $p < .01$; *** $p < .001$.

For our moderating results, we visualized the interaction effects (see Figure 2). We found that opportunity to perform was higher in HM for work allocation compared to training allocation. However, this changed in the AM condition as opportunity to perform was higher for training allocation compared to work allocation. Furthermore, the results showed that opportunity to perform was higher for work allocation compared to performance evaluation in the HM condition. However, in AM both work allocation and performance evaluation were perceived equally low for opportunity to perform. We observed a similar phenomenon for algorithm transparency, as we only found differences in the HM condition for opportunity to perform and no differences in the AM condition.

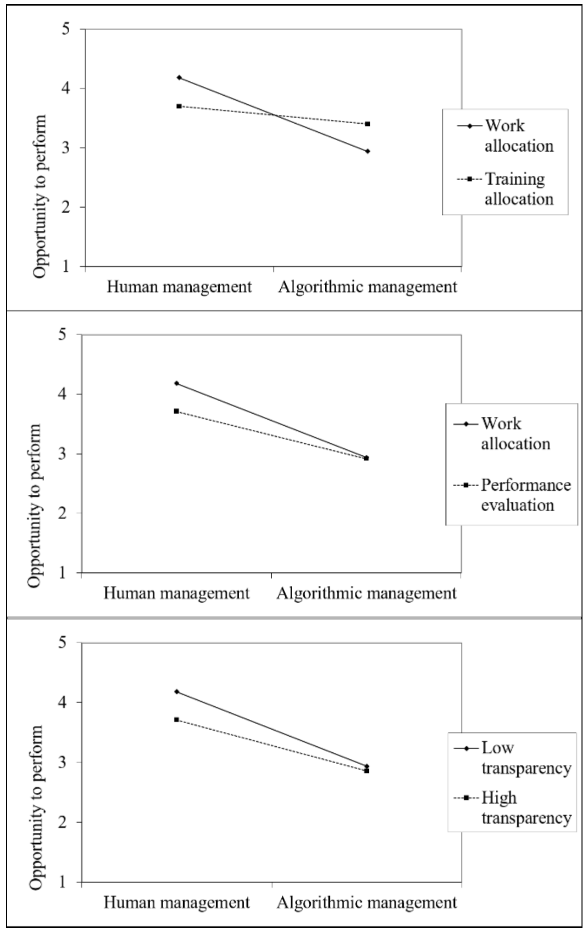


Figure 2. Interaction effects between opportunity to perform and moderators.

5. Discussion

The aim of this study was to investigate employee affective reactions to AM in different contexts (i.e., work allocation, training allocation, performance evaluation) with varying levels of algorithm transparency (i.e., low vs. high). The results showed that AM was perceived with higher emotional creepiness and lower opportunity to perform compared to HM. We showed that AM in the context of work allocation decreased the opportunity to perform compared to training allocation. For algorithm transparency, we found that a high level of transparency had a negative effect on opportunity to perform in HM, but we did not find differences in AM. Furthermore, emotional creepiness and opportunity to perform mediated the reactions between the deciding entity and turnover intention, whereas privacy concerns were less important.

This study found that AM in training allocation was perceived with a higher opportunity to perform compared to work allocation. These results are surprising, as we designed the scenarios for training allocation with higher needed human skills compared to work allocation, based on the findings of Lee (2018). Therefore, we expected affective reactions to be less positive in the training allocation scenarios. AM was perceived similarly in terms of affective reactions in both performance evaluation and work allocation. These findings are also surprising, as we designed the scenarios for performance evaluation in a way that we expected higher aversion towards AM. As we were not able to replicate Lee's (2018) results, other factors might play a role in the acceptance of AI.

One reason might be that this study used a German sample, while the sample of Lee (2018) consisted of employees of the United States; hence, the results might be subject to the German culture. Eitle and Buxmann (2020) state that the level of individualism-collectivism in a country could lead to different acceptance patterns of AI. In the United States, the level of individualism is higher than in Germany as proposed by Hofstede (2011), which might explain the different study outcomes. According to Mahmud et al. (2022), AI in contexts with higher uncertainty is perceived more negatively as the consequences of the decision cannot be predicted intuitively. AI is increasingly used in e-learning settings; hence, employees might have become more familiar with AM in training allocation (Kashive et al., 2020). Moreover, since the advent of Large Language Models (e.g., ChatGPT) in 2022, employees in Germany might be more familiar with AI in general, which could also explain our findings of AM in training allocation.

For work allocation, German organizations rarely use AI thus far, which could explain that our sample showed slightly higher aversion towards AM. Lee (2018) postulated that work allocation requires lower human skills. However, this notion might also be subject to the employees' culture as not every culture perceives the level of human skill the same. In Germany, work allocation can be associated with a good relationship to the supervisor or other colleagues. This implies that German employees might expect higher human skills for work allocation in our study.

Finally, Lee (2018) examined trust and fairness, which include different elements than our employee affective reactions. Hence, our results might be a fruitful avenue to investigate the role of contexts in greater detail.

Concerning algorithm transparency, our results showed that the level of transparency did not change reactions in our AM scenarios with the exception that that a high transparency had negative effects in the HM scenarios. We hypothesized differently as we expected a high level of insights into the algorithm to be perceived negatively. Thus, just mentioning the usage of AM already leads to negative reactions, regardless of further information about the algorithm. We argue that several cognitive processes take place during the evaluation of such a situation; hence, the outcome might be the same, but the reasoning could be different. For instance, on the one hand, individuals might perceive a high level of algorithm transparency positively in a sense that the black-box phenomenon of the algorithm is diminished (Nordström, 2020). On the other hand, they might feel that having detailed information about the algorithm invades their privacy as they know in detail which type of data is used for which cause (Zhou et al., 2023). Therefore, we propose that both mechanisms are at play at the same time, leading to similar results than having no information available at all.

5.1. Theoretical implications

This study provides four important contributions to the current debate on employee affective reactions toward AM. Firstly, it was shown that the implementation of AM causes negative employee reactions, which adds to the current state of research on algorithm aversion (Dietvorst et al., 2014). For contexts beyond recruiting, research on AM is still in its infancy, hence, the study results expand the aversion concept for our contexts. We embedded our research in the ARM (Zhang, 2013) which helped us to derive theoretical implications and extended affective reactions towards human-AI interaction.

Second, this study shows that acceptance of AM depends on the context it is applied in. However, contrary to our hypothesis, the implementation of AM in assigning work tasks is perceived considerably worse than the introduction of AM in allocating training programs. Therefore, we bring novel insights to the literature regarding context-specific investigation of employee reactions towards AM and show that organizations may lose qualified employees when implementing AM in allocating work tasks contrary to findings of previous literature (2018).

Third, our findings confirm the mediating effects of opportunity to perform and emotional creepiness, which underpin the importance of examining these variables and have thus expanded Zhang's (2013)

ARM. These emotional mechanisms appear to be gaining relevance as they have effects on organizations. Specifically, opportunity to perform is a construct that has primarily been analyzed in the recruiting context (Köchling et al., 2023). However, this study shows that opportunity to perform has a mediating effect between AM and turnover intention and, thus, should be integrated into future studies.

Finally, our findings indicate that privacy concerns assume a diminished role in AM, contradicting previous findings within the recruitment domain (Hunkenschroer & Luetge, 2022). We posit that in the applicant-organization dynamic, privacy concerns may intensify as organizations receive extensive applicant data while providing limited reciprocal information, suggesting information asymmetry (van Berkel et al., 2020). Conversely, in the employee-organization relationship, employees typically possess a greater degree of information about the organization, implying a more balanced information exchange. Consequently, we derive that employees might feel less privacy concerns compared to recruiting.

5.2. Practical implications

The findings of this study carry significant practical implications for organizations and managers. While AM presents many advantages, organizations must weigh potential negative employee reactions when implementing AM. Our results indicate that AM elicits fewer adverse employee reactions when used to allocate trainings compared to work tasks. Thus, our findings suggest that training allocation may serve as a more suitable context to introduce AM.

It is worth noting that employee reactions toward AM may evolve over time. On one hand, we may observe a shift in employee attitudes, potentially moving toward a more positive outlook. This shift could be attributed to increased exposure to ongoing discussions surrounding AI usage (Mahmud et al., 2022), potentially leading to a more positive evaluation of AM as a symbol of innovation and technological proficiency. On the other hand, it is possible that negative employee reactions may intensify in response to the public discourse on AI. Consequently, companies should strive to optimize the use of AM to create an environment conducive to the harmonious coexistence of employees and AM.

5.3. Limitations and future research

While our study explored three contexts, employee reactions to AM may evolve over time, making a longitudinal study valuable for understanding developments of their reactions. Besides our three depicted contexts, we are aware that other contextual or individual factors, for example, organizational culture, job insecurity, or trust in technology, could also attribute to differences in employee reactions. Hence, more research concerning employee reactions to AI is needed to increase our understanding of how and why employees react to the implementation of AI.

Previous research emphasized the importance of transparency in affecting employee reactions positively (Köchling & Wehner, 2023). We offer new insights about how transparency influence affective reactions by dividing transparency into high and low levels. Despite these insights, we did not address all possible nuances of transparency, for example, whether the level of explainability or auditability might matter for employees. Thus, researchers could examine algorithm transparency in more detail in future studies. Finally, we did not address process transparency further in our study; hence, future studies could elaborate on the interplay between process and algorithm transparency in more detail.

6. References

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