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The Role of AI in Performance Appraisal: A Mixed-Method Study of Employee Experience Through a Relational Lens

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Received: 21 March 2024 | **Revised:** 22 July 2025 | **Accepted:** 12 December 2025

Keywords: algorithmic HRM | artificial intelligence | performance appraisal satisfaction | sociomateriality

ABSTRACT

As artificial intelligence (AI) becomes more common in human resource management (HRM), especially in performance appraisals, questions arise about how employees respond to AI involvement in these processes. While existing research often treats AI as a technical tool, this study also views AI as a social actor that interacts with employees. Using sociomateriality and attribution theory, we examine how AI's characteristics and its role in appraisal procedures influence employee satisfaction with performance appraisals. Across three scenario-based experiments with 1002 participants and one survey with 321 respondents, we find that certain characteristics of the AI rater and the decision-making power distribution in AI appraisal procedures have a significant impact on employees' performance appraisal satisfaction. These results highlight the importance of considering the technical and social dimensions of AI in HRM practices. Our findings offer practical guidance for organizations implementing AI in performance appraisals and contribute to a deeper understanding of AI's impact on the employee experience.

1 | Introduction

The rapid rise of artificial intelligence (AI) is reshaping human resource management (HRM). AI refers to systems that can accumulate and learn from experience and perform cognitive tasks, often mimicking human reasoning and social behavior (Pan and Froese 2023). With this capacity, AI has a great influence on employee experience in HRM practices such as recruitment (Lambrecht and Tucker 2019; Suen et al. 2019) and performance appraisals (Lee 2018; Newlands 2021; Newman et al. 2020). Although scholars widely recognize the importance of AI in HRM (Budhwar et al. 2023; Tambe et al. 2019), research on its impact remains inconsistent (Pan and Froese 2023). Some studies highlight benefits such as greater efficiency (Suen et al. 2019), enhanced employee experience (Malik et al. 2023), and lower turnover (Malik et al. 2022). Others raise concerns about fairness (Lambrecht and Tucker 2019; Lee 2018; Newman et al. 2020) and deteriorating work conditions (Newlands 2021). These conflicting findings may stem from a common assumption: that AI is a neutral, standalone tool. In reality, AI interacts with people in complex ways, forming sociotechnical entanglements (Makarius et al. 2020). Overlooking this social dimension may limit our understanding of AI's true impact on HRM.

The AI-based performance appraisal offers a compelling example of AI–human entanglement in the workplace, as AI can take over appraisal tasks traditionally handled by humans, thus positioning itself as a social actor in employee interactions (Budhwar et al. 2023). In prior research, employee satisfaction with appraisals is a key indicator of their experience (Schleicher et al. 2019). While negative perceptions remain prevalent (DeNisi and Murphy 2017; Dusterhoff et al. 2014; Schleicher et al. 2019), positive employee reactions are essential, as they help translate appraisals into constructive behaviors and favorable outcomes for organizations (DeNisi and Murphy 2017; Dusterhoff et al. 2014; Kuvaas 2006; Memon et al. 2020). Extant studies

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consistently show that the rater and the appraisal procedure significantly influence satisfaction (DeNisi and Murphy 2017; Schleicher et al. 2019). However, employees may respond differently to AI versus human raters (Lee 2018; Newman et al. 2020). While much of the literature on AI in performance appraisals has focused on ethical concerns, such as fairness and surveillance (Lee 2018; Newman et al. 2020; Newlands 2021), employee satisfaction remains an understudied but increasingly important dimension of the AI-enabled appraisal experience.

To address shortcomings in the existing literature, we investigate the antecedents of employee satisfaction with AI-based performance appraisals, with particular attention to the complex entanglement between AI and human actors. Drawing on the sociomateriality paradigm (Orlikowski and Scott 2008; Jones 2014; Scott and Orlikowski 2014) and attribution theory (Eberly et al. 2011; Weiner 1974), our study makes several contributions to the literature. First, we introduce the sociomateriality paradigm to the HRM domain by applying it to the context of AI-based performance appraisals. While the HRM literature treats AI and humans as separate entities (Malik et al. 2022; Pan et al. 2022), the sociomateriality paradigm conceptualizes technology as inherently interwoven with social structures (Orlikowski and Scott 2008; Scott and Orlikowski 2014). It sees technology as meaningful and influential only when it is in relationship with people (Jones 2014; Scott and Orlikowski 2014). By adopting this relational lens, our study offers a novel theoretical approach to understanding AI in HRM and contributes to strengthening the conceptual foundations for future research on AI–human dynamics in the workplace.

Second, we build on the sociomateriality paradigm by incorporating attribution theory to better explain how people interpret AI–human entanglements. While sociomateriality emphasizes the relational nature of technology (Jones 2014), it offers limited guidance on how to understand the relationship with technology from the perspective of individual users. By integrating attribution theory, we provide a framework for examining how employees form reactions based on different types of attributions within AI-driven performance-appraisal contexts. This integration strengthens the sociomaterial approach by adding a more precise lens for analyzing employee responses to AI.

Third, we contribute to the HRM literature by deepening the knowledge of employee satisfaction with AI-based performance appraisals. The literature on AI-based performance appraisals mostly focuses on the justice of an appraisal (Lee 2018; Newman et al. 2020). Considering the importance of performance appraisal satisfaction in improving employee productivity and organizational outcomes (Dusterhoff et al. 2014; Memon et al. 2020; Schleicher et al. 2019), we extend the HRM literature by identifying the antecedents of performance appraisal satisfaction within the emerging context of AI-based performance appraisals.

2 | Theoretical Background: The Sociomateriality of AI

The performance appraisal is one of the most important HRM activities for organizations and employees (Aguinis 2023; DeNisi and Murphy 2017). Employee experience in appraisals plays a key role in determining appraisal effectiveness (DeNisi and Pritchard 2006; DeNisi and Murphy 2017), shaping outcomes such as satisfaction, commitment, and performance (DeNisi and Pritchard 2006; DeNisi and Murphy 2017; Farndale and Kelliher 2013). Malik et al. (2023) defined employee experience in AI-assisted HRM applications as nondeliberate and spontaneous employee reactions to diverse stimuli. Because employees' satisfaction is one of the most fundamental indicators of employee experience (Chen and Fulmer 2018), we use performance appraisal satisfaction as a proxy for overall employee experience in AI-based performance appraisals.

Prior research has identified rater characteristics and appraisal procedures as central to the employee experience in performance appraisals (e.g., Aguinis 2023; DeNisi and Murphy 2017; Dusterhoff et al. 2014; Farndale and Kelliher 2013; Schleicher et al. 2019). Traditionally, "rater" refers to the manager or supervisor who performs the appraisal, and "procedure" refers to the arrangement of tasks, methods, and norms in the appraisal (Aguinis 2023; Schleicher et al. 2019). Employees may have a better experience when they trust the raters and believe the procedures are fair (Farndale and Kelliher 2013). Consequently, employees' performance appraisal satisfaction increases when they believe in the rater's trustworthiness and expertise (Schleicher et al. 2019) or when employees can voice their opinions freely (Shrivastava and Purang 2011; Williams and Levy 2000) and understand the appraisal process (Schleicher et al. 2019; Williams and Levy 2000).

When AI is involved in performance appraisals, employees encounter a novel form of human–technology entanglement. Drawing from the sociomateriality paradigm (Orlikowski and Scott 2008; Jones 2014), we use "entanglement" to describe the inseparable relationship between AI and human actors in appraisals. This perspective, rooted in actor-network theory (Latour 2007), emphasizes that technology is not an external tool but an intrinsic part of social structures and practices. The meaning of technology usage emerges only through ongoing interaction between material (AI) and social (human) elements (Jones 2014; Scott and Orlikowski 2014).

In AI-based performance appraisals, supervisors may rely on AI-generated evaluations, or AI may fully replace human judgment. In the former case, AI acts as a partial rater by influencing decisions; in the latter, it serves as the sole rater. Thus, the rater is no longer just a human supervisor, as AI now holds full or shared decision-making power. This introduces a more complex power dynamic, where employees must make sense not only of influence from humans (Shrivastava and Purang 2011; Williams and Levy 2000) but also of the authority given to AI. As a result, AI-based performance appraisals represent a fusion of technical and social elements. The material (rater characteristics) and social (appraisal procedures) aspects are deeply entangled, jointly shaping how power is enacted and experienced (Scott and Orlikowski 2014; Jones 2014). This new form of appraisal practice directly influences employee satisfaction in the AI-mediated appraisal experience.

The sociomateriality of AI, as reflected in the characteristics of the AI rater and the involvement of AI in the appraisal

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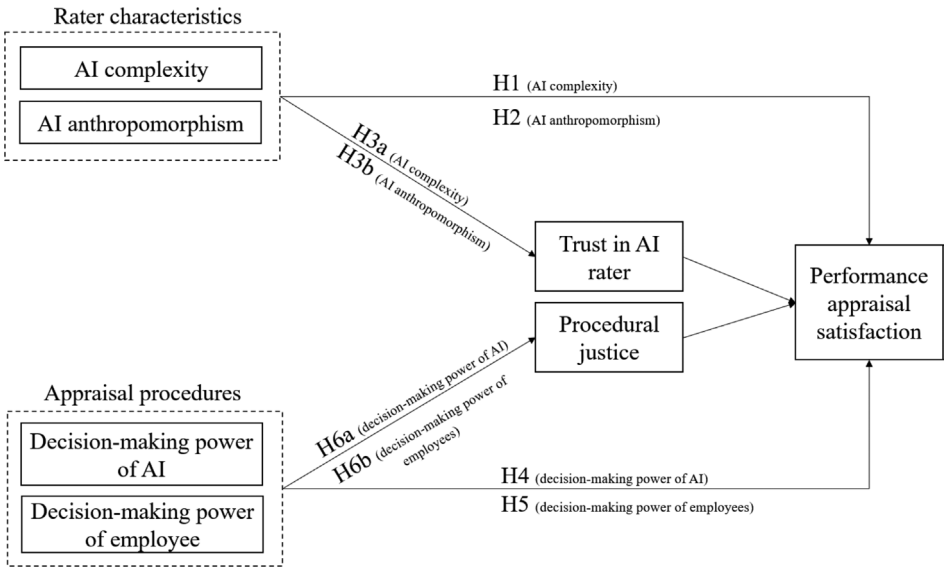

FIGURE 1 | Conceptual model.

procedures, aligns with the HRM literature to emphasize the importance of raters and procedures in determining employees' performance appraisal satisfaction (Schleicher et al. 2019; Williams and Levy 2000). While sociomateriality offers a relational lens, it does not fully explain how individuals psychologically interpret these entanglements. Therefore, we integrate attribution theory (Eberly et al. 2011; Weiner 1974) to further interpret employee experience in AI-based performance appraisals through the relational lens. In doing so, we identify rater characteristics, represented by AI complexity and AI anthropomorphism, and appraisal procedures related to decision authority, represented by the decision-making power of AI and that of employees, as psychological antecedents of performance appraisal satisfaction.

3 | Hypotheses Development: Attributions of AI-Based Performance Appraisals

Classical attribution theory (Weiner 1974) argues that people try to make sense of novel, unexpected, or negative events by analyzing cues related to actors involved, the situation, and the timing. Based on those cues, individuals attribute the cause of such events to either themselves (i.e., internal attribution) or external factors such as other people or situations (i.e., external attribution). Expanding on this view, Eberly et al. (2011) introduced the concept of relational attribution, where individuals attribute the cause of an event to their relationships with others.

In the context of AI-based performance appraisals, employees may interpret AI through relational and internal/external attributions. First, employees may attribute the cause of an appraisal to their relationships with the AI rater. Therefore, the characteristics of an AI rater may influence relational attribution, as employees are more likely to build relationships with certain types of AI. Second, employees may attribute the cause of an appraisal either to themselves when they acquire a high level of decision-making power in the appraisal procedures or to an external party (i.e., AI) when AI acquires a high level of decision-making power. Therefore, the power arrangements of procedures may induce employees' internal/external attributions. The following section explains how AI characteristics and appraisal procedures influence employee experience in performance appraisals and thus serve as antecedents of employees' performance appraisal satisfaction through the attribution lens. Figure 1 presents the conceptual model of this study.

3.1 | Attribution Toward AI Raters: AI Characteristics and Trust in AI

The characteristics of an AI rater largely depend on the technological features of the AI application used in the appraisal. The technological features of AI have attracted considerable research attention (e.g., Budhwar et al. 2023; Pan et al. 2022; Lambrecht and Tucker 2019). However, most of these studies focus on AI as a technical tool (Lambrecht and Tucker 2019; Malik et al. 2022; Pan et al. 2022; Suen et al. 2019), thus overlooking its social and material entanglement. Through the relational lens in the sociomateriality paradigm and attribution theory, AI's technological features have meaning only when involving social relationships. Such features serve as information cues that shape how employees make relational attributions when AI undertakes a social role as a performance appraisal rater. Prior studies on AI-based HRM indicate that AI complexity (Pan et al. 2022) and AI anthropomorphism (Li and Sung 2021) are two highly relevant features related to employees' perceptions of AI. Therefore, we focus on these two dimensions: one traditional technological feature (i.e., AI complexity) and one AI-specific feature (i.e., AI anthropomorphism) to respectively capture the general and distinctive characteristics of AI.

AI complexity refers to the perceived difficulty of using AI technology (Pan et al. 2022). When AI has a high level of complexity, it is difficult to understand and requires much mental effort to use (Pan et al. 2022). AI complexity is associated

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with negative experience and perceptions (Pan et al. 2022). In performance appraisals, when raters are accurate and reliable (Shrivastava and Purang 2011), and employees understand how raters operate the appraisal process (Schleicher et al. 2019), employees are more likely to be satisfied with the appraisal. Otherwise, they tend to be dissatisfied due to negative employee experience. When a highly complex AI replaces the human supervisor as the appraisal rater, employees may find the AI rater unclear, difficult to understand, and not easy to engage with. Thus, they are likely to be dissatisfied with the AI-based performance appraisal. Therefore, we propose that the AI complexity of an AI rater reduces employees' performance appraisal satisfaction.

Anthropomorphism is the tendency to attribute human characteristics or behaviors to a nonhuman entity (Epley et al. 2007). Prior research argues that people tend to perceive AI as humanlike if it appears capable of feeling compassion, showing empathy, or making cognitive or moral judgments (Pelau et al. 2021). Therefore, in this study, AI anthropomorphism refers to AI characteristics that lead employees to perceive AI as humanlike, such as friendly vocal interfaces or emotional recognition capabilities. A high degree of AI anthropomorphism can reduce the psychological distance between AI and humans (Li and Sung 2021), thereby fostering positive employee reactions through enhanced experiences (Li and Sung 2021). Given this, we propose that the AI anthropomorphism of an AI rater improves employees' performance appraisal satisfaction. This leads to the following hypotheses:

H1. *A higher level of AI complexity reduces employees' performance appraisal satisfaction.*

H2. *A higher level of AI anthropomorphism increases employees' performance appraisal satisfaction.*

Relational attribution theory posits that individuals may interpret the causes of events in terms of their relationships with others, and that these attributions can in turn alter their perceptions of those relationships (Eberly et al. 2011). In traditional performance appraisals, the rater–ratee relationship is crucial for performance appraisal satisfaction (DeNisi and Murphy 2017; Dusterhoff et al. 2014). A central aspect of this relationship is trust, which shapes the employees' experience and performance appraisal satisfaction (Schleicher et al. 2019; Shrivastava and Purang 2011). As AI undertakes the role of a rater, employees may form relational attributions toward AI, perceiving it as a social actor. Research suggests that individuals can extend trust to AI in similar ways as they do to humans (Lankton et al. 2015). From this perspective, trust in AI becomes a meaningful relational construct that may mediate the effects of AI characteristics on performance appraisal satisfaction.

When employees believe a rater is reliable, accurate, and trustworthy, they tend to trust the rater and become satisfied with the performance appraisal (DeNisi and Murphy 2017; Shrivastava and Purang 2011). Therefore, an AI rater with low complexity may increase performance appraisal satisfaction by earning employees' trust, because such AI is clear, understandable, and more trustworthy. Meanwhile, when a rater has good communication skills and shows empathy to ratees, employees are likely to be satisfied with the performance appraisal due to a better employee experience (DeNisi and Murphy 2017; Shrivastava and Purang 2011). Furthermore, the anthropomorphism of nonhuman agents has a strong impact on individuals' expectations of these agents' trustworthiness (Epley et al. 2007). Therefore, when AI with a high level of anthropomorphism acts empathically and trustworthily, such AI anthropomorphism can lead to greater trust in AI (Lankton et al. 2015; Pelau et al. 2021). Taken together, these arguments suggest that trust in AI may serve as a relational mechanism linking AI rater characteristics (complexity and anthropomorphism) to employees' satisfaction with AI-based performance appraisals. This leads to the following hypotheses:

H3a. *Employees' trust in the AI rater mediates the relationship between their performance appraisal satisfaction and AI complexity.*

H3b. *Employees' trust in the AI rater mediates the relationship between their performance appraisal satisfaction and AI anthropomorphism.*

3.2 | Attribution Toward Procedures: Decision-Making Power and Procedural Justice

The decision-making power arrangement within appraisal procedures plays a critical role in shaping employee experience and influencing how employees react to appraisals (Schleicher et al. 2019; Williams and Levy 2000). Drawing on attribution theory (Weiner 1974), such power dynamics affect employees' perceptions of controllability, which in turn determines whether they attribute appraisal outcomes internally (to themselves) or externally (to others or the situation) (Weiner 1974; Hewett et al. 2018). When AI holds greater decision-making power during appraisal procedures, employees are likely to perceive AI as the primary actor responsible for the outcome and apply external attribution. Such an external locus of causality is likely to induce negative employee reactions because individuals tend to react negatively when they feel outcomes are beyond their control (Weiner 1974; Hewett et al. 2018). Prior research shows that employees react negatively to performance appraisals when AI fully determines appraisal ratings (Lee 2018; Newman et al. 2020). Therefore, we propose that higher decision-making power of AI reduces employees' performance appraisal satisfaction.

In contrast, when employees have greater decision-making power during appraisal procedures, they are more likely to perceive themselves as responsible for the outcome, resulting in internal attribution. Individuals tend to react more positively when they feel in control (Weiner 1974). Research shows that employees report more positive experiences and greater satisfaction with performance appraisals when they are actively involved in the appraisal procedure and have the opportunity to voice their opinions (Schleicher et al. 2019; Williams and Levy 2000). These findings suggest that employees' increasing control over appraisal procedures encourages internal attribution, which in

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turn enhances performance appraisal satisfaction. Accordingly, we propose that the higher decision-making power of employees enhances employees' performance appraisal satisfaction. This leads to the following hypotheses:

H4. *Higher decision-making power of AI reduces employees' performance appraisal satisfaction.*

H5. *Higher decision-making power of employees increases employees' performance appraisal satisfaction.*

The controllability of performance appraisal procedures is highly relevant to employees' confidence in procedural justice. If employees understand how the performance appraisal is derived and have some degree of controllability in the procedures, their perceived procedural justice increases (DeNisi and Murphy 2017; Williams and Levy 2000). According to attribution theory (Weiner 1974; Hewett et al. 2018), internal attribution is more strongly associated with higher perceived controllability of an action than external attribution. Due to different perceptions regarding the controllability of performance appraisal procedures, the external and internal attributions contribute differently to employees' perceived procedural justice, which eventually leads to varying levels of performance appraisal satisfaction (Shrivastava and Purang 2011; Williams and Levy 2000).

Given that the decision-making powers of AI and employees are respectively linked to external and internal attributions, the two types of power arrangements may influence employees' performance appraisal satisfaction by altering perceived procedural justice. Prior literature confirms that the use of AI in performance appraisals can undermine perceived procedural justice (Lee 2018; Newman et al. 2020). Employees often view granting AI greater decision-making power as unfair, largely due to a lack of confidence in AI's ability to operate the appraisal procedure appropriately (Lee 2018; Newman et al. 2020). Therefore, the higher decision-making power of AI may reduce employees' performance appraisal satisfaction by diminishing their experience of procedural justice. In contrast, employee participation constitutes a key component of positive employee experience, particularly in relation to procedural justice (Dusterhoff et al. 2014). Employees are more likely to perceive appraisal procedures as fair if they have the opportunity to participate and express their voice, opinions, or preferences in decision-making (Dusterhoff et al. 2014; Williams and Levy 2000). Therefore, the higher decision-making power of employees may enhance performance appraisal satisfaction by increasing perceived procedural justice. Consequently, we propose that perceived procedural justice mediates the relationships between the decision-making power in procedures and employees' performance appraisal satisfaction, leading us to the following hypotheses:

H6a. *Employees' perceived procedural justice of AI appraisal mediates the relationship between their performance appraisal satisfaction and decision-making power of AI.*

H6b. *Employees' perceived procedural justice of AI appraisal mediates the relationship between their performance appraisal satisfaction and decision-making power of employees.*

4 | Overview of Studies

We conducted one experimental study and one survey study. Study 1 consisted of three scenario-based experiments (Study 1a–c) involving a total of 1002 employees to test our hypotheses. We opted for a series of experiments rather than a single experiment due to the methodological challenges of including multiple scenarios within one experiment. Study 2 involved a survey of 321 employees who had experienced AI-based performance appraisals to validate the experimental findings from experiments in real-world organizational contexts. The following sections present details of each study.

5 | Study 1

Aligned with the ideology of sociomateriality, each experiment in Study 1 included one manipulation for AI rater characteristic and one for decision-making power in the appraisal procedure to reflect AI–human entanglement. We also attempted to replicate some findings in serial experiments to validate our results. More specifically, Study 1a focused on AI complexity (H1 and H3a) and the decision-making power of AI (H4 and H6a). Study 1b focused on AI anthropomorphism (H2 and H3b) and replicated the main effect of AI's decision-making power in the appraisal procedures (H4), and Study 1c focused on the decision-making power of employees in the appraisal procedures (H5 and H6b) and replicated the main effect of AI complexity (H1). While the sequence of results does not strictly follow the order of hypotheses, this structure reflects the logic of our theoretical framework and the constraints of experimental design. Table 1 provides a summary of the hypotheses tests and results from Study 1.

5.1 | Methods

5.1.1 | Sample and Procedures

All three experiments adopted a between-subjects design. We varied scenarios in each experiment based on the focused sociomaterial factors while maintaining consistency in terms of measurements, control variables, experimental procedures, and analytical approaches. As employees' perceptions of performance appraisals may be influenced by the appraisal outcome (Culbertson et al. 2013; Dusterhoff et al. 2014), in the first experiment, we additionally included the scenario of appraisal outcome as a confounder to increase the robustness of the results. Each scenario was carefully written, reviewed, and revised during multiple rounds of pilot tests (see Appendix A for materials of manipulated scenarios).

Given that the introduction of AI in performance appraisals is more likely to happen in large companies, we targeted full-time employees from organizations with more than 250 employees. We recruited participants from the United States through Prolific, an online research platform that has been validated (Peer et al. 2017) and used in many studies in top journals (e.g., Mihalache and Mihalache 2022; Liao et al. 2024; Yao et al. 2022). Prior to participation, all participants received detailed instructions and provided consent. Then, they received reading materials that described a

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specific scenario, after which they completed our survey based on their perceptions of and reactions to the given scenario.

After excluding those who failed attention checks or did not complete the experiments, Study 1 retained a total of 1002 participants, with 385 in Study 1a, 360 in Study 1b, and 257 in Study 1c. The respondents across the full sample included 52% females and 48% males, with an average age of 39 years. Table 2 provides an overview of key demographics of the full sample and for each subsample. The demographics are fairly similar across the three sub-studies.

5.1.2 | Measures

We adapted established scales from previous research. All measurements were rated on seven-point Likert scales, unless otherwise noted. We measured *performance appraisal satisfaction* with three items (Culbertson et al. 2013), measured *procedural justice* with four items (Ehrhart 2004), and measured *trust in AI* with three items (Lankton et al. 2015). All items are presented in Appendix B.

We included five control variables to increase the validity of our findings. First, we controlled for industry and created a dummy for the *service industry* (1 = *service sectors*; 0 = *other sectors*) because the effect of AI differs across service and other industries (Gentili et al. 2020). Second, we controlled for *established AI applications* ("to what degree does your company use AI in your business operations?") because established organizational technology knowledge and infrastructure can influence AI usage and employees' perceptions of AI (Pan et al. 2022). Third, we controlled for *company age*, measured by years of operation, since organizational maturity can shape HRM structures (Kulik and Perry 2008) and influence employees' experiences with AI-based performance appraisals. Finally, we controlled for *education* and *age* of employees because employees with lower educational levels and younger age have been more influenced by

TABLE 1 | Summary of hypotheses and results from Study 1.

		Hypotheses	Tested in	Replicated in	Results
AI characteristics	H1	AI complexity–satisfaction	Study 1a	Study 1c	Confirmed
	H2	AI anthropomorphism–satisfaction	Study 1b		Confirmed
	H3a	AI complexity–trust in AI–satisfaction	Study 1a		Confirmed
	H3b	AI anthropomorphism–trust in AI–satisfaction	Study 1b		Confirmed
Decision-making power in procedures	H4	Decision-making power of AI–satisfaction	Study 1a	Study 1b	Confirmed
	H5	Decision-making power of employees–satisfaction	Study 1c		Confirmed
	H6a	Decision-making power of AI–procedural justice–satisfaction	Study 1a		Rejected
	H6b	Decision-making power of employees–procedural justice–satisfaction	Study 1c		Confirmed

Note: Cells are shaded to differentiate each experiment: white for Study 1a, light gray for Study 1b, and dark gray for Study 1c.

TABLE 2 | Demographic characteristics of participants in Study 1.

	Study 1a	Study 1b	Study 1c	Study 1 in total
Sample size	385	360	257	1002
Gender				
Female in %	54%	50%	49%	52%
Male in %	46%	50%	51%	48%
High-skill workers in %	76%	75%	79%	76%
Average age (years old)	39.6	39.8	38.2	39.3
Average tenure (years)	7.5	7.5	6.7	7.3
Average company size (employees)	52,348	64,222	42,097	53,985
Average company age (years in operation)	58.2	60.6	64.5	60.7

Note: High-skill workers refer to occupations with skill-level 3 or 4, such as managers or professionals, according to the International Standard Classification of Occupations (International Labor Organization 2012).

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TABLE 3 | Descriptive results of Study 1a ($n = 385$).

	Mean	SD	1	2	3	4	5	6	7	8	9	10
1. Performance appraisal satisfaction	3.52	0.09	**0.87**									
2. AI complexity	0.50	0.03	−0.17**	—								
3. Decision-making power of AI	0.51	0.03	−0.08	−0.01	—							
4. Trust in AI	3.67	0.08	0.41**	−0.29**	−0.02	**0.95**						
5. Procedural justice	3.92	0.06	0.49**	−0.32**	−0.03	0.43**	**0.81**					
6. Established AI application	3.36	0.08	0.14**	0.06	0.10*	0.33**	0.11*	—				
7. Service industry	0.87	0.02	−0.02	0.16**	−0.04	−0.06	0.00	−0.01	—			
8. Company age	58.46	2.14	−0.06	−0.02	0.05	−0.06	−0.08	−0.14**	0.04	—		
9. Education	5.64	0.13	−0.04	−0.01	−0.02	−0.02	−0.03	0.04	−0.02	0.16**	—	
10. Age	39.64	0.59	−0.04	0.16**	−0.04	0.01	−0.02	0.11*	−0.08	0.12*	0.04	—

Note: The diagonal shows Cronbach's alpha in bold.
*$p < 0.05$.
**$p < 0.01$.

AI (Blanas et al. 2019). We measured education by years spent in higher education after high school (Tierney and Farmer 2002) and age in years.

5.1.3 | Analytical Strategy

We used ANOVA to test the manipulation validity. To test our hypotheses, we conducted regression analyses and causal mediation using the approach by Dustin and Hicks (2011), applying a bootstrapping threshold of 5000 in STATA 14.0.

5.2 | Results for Study 1a

5.2.1 | Manipulation Check

Employees believed AI in the high-complexity condition ($M = 5.78$; SD = 0.11) was more complex than AI in the low-complexity condition ($M = 4.18$; SD = 0.11), $F(1, 377) = 106.62$; $p < 0.001$; $\eta^2 = 0.22$. Similarly, employees rated AI in the high-AI decision-making power condition ($M = 5.81$; SD = 0.10) as having significantly stronger decision-making power than AI in the low-decision-making power condition ($M = 4.45$; SD = 0.10), $F(1, 377) = 88.36$; $p < 0.001$; $\eta^2 = 0.19$. Finally, employees in the positive appraisal outcome condition thought they received better evaluation results ($M = 6.33$; SD = 0.08) than those in the negative appraisal outcome condition ($M = 2.15$; SD = 0.08), $F(1, 377) = 1438.29$; $p < 0.001$; $\eta^2 = 0.79$.

According to ANOVA tests of interaction terms, the appraisal outcome did not influence employees' perceived AI complexity ($F(1, 377) = 1.23$; $p = 0.268$; $\eta^2 = 0.00$) or perceived AI decision-making power ($F(1, 377) = 0.07$; $p = 0.796$; $\eta^2 = 0.00$). According to coefficients comparisons, there was no significant difference in the effect power of AI complexity ($\chi^2 = 0.02$; $p = 0.876$) and AI decision-making power ($\chi^2 = 0.01$; $p = 0.928$), with or without appraisal outcomes as a control variable. Therefore, we concluded that the appraisal outcome was not a pivotal confounder in our scenario experiments and, accordingly, excluded it from subsequent experiments.

TABLE 4 | Regression results of Study 1a ($n = 385$).

	Model 1	Model 2
AI complexity		−0.18**
Decision-making power of AI		−0.10*
Established AI application	0.15**	0.16**
Service industry	−0.02	0.01
Company age	−0.02	−0.02
Education	−0.04	−0.05
Age	−0.06	−0.04
R^2	0.03	0.07
F value	1.97	3.73**

Note: *$p < 0.05$; **$p < 0.01$.

5.2.2 | Descriptive and Regression Results

Table 3 provides an overview of means, standard deviations, Cronbach's alphas for scales, and correlations. Table 4 provides regression results.

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TABLE 5 | Descriptive results of Study 1b ($n = 360$).

	Mean	SD	1	2	3	4	5	6	7	8	9
1. Performance appraisal satisfaction	3.89	0.07	**0.82**								
2. AI anthropomorphism	0.54	0.03	0.09	—							
3. Decision-making power of AI	0.48	0.03	−0.34**	0.03	—						
4. Trust in AI	3.86	0.08	0.45**	0.08	−0.05	**0.95**					
5. Established AI application	2.90	0.08	0.06	−0.10	−0.04	0.36**	—				
6. Service industry	0.88	0.02	0.03	−0.07	−0.09	0.02	0.05	—			
7. Company age	60.60	2.33	−0.12*	0.08	0.04	−0.10	−0.19**	−0.07	—		
8. Education	4.35	0.13	−0.02	0.05	0.03	0.06	0.11*	0.13*	0.11*	—	
9. Age	39.76	0.61	0.00	−0.03	−0.12*	0.00	0.11*	−0.04	0.05	−0.11*	—

Note: The diagonal shows Cronbach's alpha in bold.
*$p < 0.05$.
**$p < 0.01$.

H1 proposes a negative relationship between AI complexity and performance appraisal satisfaction. As expected, higher AI complexity was significantly related to lower performance appraisal satisfaction ($b = -0.18$; $p < 0.001$), thus confirming H1.

H3a proposes a mediation effect of trust in AI between AI complexity and performance appraisal satisfaction. With trust in AI as a mediator, the indirect effect of AI complexity was significant (*estimate* = −0.44; 95% CI = [−0.62, −0.27]), whereas the direct effect was not significant (*estimate* = −0.22; 95% CI = [−0.59, 0.15]). Therefore, trust in AI fully mediated the effect between AI complexity and performance appraisal satisfaction, thus confirming H3a.

H4 proposes a negative relationship between the decision-making power of AI and performance appraisal satisfaction. The higher decision-making power of AI was significantly related to lower performance appraisal satisfaction ($b = -0.10$; $p = 0.046$), thus confirming H4.

H6a proposes a mediation effect of perceived procedural justice between the decision-making power of AI and performance appraisal satisfaction. The indirect effect of AI decision-making power was not significant (*estimate* = −0.08; 95% CI = [−0.24, 0.08]), with procedural justice as a mediator. Therefore, procedural justice did not mediate the relationship between the decision-making power of AI and performance appraisal satisfaction, thus rejecting H6a.

5.3 | Results for Study 1b

5.3.1 | Manipulation Check

Employees perceived that AI in the high-anthropomorphism condition ($M = 5.43$; SD = 0.11) as significantly more human-like than AI in the low-anthropomorphism condition ($M = 1.61$; SD = 0.12), $F(1, 356) = 596.17$; $p < 0.001$; $\eta^2 = 0.63$. The employees also rated AI in the high-AI decision-making power condition ($M = 6.32$; SD = 0.13) as having significantly stronger decision-making power than AI in the low-decision-making power condition ($M = 3.33$; SD = 0.12), $F(1, 356) = 285.32$; $p < 0.001$; $\eta^2 = 0.45$.

TABLE 6 | Regression results of Study 1b ($n = 360$).

	Model 1	Model 2
AI anthropomorphism		0.11*
Decision-making power of AI		−0.34**
Established AI application	0.04	0.04
Service industry	0.03	0.00
Company age	−0.10	−0.10
Education	−0.02	−0.01
Age	0.00	−0.03
R^2	0.02	0.14
F value	1.14	8.38**

Note: *$p < 0.05$, **$p < 0.01$.

5.3.2 | Descriptive and Regression Results

Descriptive statistics and regression results are shown in Tables 5 and 6, respectively.

H2 proposes a positive relationship between AI anthropomorphism and performance appraisal satisfaction. Results show that higher AI anthropomorphism was significantly related to higher performance appraisal satisfaction ($b = 0.11$; $p = 0.023$), thus confirming H2.

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TABLE 7 | Descriptive results of Study 1c ($n = 257$).

	Mean	SD	1	2	3	4	5	6	7	8	9
1. Performance appraisal satisfaction	3.95	0.08	**0.71**								
2. AI complexity	0.51	0.03	−0.14*	—							
3. Decision-making power of employees	0.52	0.03	0.34**	0.07	—						
4. Procedural justice	4.5	0.09	0.58**	−0.11	0.31**	**0.89**					
5. Established AI application	3.23	0.11	0.17**	0.00	0.10	0.28**	—				
6. Service industry	0.86	0.02	−0.01	0.01	−0.17**	0.01	−0.06	—			
7. Company age	64.45	3.44	−0.06	−0.08	0.03	−0.06	−0.22**	0.00	—		
8. Education	4.71	0.15	0.05	−0.05	−0.02	0.06	0.16**	0.00	0.09	—	
9. Age	38.2	0.68	0.09	0.04	0.06	−0.05	−0.01	−0.17**	0.05	0.01	—

Note: The diagonal shows Cronbach's alpha in bold.
*$p < 0.05$.
**$p < 0.01$.

H3b proposes a mediation effect of trust in AI between AI anthropomorphism and performance appraisal satisfaction. The indirect effect of AI anthropomorphism was significant (*estimate* = 0.14; 95% CI = [0.02, 0.26]), while the direct effect was not significant (*estimate* = 0.15; 95% CI = [−0.08, 0.37]). Therefore, trust in AI fully mediated the effect between AI anthropomorphism and performance appraisal satisfaction, thus confirming H3b.

In addition, we replicated H4 from Study 1a, which proposes a negative relationship between the decision-making power of AI and performance appraisal satisfaction. The results support this hypothesis ($b = -0.34$; $p < 0.001$), thus successfully replicating the result of Study 1a regarding H4.

5.4 | Results for Study 1c

5.4.1 | Manipulation Check

Employees perceived AI in the high-complexity condition ($M = 6.11$; SD = 0.12) as significantly more complex than AI in the low-complexity condition ($M = 1.85$; SD = 0.12); $F(1, 261) = 641.93$; $p < 0.001$; $\eta^2 = 0.71$. The employees also reported experiencing significantly greater free will in the high employee decision-making power condition ($M = 6.20$; SD = 0.13) than in the low employee decision-making power condition ($M = 1.89$; SD = 0.13); $F(1, 261) = 563.35$; $p < 0.001$; $\eta^2 = 0.68$.

5.4.2 | Descriptive and Regression Results

Descriptive statistics and regression results are shown in Tables 7 and 8, respectively.

H5 proposes a positive relationship between the decision-making power of employees and performance appraisal satisfaction. The higher decision-making power of employees was significantly related to higher performance appraisal satisfaction ($b = 0.35$; $p < 0.001$), thus confirming H5.

TABLE 8 | Regression results of Study 1c ($n = 257$).

	Model 1	Model 2
AI complexity		−0.17**
Decision-making power of employees		0.35**
Established AI application	0.16*	0.11
Service industry	0.01	0.07
Company age	−0.03	−0.06
Education	0.02	0.03
Age	0.09	0.09
R^2	0.04	0.17
F value	1.89	7.32**

Note: *$p < 0.05$; **$p < 0.01$.

H6b proposes a mediation effect of perceived procedural justice between the decision-making power of employees and performance appraisal satisfaction. Indirect (*estimate* = 0.41; 95% CI = [0.25, 0.60]) and direct (*estimate* = 0.46; 95% CI = [0.19, 0.73]) effects of employees' decision-making power were significant, with procedural justice as a mediator. Therefore, procedural justice partially mediated the effect between the decision-making power of employees and performance appraisal satisfaction, thus confirming H6b.

In addition, we replicated H1 from Study 1a, which predicts a negative relationship between AI complexity and performance appraisal satisfaction. The results confirmed this relationship ($b = -0.17$; $p = 0.003$), thereby successfully replicating the result of Study 1a.

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5.5 | Discussion

Taken together, the results from the three experiments in Study 1 demonstrate that the characteristics of AI raters and the decision-making power in appraisal procedures influence employees' performance appraisal satisfaction. Furthermore, employees' trust in AI fully mediates the relationship between AI characteristics and performance appraisal satisfaction, while perceived procedural justice partially mediates between decision-making power in appraisal procedures and performance appraisal satisfaction. Although experiments are well suited for establishing causal relationships (Neuman 2007), Study 1 is subject to two limitations. First, as with the other scenario-based experiments, it may have limited ecological validity, as it relies on fictional, manipulated scenarios that may not fully capture the complexity of real-world organizational contexts. Second, although we aimed to align our design with the ideology of sociomateriality, it was methodologically infeasible to include all four sociomaterial factors within a single experimental study. To address these limitations, we conducted Study 2.

6 | Study 2

In Study 2, we surveyed 321 employees who had experience with AI-based performance appraisals to test the external validity of our findings in a real-world business context. To ensure comparability, we maintained consistency with the design and constructs of Study 1, wherever it was reasonable and feasible to do so

6.1 | Methods

6.1.1 | Procedures and Samples

We recruited participants from the United States through Prolific. We first conducted a screening study with 2059 individuals to identify those who met the following eligibility criteria: (1) full-time employment; (2) fluency in English; and (3) experience with AI-based performance appraisals in their jobs. Based on these criteria, we invited 901 eligible respondents to participate in the main survey. We received 351 completed responses, and after excluding participants who failed attention checks, the final sample consisted of 321 participants. The sample includes 59% male and 41% female, with an average age of 38 years and tenure of 6 years. According to the International Standard Classification of Occupations (International Labor Organization 2012), 69% of participants were employed in high-skill occupations. The average company size was 28,898 employees, and the average company age was 21 years. In conclusion, the samples in Study 2 and Study 1 exhibit fairly similar characteristics, supporting the comparability of the two study populations.

6.1.2 | Measures

All measures were rated on seven-point Likert scales unless otherwise noted. We used the same scales as in Study 1 to measure *performance appraisal satisfaction* (Culbertson et al. 2013), *procedural justice* (Ehrhart 2004), and *trust in AI* (Lankton et al. 2015). The values of Cronbach's α for these measures were 0.64, 0.89, and 0.91, respectively. Whereas we experimentally manipulated AI rater characteristics and appraisal procedures in Study 1, we used established Likert scales to measure employees' actual experiences. Specifically, we measured *AI complexity* with four items (Pan et al. 2022; Cronbach's $\alpha = 0.85$), *AI anthropomorphism* with five items (Li and Sung 2021; $\alpha = 0.93$), *decision-making power of AI* with three items (Bakan et al. 2004; Long 1979; $\alpha = 0.87$), *decision-making power of employees* with three items (Anderson and Berdahl 2002; $\alpha = 0.95$). All items are presented in Appendix B.

Consistent with Study 1, we controlled for *service industry*, *established AI applications*, *company age*, *education*, and *age*. Similar to Study 1a, we also controlled for *appraisal outcome* and measured it using the question: "Overall, I received a rather positive outcome in that AI-based performance appraisal compared to my peers or my usual appraisal results" (1 = *disagree*; 2 = *agree*).

6.2 | Results

Before testing the hypotheses, we validated the scales and conducted descriptive analysis. The confirmatory factor analysis results demonstrate a good model fit ($\chi^2 = 533.427$; df = 254; χ^2/df = 2.100; CFI = 0.957; RMSEA = 0.059; $p < 0.001$). All scales showed adequate average variance extracted (AVE > 0.50) and composite reliability (CR > 0.70), indicating strong convergent validity of measurements (Hair et al. 2014). We conducted the common latent factor test to detect potential common method variances. The common latent factor model did not demonstrate better model fit ($\chi^2 = 533.427$; df = 253; χ^2/df = 2.108; CFI = 0.957; RESEA = 0.059; $p < 0.001$), and loading differences of all factors between the original model and the common latent factor model were less than 0.001. Therefore, common method bias was not a significant concern in Study 2. Table 9 provides a descriptive overview of the data.

We used the same statistical approach as in Study 1 to test the hypotheses. Tables 10 and 11 present the regression and mediation results, respectively.

H1 proposes a negative relationship between AI complexity and performance appraisal satisfaction. The results ($b = -0.47$; $p < 0.001$) confirmed H1 and thus replicated the results of Study 1. H2 proposes a positive relationship between AI anthropomorphism and performance appraisal satisfaction. The results ($b = 0.16$; $p = 0.004$) confirmed H2 and thus replicated the results of Study 1.

H3a proposes a mediation effect of trust in AI between AI complexity and performance appraisal satisfaction. The indirect effect (*estimate* = −0.14; 95% CI = [−0.21, −0.09]) and direct effect (*estimate* = −0.34; 95% CI = [−0.46, −0.23]) of AI complexity were both significant, with trust in AI as a mediator. Therefore, trust in AI partially mediated the effect between AI complexity and performance appraisal satisfaction, thus confirming H3a and partially replicating the results of Study 1. H3b proposes a mediation effect of trust in AI between AI anthropomorphism and performance appraisal satisfaction.

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TABLE 9 | Descriptive results of Study 2 ($n = 321$).

	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Satisfaction	4.71	0.06	**0.64**												
2. AI complexity	2.35	0.06	−0.61**	**0.85**											
3. AI anthropomorphism	4.07	0.09	0.39**	−0.39**	**0.93**										
4. Decision-making power of AI	4.99	0.07	0.10	−0.21**	0.37**	**0.87**									
5. Decision-making power of employees	4.77	0.09	0.44**	−0.47**	0.53**	0.26**	**0.95**								
6. Trust in AI	5.23	0.07	0.60**	−0.63**	0.44**	0.36**	0.52**	**0.91**							
7. Procedural justice	5.43	0.06	0.66**	−0.68**	0.43**	0.20**	0.53**	0.71**	**0.89**						
8. Established AI application	4.79	0.08	0.21**	−0.31**	0.35**	0.26**	0.31**	0.38**	0.32**	—					
9. Service industry	0.84	0.02	−0.07	0.11	−0.10	−0.11*	−0.21**	−0.16**	−0.06	−0.06	—				
10. Company age	21.41	1.1	−0.02	0.09	−0.26**	−0.13*	−0.16**	−0.06	−0.08	−0.11	0.02	—			
11. Education	4.75	0.14	0.08	0.01	0.24**	0.10	0.22**	0.15**	0.11*	0.22**	−0.02	0.01	—		
12. Age	38.35	0.71	0.01	0.03	−0.10	0.01	−0.09	0.04	0.02	0.00	−0.01	0.22	0.10	—	
13. Appraisal outcome	1.91	0.02	0.39**	−0.31**	0.25**	0.17**	0.29**	0.35**	0.38**	0.17**	−0.02	−0.04	0.11	0.06	—

Note: The diagonal shows Cronbach's alpha in bold.
*$p < 0.05$.
**$p < 0.01$.

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The indirect effect of AI anthropomorphism was not significant (*estimate* = 0.01; 95% CI = [−0.01, 0.03]), with trust in AI as a mediator. Therefore, trust in AI did not mediate the relationship between AI anthropomorphism and performance appraisal satisfaction, thus rejecting H3b and not replicating the results of Study 1.

TABLE 10 | Regression results of Study 2 ($n = 321$).

	Model 1	Model 2	Whether replicate findings from Study 1
AI complexity		−0.47**	Replicated
AI anthropomorphism		0.16**	Replicated
Decision-making power of AI		−0.10*	Replicated
Decision-making power of employees		0.14*	Replicated
Established AI application	0.15**	−0.03	
Industry	−0.06	0.01	
Company age	0.02	0.07	
Education	0.00	0.01	
Age	−0.03	0.01	
Appraisal outcome	0.37**	0.19**	
R^2	0.18	0.46	
F value	11.11**	26.54**	

Note: *$p < 0.05$; **$p < 0.01$.

H4 proposes a negative relationship between the decision-making power of AI and performance appraisal satisfaction. The results ($b = -0.10$; $p = 0.027$) confirmed H4, thus replicating the results of Study 1. H5 proposes a positive relationship between the decision-making power of employees and performance appraisal satisfaction. The results ($b = 0.14$; $p = 0.011$) confirmed H5, thus replicating the results of Study 1.

H6a proposes a mediation effect of perceived procedural justice between the decision-making power of AI and performance appraisal satisfaction. The indirect effect of AI's decision-making power was not significant (*estimate* = −0.00; 95% CI = [−0.03, 0.02]), with procedural justice as a mediator. Therefore, procedural justice did not mediate the relationship between the decision-making power of AI and performance appraisal satisfaction, thus rejecting H6a and replicating the results of Study 1. H6b proposes a mediation effect of perceived procedural justice between the decision-making power of employees and performance appraisal satisfaction. The indirect effect of employees' decision-making power was significant (*estimate* = 0.05; 95% CI = [0.02, 0.08]), whereas the direct effect was not significant (*estimate* = 0.04; 95% CI = [−0.03, 0.10]). Therefore, procedural justice fully mediated the effect between the decision-making power of employees and performance appraisal satisfaction, thus confirming H6b and partially replicating the results of Study 1.

In summary, Study 2 supports the robustness of our research by successfully replicating most of the key findings from the experiments in Study 1 (also see Tables 10 and 11). Specifically, Study 2 fully replicated the results for H1, H2, H4, H5 and H6a, and partially replicated findings for H3a and H6b. Only H3b was not replicated. Given the reasonable variation expected between experimental and field settings, we argue that Study 2 fully replicates the main effects and largely replicates the mediation effects observed in Study 1. These results provide support for the external validity and generalizability of our findings.

TABLE 11 | Mediation results of Study 2 ($n = 321$).

	Indirect effect			Direct effect			Total effect			Whether replicate findings from Study 1
	est.	95% CI		est.	95% CI		est.	95% CI		
AI complexity–trust in AI–satisfaction	−0.14	[−0.21]	[−0.09]	−0.34	[−0.46]	[−0.23]	−0.49	[−0.59]	[−0.38]	Replicated
AI anthro.–trust in AI–satisfaction	0.01	[−0.01]	[0.03]	0.08	[0.02]	[0.15]	0.10	[0.03]	[0.16]	Not replicated
Decision-making power of AI–justice–satisfaction	0.00	[−0.03]	[0.02]	−0.08	[−0.15]	[−0.01]	−0.09	[−0.16]	[−0.01]	Replicated
Decision-making power of employees–justice–satisfaction	0.05	[0.02]	[0.08]	0.04	[−0.03]	[0.10]	0.09	[0.02]	[0.16]	Replicated

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7 | General Discussion

Drawing on the sociomateriality paradigm and attribution theory, this study investigated the antecedents of employees' performance appraisal satisfaction when AI is involved in the appraisal process. Our findings suggest that the characteristics of AI raters and decision-making power in appraisal procedures influence performance appraisal satisfaction. With respect to AI rater characteristics, higher AI complexity was associated with lower performance appraisal satisfaction, mediated by reduced trust in AI, while higher AI anthropomorphism was associated with higher performance appraisal satisfaction, mediated by enhanced trust in AI. Regarding the decision-making power in appraisal procedures, the higher decision-making power of AI was associated with lower performance appraisal satisfaction, and this relationship was not mediated by procedural justice. The higher decision-making power of employees was associated with higher performance appraisal satisfaction, mediated by increased perceived procedural justice.

7.1 | Theoretical Contributions

This study makes several important theoretical contributions. First, it introduces the sociomateriality paradigm into the HRM discipline, as exemplified by the context of AI-based performance appraisals. The literature on technology in organizations presents an ongoing debate on the relationships between technological and social elements (Orlikowski and Scott 2008). Most existing research treats these elements as separate, self-contained entities that influence one another (Orlikowski and Scott 2008). The literature on AI-based HRM largely follows this perspective, examining the influence of AI on employee experience through a unidirectional lens (Malik et al. 2022; Suen et al. 2019). However, AI increasingly functions not only as a technical tool but also as a social actor embedded in human interactions (Einola and Khoreva 2023; Makarius et al. 2020). Thus, the prevailing theoretical lens in HRM literature may have overlooked the entangled nature of AI and human elements, despite their inherent interdependence. By adopting the sociomateriality paradigm, which views technological and social elements as inextricably interwoven (Jones 2014), we offer a novel theoretical perspective to better understand how AI shapes employee experience in HRM contexts.

Second, this study extends the sociomateriality paradigm by integrating it with attribution theory to deepen our understanding of AI–human entanglement. The sociomateriality paradigm argues that the meanings and perceptions of technology emerge through social relationships (Jones 2014; Orlikowski and Scott 2008). Unfortunately, the paradigm provides little guidance for interpreting the antecedents and consequences of technologies through a relational lens. Prior studies based on sociomateriality primarily relied on qualitative methods (Cecez-Kecmanovic et al. 2014) and often remained rather broad, thus providing limited insights into the causal mechanisms of sociotechnical entanglements (Jones 2014; Scott and Orlikowski 2014). To address this limitation, we draw on attribution theory, which offers a well-established explanatory framework for explaining human relational dynamics. Specifically, we refer to the relational attribution to help interpret how the characteristics of an AI rater (exemplified by AI complexity and AI anthropomorphism) shape trust in the AI–human relationship and the consequences of such a relationship. Meanwhile, the external/internal attributions inform us how different levels of decision-making power in appraisal procedures, held by AI or employees, influence individuals' perceptions of performance appraisals. By integrating the sociomateriality paradigm with attribution theory, we offer a relational lens that captures not only the entanglement of AI and human elements but also the mechanisms through which this entanglement influences employee experience. In doing so, attribution theory enhances the explanatory power of sociomateriality in understanding AI–human dynamics.

Third, this study extends our understanding of AI-based performance appraisals. While the extant literature on AI-based performance appraisals focuses more on employees' perceived justice (Lee 2018; Newman et al. 2020), our study shifts the focus toward employees' performance appraisal satisfaction, which is more directly tied to employee experience, appraisal effectiveness, individual productivity, and organizational outcomes (Kuvaas 2006; Memon et al. 2020; Schleicher et al. 2019). In doing so, we contribute to the HRM field by identifying key antecedents of employee satisfaction with AI-based performance appraisals, responding to calls for a deeper understanding of the employee experience under AI implementation (Budhwar et al. 2023; Malik et al. 2023). The literature on performance appraisals indicates that appraisals are more likely to be effective and employees tend to be more satisfied when raters and ratees share a positive relationship and when appraisal procedures are perceived as fair (Aguinis 2023; DeNisi and Pritchard 2006; DeNisi and Murphy 2017; Dusterhoff et al. 2014). Our findings extend this logic to AI-based performance appraisals, showing that rater characteristics and appraisal procedures remain central, even when AI acts as a rater and plays a significant role in decision-making power during the appraisal procedure.

7.2 | Practical Implications

This study has several practical implications for organizations implementing AI-based performance appraisal systems. First, we encourage organizations to integrate anthropomorphic characteristics into AI applications used for performance appraisals. In traditional performance appraisals, it is important for human raters to behave consistently and communicate effectively during the appraisal (Shrivastava and Purang 2011). When AI serves as a rater, it should similarly embody characteristics that align with employees' expectations of consistent behavior and high-quality communication. Our findings highlight the importance of AI complexity and AI anthropomorphism in determining employees' psychological reactions to performance appraisals. Employees tend to distrust AI raters that appear overly complex or lack human-like qualities, which in turn diminishes satisfaction with AI-based HRM. While prior research has emphasized the need to reduce AI complexity for better usability (Pan et al. 2022), our results suggest that emotional user-friendliness is equally important. We therefore recommend that organizations not only design AI systems that are functionally intuitive but also emotionally relatable, incorporating features such as a friendly voice, perceived integrity, or empathy cues to enhance trust and engagement.

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Second, we encourage organizations to grant some degree of decision-making power to employees when implementing AI-based performance appraisals. The use of AI in HRM is typically driven by organizational-level decisions, with limited involvement from individual employees. Prior studies on the consequences of AI-based HRM tend to take the implementation of AI as a given (Einola and Khoreva 2023; Li and Sung 2021; Malik et al. 2022), in which employees have little say in choosing between AI or human raters. However, overlooking employee agency in this context may be problematic, because employee satisfaction with performance appraisals varies depending on their level of decision-making power (Schleicher et al. 2019; Williams and Levy 2000). Our findings confirm that the decision-making power of employees plays an important role in increasing employee satisfaction with AI-based performance appraisals. If employees can choose how they are evaluated, such as selecting between AI and human raters, they may perceive the AI-based performance appraisal as fair and ultimately become more satisfied with the procedure. Therefore, it is crucial for organizations to involve employees in decisions about AI adoption or, at a minimum, consider their preferences during implementation. Doing so may improve acceptance, fairness perceptions, and overall satisfaction with AI-based performance appraisals.

Third, we recommend that organizations assign final decision-making authority to human supervisors to mitigate potential psychosocial harm associated with AI-based performance appraisals. Prior studies argue that individuals generally dislike AI-based performance appraisals (Lee 2018; Newman et al. 2020). Our findings suggest that employees appear to be more comfortable with AI involvement when AI is not the final decision-maker. In contrast, employees express greater dissatisfaction and resistance when AI assumes full control over appraisal outcomes. To reduce these negative reactions, organizations should exercise careful discretion in distributing decision-making power, ensuring that final appraisal decisions remain in the hands of human supervisors. This approach may help reduce perceived alienation or unfairness associated with AI domination.

7.3 | Limitations and Future Research

While our research establishes causal relationships through multiple experiments and a field survey, it nonetheless has limitations that suggest directions for future research. First, this study collected data exclusively from the United States. The adoption and impact of AI usage are influenced by macroenvironmental factors such as regulatory frameworks, economic conditions, and culture (Gentili et al. 2020). Although the United States represents one of the most advanced and influential contexts for AI development and implementation (Maslej et al. 2023), future studies should examine the use of AI in performance appraisals in different contexts to understand the environmental boundary conditions that shape AI's role in HRM.

Second, Study 1 relied on scenario experiments to test its hypotheses. Given that the usage of AI in HRM is a novel phenomenon, most empirical studies on AI-based HRM have used qualitative designs (e.g., Malik et al. 2022, 2023; Einola and Khoreva 2023) or scenario experiments (e.g., Jackson et al. 2020; Lee 2018; Newman et al. 2020). While scenario experiments offer strong internal validity and enable causal inference (Neuman 2007), they also suffer from limited realism. In our study, we implemented experiments with great care, incorporated multiple attention and manipulation checks, and strictly followed protocols across experiments to ensure data validity. Moreover, we complemented the experimental findings with Study 2, a survey of employees who had actual experience with AI-based performance appraisals. This survey fully replicated the main effects and largely replicated the mediation effects found in Study 1, reinforcing the robustness of our conclusions. Nonetheless, future research may provide additional empirical evidence and further examine the impact of AI in AI–human entanglements using other research methods, such as field experiments.

Finally, future research may extend our findings by identifying potential boundary conditions for the influence of AI characteristics and decision-making power in AI-based performance appraisals. In this study, we focused on the facilitating mechanisms of employees' performance appraisal satisfaction and confirmed the importance of employees' trust in AI and perceived procedural justice. Although the mediation effects are crucial for understanding how AI affects employee reactions, such an influence may also depend on boundary factors, such as employees' beliefs in AI's ability (Newman et al. 2020) or organizational resources (Pan et al. 2022). Therefore, future research may consider plausible moderation effects in this context.

8 | Conclusion

AI-based performance appraisals are becoming an increasingly realistic feature of contemporary organizations. However, existing HRM research often overlooks the social dimensions of AI–human interactions. Drawing on sociomateriality and attribution theory, this study investigated employee experience with AI-based performance appraisals, where AI and humans are deeply entangled. Our findings suggest that the characteristics of AI raters and the distribution of decision-making power in appraisal procedures significantly influence employees' performance appraisal satisfaction. By applying a relational lens, we contribute to the literature by distinguishing between the material and social aspects of AI and showing how each influences employee reactions. Future research may extend these findings by identifying boundary conditions that clarify how employee experience responds to AI–human entanglements.

Acknowledgments

Open Access funding enabled and organized by Projekt DEAL. [Correction added on 5 January 2026, after first online publication: Projekt DEAL funding statement has been added.]

Funding

This work was supported by the Fundamental Research Funds for the Central Universities (ZYGX2025WXJ010).

Conflicts of Interest

The authors declare no conflicts of interest.

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Data Availability Statement

The data that support the findings of this study are available on request from the first author. The data are not publicly available due to privacy or ethical restrictions.

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Appendix A

Materials for Manipulated Scenarios of Three Experiments

	High	Low
AI complexity (derived from Pan et al. 2022)	The AI is unclear, difficult to understand, and hard to use, so interacting with the AI requires much mental effort, and getting the AI to do what the company wants is NOT easy.	The AI is clear, understandable, and easy to use, so interacting with the AI does NOT require much mental effort, and getting the AI to do what the company wants is easy.
AI anthropomorphism (derived from Pelau et al. 2021)	The AI is human-like. It CAN engage in reasoning and make moral judgments, or understand others' thoughts and feelings, and is easy to communicate like human.	The AI is NOT human-like. It CAN NOT engage in reasoning and make moral judgments, nor understand others' thoughts and feelings, and is NOT easy to communicate like human.
Decision-making power of AI	Your performance evaluation is entirely determined by the AI evaluation.	Your performance evaluation is determined by your supervisor, who may or may not consider the AI evaluation.
Decision-making power of employees	Joining the AI evaluation is NOT mandatory. You have the option to choose between human or AI evaluation according to your preference.	Joining the AI evaluation is mandatory. You must choose AI evaluation regardless of your preference.
Appraisal outcome	In the final evaluation, your score is higher than average compared to your peers.	In the final evaluation, your score is lower than average compared to your peers.

Appendix B

Measurement Items

Construct		Items
Performance appraisal satisfaction	PAS1	I am satisfied with the performance appraisal outcome.
	PAS2	I feel good about the way the appraisal was conducted.
	PAS3	There are many ways in which I would have liked the appraisal to be different.
Procedural justice	PJ1	I have been able to express my views and feelings during the evaluation procedures.
	PJ2	The evaluation procedures have been applied consistently.
	PJ3	The evaluation procedures have been free of bias.
	PJ4	The evaluation procedures upheld ethical and moral standards.
Trust in AI	TA1	When I do my job, I feel I can depend on AI applications.
	TA2	I can always rely on AI applications for a tough job task.
	TA3	I feel I can count on AI application when doing my job.
AI complexity	AIC1	The AI was clear and understandable.
	AIC2	Interacting with the AI did not require much mental effort.
	AIC3	The AI we used in our performance appraisal was easy to use.
	AIC4	It was easy to get the AI to do what we want it to do.
AI anthropomorphism	AIH1	That AI had intentions in moral judgments.
	AIH2	That AI had free will in moral judgments or communications.
	AIH3	That AI could understand emotions in communication.
	AIH4	That AI had consciousness similar to human.
	AIH5	That AI had a mind of its own in reasoning.

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Construct		Items
Decision-making power of AI	AIP1	The used AI had influence on overall policies or procedures of the appraisal.
	AIP2	The used AI determined matters affecting my own appraisal outcome.
	AIP3	The used AI influenced how my own appraisal was done.
Decision-making power of employees	EFW1	I was in control in choosing AI evaluation.
	EFW2	I was dominant in choosing AI evaluation.
	EFW3	I led my decision on choosing AI evaluation.

Appendix C

Results of Mediation Analyses Conducted in Study 1

	Indirect effect		Direct effect		Total effect		
	Est.	95% CI	Est.	95% CI	Est.	95% CI	Source
AI complexity–trust in AI–satisfaction	−0.44	[−0.62, −0.27]	−0.22	[−0.59, 0.15]	−0.65	[−1.03, −0.29]	Study 1a
AI anthro.–trust in AI–satisfaction	0.14	[0.02, 0.26]	0.15	[−0.08, 0.37]	0.29	[0.03, 0.54]	Study 1b
Decision-making power of AI–justice–satisfaction	−0.08	[−0.24, 0.08]	−0.29	[−0.62, 0.03]	−0.38	[−0.74, −0.02]	Study 1a
Decision-making power of employee–justice–satisfaction	0.41	[0.25, 0.60]	0.46	[0.19, 0.73]	0.88	[0.58, 1.18]	Study 1c

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