E-ISSN: 3108-4176

APSSHS

Academic Publications of Social Sciences and Humanities Studies

2025, Volume 6, Page No: 142-155

Available online at: https://apsshs.com/

Annals of Organizational Culture, Leadership and External Engagement Journal

Compensation Fairness and Employee Task Performance: The Roles of Emotional Engagement, Emotional Intelligence, and AI Adoption

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Abstract

The rapid advancement of artificial intelligence (AI) is significantly shaping employee behavior in modern enterprises. Enhancing employee engagement and performance has thus become a critical challenge for organizational management. Drawing on the Group Engagement Model (GEM), this study examines how different dimensions of compensation fairness—distributive, procedural, and interactional—affect task performance through emotional engagement, while considering the moderating roles of emotional intelligence (EI) and AI adoption (AIA). Using structural equation modeling and three-way interaction analyses, we analyzed data from 311 employees in Chinese media organizations. Findings reveal that all three compensation fairness dimensions positively influence emotional engagement, which in turn enhances task performance. Distributive fairness showed the strongest link with emotional engagement, whereas procedural fairness exerted the greatest overall effect on task performance. Moreover, the moderating effect of emotional intelligence on the interactional fairness–emotional engagement relationship is strengthened in the context of higher AI adoption, confirming a moderated-moderated mediation effect. These results extend the GEM framework and suggest that organizations should design compensation policies and technology strategies that foster employee engagement, improve productivity, and support sustainable organizational development.

Keywords: Distributive fairness, Procedural fairness, Interactional fairness, Emotional engagement, Task performance, AI adoption

How to cite this article: Walker E, Hill M. Compensation Fairness and Employee Task Performance: The Roles of Emotional Engagement, Emotional Intelligence, and AI Adoption. Ann Organ Cult Leadersh Extern Engagem J. 2025;6:142-55. https://doi.org/10.51847/RIdRJfoBeq

Received: 02 August 2025; **Revised:** 16 October 2025; **Accepted:** 17 November 2025

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Introduction

The concepts of fairness and efficiency have long been central to both the theory and practice of organizational management. Employees' perceptions of fairness can profoundly influence their motivation and productivity. For instance, when individuals perceive inequity in compensation, their enthusiasm and work efficiency tend to decline, which can negatively affect overall organizational performance [1, 2]. Ensuring fair compensation is therefore not only an ethical concern but also a strategic necessity for sustaining employee performance and maintaining competitive human capital [3, 4].

Despite its importance, there is ongoing debate about how to conceptualize compensation fairness (CF). Some researchers focus on internal vs. external fairness [5, 6], while others differentiate distributive fairness (DF), procedural fairness (PF), and interactional fairness (IF) [7, 8]. However, there remains limited understanding of how these specific dimensions influence emotional engagement (EE), a critical facet of work engagement, and whether their effects differ in magnitude. The Group Engagement Model (GEM) posits that DF, PF, and IF shape employee engagement through social identity and resource exchange mechanisms [9]. Yet, empirical studies testing GEM are scarce, particularly regarding the mediating role of EE on task performance (TP). Research consistently shows that engaged employees demonstrate higher productivity, better health outcomes, and more positive workplace attitudes [10, 11], highlighting the importance of examining EE as a performance driver.

Another limitation of prior work is the lack of attention to moderating factors that may influence the CF–EE relationship. Emotional intelligence (EI) is one such factor. EI encompasses the ability to perceive, understand, manage, and express one's own emotions, as well as to recognize and respond to others' emotions [12, 13]. Evidence suggests that EI can buffer or amplify the effects of workplace resources on engagement and mitigate job stress or burnout [14, 15]. However, whether EI moderates the influence of specific CF dimensions on EE, and whether this moderation interacts with broader organizational factors such as artificial intelligence adoption (AIA), has not been fully explored.

AI adoption is reshaping contemporary work environments. By 2022, 35% of organizations worldwide had adopted AI, with China reporting an even higher rate of 58%, and nearly half integrating AI into their workflows [16]. AI can transform work processes, altering how employees perceive fairness and engage with their tasks. In some contexts, AI adoption may enhance employee performance by streamlining work, while in others it may create stress or reduce engagement due to perceived surveillance or job insecurity [17]. Despite its growing influence, few studies have examined AI as a higher-order moderator of the relationship between CF and employee engagement.

This study seeks to fill these gaps by addressing three key questions: (1) How do DF, PF, and IF influence EE? (2) Does EE mediate the relationship between these CF dimensions and TP? (3) Do EI and AIA jointly moderate the effect of CF on EE? By examining these questions, this research contributes to theory and practice. It provides a nuanced understanding of how different CF dimensions influence engagement and performance, highlights EE as a bridge between fairness and productivity, and investigates the interactive roles of psychological and technological factors. Ultimately, the study extends GEM and equity theory, offering a framework for organizations seeking to optimize employee engagement and performance in AI-driven workplaces.

Theoretical foundations

The Group Engagement Model (GEM), introduced by Tyler and Blader, offers a framework for understanding how employees develop emotional commitment and cooperative behaviors in organizational settings. By integrating social identity theory and resource exchange theory, GEM highlights the role of distributive fairness (DF), procedural fairness (PF), and interactional fairness (IF) in shaping employees' engagement with their work and organization [9].

Social identity perspective

According to social identity theory, individuals derive part of their self-concept from the social groups to which they belong, particularly those that share similar beliefs, values, or norms [18]. Through comparison with other groups, employees assess their group's standing, which strengthens their sense of belonging and identification [19]. When personal and group values align, employees are more inclined to prioritize group goals, engage in cooperative behaviors, and demonstrate loyalty to the organization [20-23]. GEM expands on this by incorporating interactional fairness within procedural fairness, emphasizing both formal and informal aspects of decision-making and interpersonal treatment. Employees who perceive high procedural fairness feel respected and valued, enhancing their group identification and fostering both psychological and behavioral engagement [9].

Resource exchange perspective

Resource exchange theory posits that relationships develop through the transfer of valuable resources, and the quality of these exchanges determines the strength of interpersonal connections [24, 25]. Employees typically exchange intangible resources—such as time, effort, and expertise—rather than material assets. Work engagement represents a significant investment of these resources. GEM suggests that fair compensation encourages employees to reciprocate by investing greater effort, first through a perception of resource equity and subsequently through identification with the organization. When employees view the allocation of resources as fair, they perceive the organization as supportive and trustworthy, which enhances their commitment and willingness to exert discretionary effort [9, 26].

Research hypotheses

Compensation fairness and emotional engagement

Compensation fairness reflects employees' perception of equity and justness in organizational pay systems. It is commonly divided into three dimensions: DF, PF, and IF [7, 8, 27-29]. Distributive fairness (DF) concerns the perceived equity of outcomes relative to others. Procedural fairness (PF) addresses employees' views on the fairness of organizational processes for determining outcomes [9, 30]. Interactional fairness (IF) focuses on the interpersonal treatment employees receive, including respect, trust, and consideration during decision-making [7, 31].

Emotional engagement (EE) refers to employees' psychological and emotional investment in their work, including pride in contributing to the organization and a commitment to staying engaged over time [32]. EE is a critical component of overall work engagement [33-38]. GEM proposes that when employees perceive equitable compensation, their identification with the organization strengthens, motivating greater engagement and discretionary effort [9, 26]. Furthermore, high procedural and interactional fairness increases employees' sense of recognition and respect, further reinforcing their engagement with organizational goals [9, 27]. Based on these theoretical considerations, the following hypotheses are formulated **(Figure 1)**:

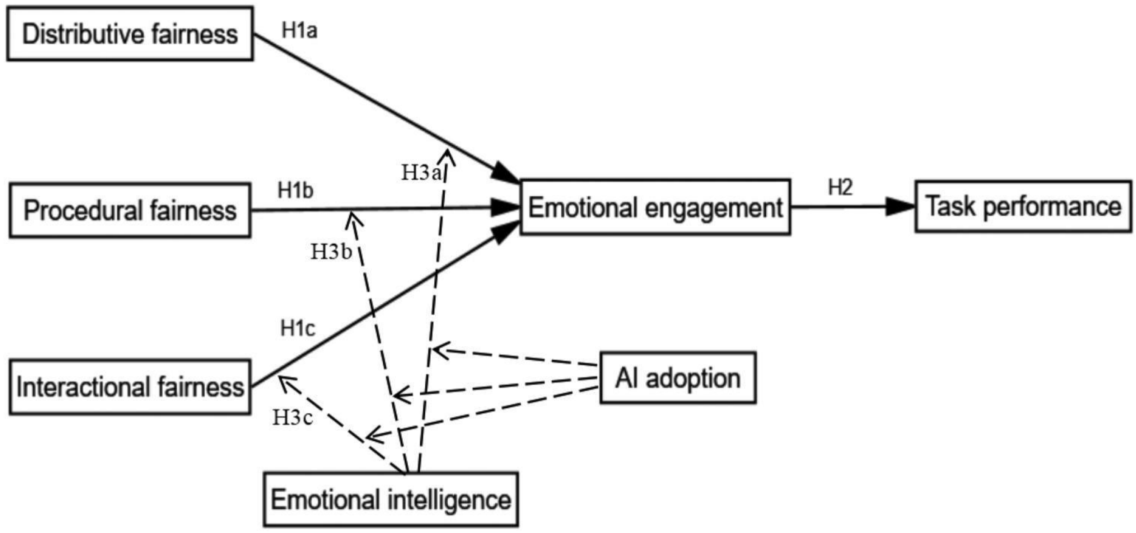

Figure 1. Conceptual model. H1a: DF is positively related to EE. H1b: PF is positively related to EE. H1c: IF is positively related to EE.

Emotional engagement and task performance

Task performance (TP) refers to the extent to which employees carry out responsibilities that directly contribute to organizational goals. It encompasses the efficiency, skill, and applied knowledge employees bring to their roles, as well as the tangible outcomes of their work [39, 40]. TP reflects not only the completion of assigned duties but also the quality and effectiveness with which these tasks are executed, highlighting employees' contributions to the organization's overall functioning [41].

Emotional engagement (EE), representing employees' investment of emotions and energy into their work, has been shown to positively affect TP. Engaged employees are more motivated, demonstrate higher persistence, and devote greater effort to their tasks. They are also more likely to seek skill development and learning opportunities, which further enhances their work efficiency and quality. Recent empirical studies consistently find that higher engagement is associated with improved job performance, productivity, and work outcomes across diverse industries and contexts [10, 42-47].

Hypothesis H2: Emotional engagement is positively associated with task performance.

Moderating roles of emotional intelligence and AI adoption

Emotional intelligence (EI) is an individual's ability to perceive, understand, and regulate their own emotions while interpreting and responding to the emotions of others [48]. Employees with high EI are better equipped to navigate workplace challenges, recognize opportunities for constructive interaction, and respond adaptively to stressors, ultimately shaping both their own performance and that of their peers [13, 49, 50]. EI has been shown to influence the relationship between workplace resources and engagement, and to buffer against burnout and work-related strain [14, 15].

Artificial intelligence adoption (AIA) has become a critical factor in modern workplaces, reshaping workflows, responsibilities, and interpersonal dynamics [51]. Its impact on employees is dual: AI can induce anxiety, insecurity, or role ambiguity due to perceived replacement or diminished personal value, potentially lowering engagement and job satisfaction [52-54]. Conversely, AI can enhance performance, streamline tasks, support decision-making, and increase productivity, thereby encouraging more proactive and engaged behaviors [31, 55-57].

When combined, EI and AIA interact in ways that influence how compensation fairness translates into emotional engagement. Employees with high EI are better able to adapt to AI-driven changes, manage any stress or uncertainty, and leverage technology to enhance their engagement and productivity. In this context, AI adoption acts as a reinforcing factor, amplifying the positive influence of EI on the link between CF and EE.

Hypotheses:

H3a: The moderating effect of EI on the relationship between distributive fairness and EE is strengthened under higher AI adoption.

H3b: The moderating effect of EI on the relationship between procedural fairness and EE is strengthened under higher AI adoption.

H3c: The moderating effect of EI on the relationship between interactional fairness and EE is strengthened under higher AI adoption.

Materials and Methods

Measures

The instruments used in this study were primarily adapted from prior validated research to ensure reliability and accuracy. Compensation fairness (CF) was measured using items derived from Niehoff and Moorman [58], encompassing three dimensions: distributive fairness (DF), procedural fairness (PF), and interactional fairness (IF). DF was assessed with four items, for example, “My compensation level is reasonable.” PF included three items, such as “The company’s remuneration process follows clear rules and is applied consistently to all employees.” IF was evaluated using five items, including “When decisions affect me, my supervisor discusses them with me sincerely.”

Emotional engagement (EE) was measured with four items adapted from May *et al.* [59] and Rich *et al.* [37], for example, “I feel proud to be part of this company.” Task performance (TP) was measured with four items from Farh and Cheng [60] and Pan [61], such as “My work performance consistently meets my supervisor’s expectations.” Emotional intelligence (EI) was captured using three items from Wong and Law [13], e.g., “I can control my temper and address difficulties rationally.” AI adoption (AIA) was measured using four items adapted from Tang *et al.* [62], for instance, “I use artificial intelligence to perform most of my job responsibilities.”

The survey was originally developed in English and then translated into Chinese by a human resources expert. A separate HR scholar independently back-translated it into English, and the two English versions were compared to ensure accuracy and consistency. All variables were measured using a five-point Likert scale, ranging from 1 (“strongly disagree”) to 5 (“strongly agree”).

Sampling and data collection

Ethical approval for the study was obtained from the Science Ethics Committee of Hanshan Normal University. The target population consisted of employees working in media enterprises across China. A **convenience sampling** method was employed, and online questionnaires were distributed between May and July 2024. Participants were required to read and provide informed consent before completing the survey.

A total of 342 responses were collected. The questionnaire was designed to prevent submission with missing responses, ensuring completeness. Responses were screened for validity; questionnaires with excessively short completion times, uniform answers, inconsistencies in reverse-coded items, or identified as outliers via Mahalanobis distance were removed, resulting in 311 valid responses for analysis.

The sample comprised 141 males (45.3%) and 170 females (54.7%). In terms of education, 59 respondents (19%) held an associate degree or lower, 214 (68.8%) had a bachelor’s degree, and 38 (12.2%) had a postgraduate degree. Age distribution included 37% aged 20–29, 23.8% aged 30–39, and 39.2% over 40.

Normality checks were conducted for all variables (DF, PF, IF, EE, TP, EI, AIA). P-P plots showed data points aligned closely with the diagonal, and skewness and kurtosis values were all below 1, indicating that the data approximated a normal distribution and were suitable for subsequent statistical analyses.

Common method bias

To assess potential common method bias, Harman’s single-factor test [63] was first applied using exploratory factor analysis (EFA). Six factors emerged with eigenvalues greater than 1.0, and the first factor explained 36.11% of the variance—well below the majority threshold of total variance (74.40%).

A confirmatory factor analysis (CFA) was also conducted to evaluate the single-factor model following Sanchez and Brock [64]. The model fit indices were poor: $\chi^2(324) = 3573.461$, CFI = 0.480, GFI = 0.449, AGFI = 0.358, TLI = 0.436, RMSEA = 0.180, SRMR = 0.1564, indicating the single-factor model did not fit the data. These results suggest that the influence of common method bias in this study is minimal.

Measurement model

Ensuring the validity of the questionnaire entails a multifaceted approach, encompassing a comprehensive literature review and pilot testing involving 80 employees from media companies. Feedback garnered from these employees was instrumental in guiding revisions to the questionnaire. Construct reliability was assessed through a two-step approach, as proposed by Narasimhan and Jayaram [65].

Firstly, Cronbach’s α was computed to evaluate the reliability of the scales, with all constructs yielding values over 0.70, thereby indicating reliable measurement [66]. Additionally, all corrected item-total correlation (CITC) values surpassed the threshold of 0.30, meeting the minimum acceptable standard **(Table 1)**. Secondly, Exploratory Factor Analysis (EFA) was conducted, employing principal components and varimax rotation with Kaiser normalization, to examine the unidimensionality of the constructs. The results demonstrated that the relevant items predominantly loaded onto their intended constructs, thereby supporting the unidimensionality of the constructs **(Table 2-3)**.

Table 1. Reliability analysis

Construct	Number of items	Cronbach's α	CITC range
DF	4	0.844	0.650 - 0.710
PF	3	0.831	0.605 - 0.751
IF	5	0.950	0.838 - 0.890
EE	4	0.909	0.729 - 0.821
TP	4	0.850	0.673 - 0.713
EI	3	0.785	0.570 - 0.676
AIA	4	0.932	0.805 - 0.908

Table 2. EFA of DF, PF, IF, and TP

Items	Factor loadings			
	IF	DF	TP	PF
DF1	0.233	0.802	0.135	−0.026
DF2	0.194	0.783	0.106	0.241
DF3	0.209	0.763	0.148	0.204
DF4	0.304	0.715	0.027	0.252
PF1	0.164	0.194	0.166	0.840
PF2	0.498	0.275	0.135	0.646
PF3	0.490	0.265	0.075	0.647
IF1	0.831	0.258	0.097	0.197
IF2	0.848	0.291	0.085	0.179
IF3	0.884	0.218	0.149	0.141
IF4	0.854	0.202	0.123	0.211
IF5	0.859	0.165	0.146	0.147
TP1	0.205	0.116	0.786	0.006
TP2	0.102	0.087	0.821	−0.012
TP3	0.000	0.057	0.826	0.185
TP4	0.127	0.113	0.824	0.158
Eigenvalue	4.471	2.838	2.833	1.922
Total variance explained (%)	75.400			

Table 3. EFA of EE, AIA, and EI

Items	Factor loadings		
	AIA	EE	EI
EE1	0.005	0.875	0.217
EE2	0.013	0.893	0.156
EE3	0.048	0.879	0.182
EE4	−0.026	0.822	0.190
EI1	0.002	0.214	0.769
EI2	0.039	0.225	0.812
EI3	0.070	0.161	0.855
AIA1	0.914	0.069	0.012
AIA2	0.953	−0.002	−0.006
AIA3	0.893	−0.024	0.013
AIA4	0.884	−0.004	0.113
Eigenvalue	3.332	3.138	2.136
Total variance explained (%)		78.231	

Convergent and discriminant validity were evaluated using Confirmatory Factor Analysis (CFA), following the guidelines of Scott and Vokurka (1998). The CFA results indicated a good model fit, with $\chi^2(303) = 703.262$, CFI = 0.937, GFI = 0.858, RMSEA = 0.065, NNFI = 0.927, IFI = 0.937, and SRMR = 0.045 **(Table 4)**. All factor loadings exceeded 0.50 and associated t-values were greater than 2.0, supporting adequate convergent validity [67]. Discriminant validity was assessed by comparing the square root of the Average Variance Extracted (AVE) for each construct with the correlations between constructs. The results confirmed that discriminant validity was satisfactory (Fornell & Larcker [68]; **Table 5**).

Table 4. Fit indices for the measurement model

Measurement	Statistics	Desirable range	References
Degrees of freedom	303		Hu *et al.* (1992) and Hu and Bentler [69]
Minimum fit function χ 2	703.262		
Root mean square error of approximation (RMSEA)	0.065	⩽0.08	
Non-normed fit index (NNFI)	0.927	⩾0.90	
Comparative fit index (CFI)	0.937	⩾0.90	
IFI	0.937	⩾0.90	
GFI	0.858	⩾0.80	
AGFI	0.823	⩾0.80	
Standardized root mean squared residual (SRMR)	0.045	⩽0.05	

Table 5. Correlational matrix

Construct	Mean	SD	DF	PF	IF	EE	TP	EI	AIA
DF	3.331	0.830	.760[a]						
PF	3.297	0.890	0.567**	.798[a]					
IF	3.208	0.891	0.553**	0.653**	0.890[a]				
EE	3.502	0.835	0.569**	0.546**	0.539**	0.848[a]			
TP	3.770	0.625	0.286**	0.314**	0.298**	0.498**	.765[a]		
EI	3.770	0.624	0.226**	0.328**	0.331**	0.438**	0.704**	0.748[a]	
AIA	2.674	0.953	0.029	0.101	0.199**	0.029	0.035	0.081	.881[a]

Notes: n = 311, [a] Square root of AVE values. ** $p < 0.01$.

Results and Discussion

Covariance-based structural equation modeling (CB–SEM) was employed to test the proposed model, as this method is suitable for theory testing and model validation [70, 71]. Analyses were performed using Amos 23 with maximum likelihood estimation. The model demonstrated a good fit to the data, with $\chi^2(163) = 446.506$, CFI = 0.939, GFI = 0.877, AGFI = 0.842, NNFI = 0.928, IFI = 0.939, RMSEA = 0.075, and SRMR = 0.0469, satisfying the recommended criteria [69].

Multicollinearity among the predictors—distributive fairness, procedural fairness, and interactional fairness—was assessed using variance inflation factors, which ranged from 1.613 to 1.949, indicating no serious multicollinearity.

Hypotheses were tested using Model 4 in the PROCESS macro, applying 5,000 bootstrap samples and a 95% percentile confidence interval [72]. The results showed that all three dimensions of compensation fairness were positively associated with emotional engagement. Distributive fairness had a coefficient of 0.326 ($p < 0.001$), procedural fairness 0.209 ($p < 0.001$), and interactional fairness 0.201 ($p < 0.001$). Emotional engagement, in turn, was positively linked to task performance, with a coefficient of 0.352 ($p < 0.001$). These findings support hypotheses H1a, H1b, H1c, and H2.

The direct effects of distributive, procedural, and interactional fairness on task performance were not significant, with coefficients of −0.020, 0.041, and 0.015 respectively. However, the indirect effects through emotional engagement were all significant: distributive fairness 0.115, procedural fairness 0.073, and interactional fairness 0.071.

When examining total effects, only procedural fairness showed a significant impact on task performance (0.115, $p < 0.05$), while the total effects of distributive and interactional fairness were not significant. These results indicate that emotional engagement fully mediates the relationship between procedural fairness and task performance, highlighting its role as a key mechanism linking compensation fairness to employee performance.

Table 6. Direct effects.

DV	IV	Coeff	SE	t	p	LLCI	ULCI	Std. coeff	R-sq	F	p
EE	const	1.084	0.166	6.534	0.000	0.758	1.410		0.421	74.510	0.000
	IF	0.201	0.056	3.580	0.000	0.090	0.311	0.215			
	DF	0.326	0.055	5.877	0.000	0.217	0.435	0.324			
	PF	0.209	0.057	3.668	0.000	0.097	0.320	0.222			

TP	const	2.422	0.151	16.022	0.000	2.124	2.719		0.251	25.624	0.000
	IF	0.015	0.049	0.304	0.762	−0.081	0.111	0.021			
	EE	0.352	0.049	7.218	0.000	0.256	0.448	0.469			
	DF	−0.020	0.050	−0.400	0.690	−0.118	0.078	−0.026			
	PF	0.041	0.050	0.832	0.406	−0.056	0.139	0.059			

Notes: DV = dependent variable, IV = Independent variable, Coeff = Coefficient, SE = Standard error, LLCI = Lower confidence limit, ULCI = Upper confidence limit, Std. coeff = Standardized coefficient, R-sq = R-squared, const = constant.

Table 7. Indirect effects

IV	Indirect effect(s)				Completely standardized indirect effect(s)			
	Effect	**BootSE**	**BootLLCI**	**BootULCI**	**Effect**	**BootSE**	**BootLLCI**	**BootULCI**
IF	0.071	0.029	0.021	0.135	0.101	0.040	0.030	0.189
DF	0.115	0.030	0.062	0.178	0.152	0.038	0.083	0.233
PF	0.073	0.027	0.024	0.127	0.104	0.037	0.034	0.181

Notes: TP is the outcome variable, and EE is the mediator.

Table 8. Total effects

DV	IV	Coeff	SE	t	p	LLCI	ULCI	Std. coeff	R-sq	p
TP	const	2.803	0.153	18.325	0.000	2.502	3.104		0.123	0.000
	IF	0.086	0.052	1.652	0.099	−0.016	0.187	0.122		
	DF	0.095	0.051	1.851	0.065	−0.006	0.195	0.126		
	PF	0.115	0.052	2.186	0.030	0.011	0.218	0.163		

Notes: The path coefficients represent standardized coefficients, ** indicates $p < 0.01$.

The study also investigated whether emotional intelligence and AI adoption jointly influence how compensation fairness relates to emotional engagement. Using the PROCESS macro, Model 7 and Model 11 were applied with 5,000 bootstrap samples and 95% confidence intervals, in line with Hayes [72].

The analysis showed that, when AI adoption was not considered, emotional intelligence did not significantly alter the relationship between any of the compensation fairness dimensions—distributive, procedural, or interactional—and emotional engagement. When the interaction with AI adoption was included, the results indicated that the effect of emotional intelligence on the link between distributive fairness and emotional engagement remained non-significant ($\beta = 0.058$, $p = 0.451$), which did not support H3a. Similarly, emotional intelligence did not significantly moderate the effect of procedural fairness on engagement in combination with AI adoption ($\beta = 0.119$, $p = 0.069$), contradicting H3b.

In contrast, a significant conditional effect emerged for interactional fairness. The moderating influence of emotional intelligence on the relationship between interactional fairness and engagement became significant under higher levels of AI adoption ($\beta = 0.139$, $p = 0.03$), providing support for H3c. Overall, the combined moderating effects of emotional intelligence and AI adoption accounted for 0.8% of the variance in emotional engagement **(Table 9)**.

Table 9. Interactions of EI and AIA

Model	Product terms	Coeff	SE	t	p	LLCI	ULCI	R-sq	F
Model 7	DF * EI	0.072	0.060	1.209	0.228	−0.045	0.190	0.002	1.461
	PF * EI	−0.039	0.055	−0.707	0.480	−0.146	0.069	0.001	0.500
	IF * EI	−0.009	0.050	−0.191	0.849	−0.107	0.088	0.000	0.036
Model 11	DF * EI * AIA	0.058	0.077	0.754	0.451	−0.094	0.210	0.001	0.569
	PF * EI * AIA	0.119	0.065	1.825	0.069	−0.009	0.248	0.006	3.331
	IF * EI * AIA	0.139	0.064	2.184	0.030	0.014	0.264	0.008	4.769

Notes: EE is the outcome variable, and DF, PF, and IF are independent variables.

Table 10 indicates that the best-fitting model with EE as the outcome variable is as follows:

$$\widehat{EE} = -4.951 + 1.744\,IF + 1.685\,EI + 1.765\,AIA - 0.405\,IF\ x\ EI - 0.544\,IF\ x\ AIA - 468\,EI\ x\ AIA + 0.139\,IF\ x\ EI\ x\ AIA + 0.311\,DF + 0.164\,PF \tag{1}$$

Table 10. Model 11 summary with EE as the outcome variable, IF as the focal antecedent variable, DF and PF as covariates, EI as the primary moderator, and AIA as the secondary moderator

IV	Coeff	SE	t	p	LLCI	ULCI	R-sq	p
Constant	−4.951	2.438	−2.030	0.043	−9.750	−0.152	0.489	0.000
IF	1.744	0.770	2.263	0.024	0.228	3.260		
EI	1.685	0.623	2.703	0.007	0.458	2.912		
IF * EI	−0.405	0.193	−2.100	0.037	−0.784	−0.025		
AIA	1.765	0.831	2.125	0.034	0.130	3.400		
IF * AIA	−0.544	0.258	−2.106	0.036	−1.053	−0.036		
EI * AIA	−0.468	0.211	−2.223	0.027	−0.883	−0.054		
IF * EI * AIA	0.139	0.064	2.184	0.030	0.014	0.264		
DF	0.311	0.054	5.751	0.000	0.205	0.418		
PF	0.164	0.055	3.001	0.003	0.056	0.271		

Analysis revealed a positive link between interactional fairness (IF) and emotional engagement (EE). The regression results indicated a statistically significant three-way interaction among IF, emotional intelligence (EI), and AI adoption (AIA). This means that the effect of EI in moderating the relationship between IF and EE varies depending on the level of AIA.

To examine the nature of this interaction in more detail, the Johnson-Neyman technique was applied, following Hayes [72], with floodlight analysis [73] used to visualize the effects. Unlike traditional spotlight tests, this approach is better suited for continuous moderators such as EI and AIA, as it identifies the specific ranges where moderation occurs. Using 5,000 bootstrap samples and a 95% confidence interval, it was found that at moderate levels of AIA (between 1.217 and 4.527), EI did not significantly influence the IF–EE relationship. For example, when AIA was 3, the moderation coefficient was 0.012 (p = 0.815), indicating no meaningful effect.

In contrast, when AIA was either low (<1.217) or high (>4.527), EI significantly affected the relationship. At a low AIA level of 1.2, EI had a negative moderating effect (coefficient = −0.238, p = 0.0496), whereas at a high level of 4.8, the moderating effect was positive (coefficient = 0.262, p = 0.0442). These results suggest that EI's influence on the link between IF and EE becomes stronger as AI adoption reaches more extreme levels, either low or high, highlighting a conditional pattern in the interaction **(Table 11 and Figure 3)**.

Table 11. Test of conditional IF × EI interaction at values of AIA

AIA	Effect	F (1, 301)	p
1.200	−0.238	3.887	0.0496
3.000	0.012	0.055	0.8150
4.800	0.262	4.083	0.0442

We examined how interactional fairness (IF) influenced emotional engagement (EE) across different combinations of AI adoption (AIA) and emotional intelligence (EI). At a low AIA level of 1.2, IF had a notable positive impact on EE only when EI was relatively low (16th percentile, EI = 3; b = 0.376, p = 0.006). As EI increased to the median (EI = 4) or higher (84th percentile, EI = 4.333), the effect of IF on EE weakened and became statistically insignificant (b = 0.138, p = 0.106; b = 0.059, p = 0.555).

When AIA was moderate (3), IF consistently enhanced EE across all EI levels. Even at the lowest EI percentile, IF exerted a positive influence (b = 0.146, p = 0.040), which remained significant at the median (b = 0.158, p = 0.007) and high EI levels (b = 0.162, p = 0.011).

At a high AIA level of 4.8, the effects of IF were more selective. At low EI, IF had no meaningful impact on EE (b = −0.083, p = 0.632), and at median EI, the effect was still non-significant (b = 0.179, p = 0.103). Only when EI was high (84th percentile) did IF significantly boost EE (b = 0.266, p = 0.022). Overall, these patterns suggest that the combined levels of AIA and EI determine the strength of IF's effect on EE, with the largest positive effects observed when both AIA and EI are high **(Table 12)**.

Table 12. Conditional effects of IF on EE at values of the moderators

AIA	EI	Effect	SE	t	p	LLCI	ULCI
1.200	3.000	0.376	0.137	2.749	0.006	0.107	0.646
1.200	4.000	0.138	0.085	1.622	0.106	−0.030	0.306
1.200	4.333	0.059	0.100	0.591	0.555	−0.137	0.255

3.000	3.000	0.146	0.071	2.063	0.040	0.007	0.286
3.000	4.000	0.158	0.059	2.709	0.007	0.043	0.273
3.000	4.333	0.162	0.064	2.558	0.011	0.038	0.287
4.800	3.000	−0.083	0.174	−0.480	0.632	−0.425	0.258
4.800	4.000	0.179	0.109	1.638	0.103	−0.036	0.393
4.800	4.333	0.266	0.115	2.308	0.022	0.039	0.493

When examining task performance (TP) as the outcome, with emotional engagement (EE) serving as the mediator, interactional fairness (IF) as the key antecedent, distributive fairness (DF) and procedural fairness (PF) as control variables, emotional intelligence (EI) as the primary moderator, and AI adoption (AIA) as the secondary moderator, the index of moderated-moderated mediation was calculated at 0.049. The 95% bootstrap confidence interval, ranging from 0.005 to 0.100, did not include zero, indicating that the conditional mediation effect was statistically significant.

The findings highlight how different dimensions of compensation fairness—DF, PF, and IF—affect EE and, in turn, TP. All three components positively influenced EE, reinforcing the validity of the Group Engagement Model (GEM) proposed by Tyler and Blader [9]. Among the three, DF exhibited the strongest effect on EE, suggesting that employees are particularly sensitive to the fairness of compensation levels compared with procedural or interactional considerations **(Figure 2)**. Moreover, the positive influence of EE on TP was confirmed, aligning with previous research [10, 42-47], thereby extending the explanatory power of GEM to performance outcomes.

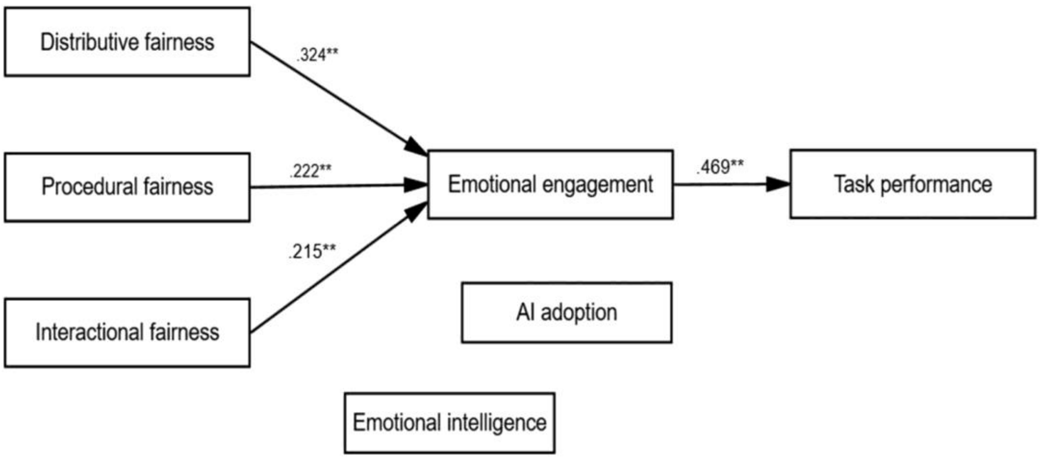

Figure 2. Resulting model

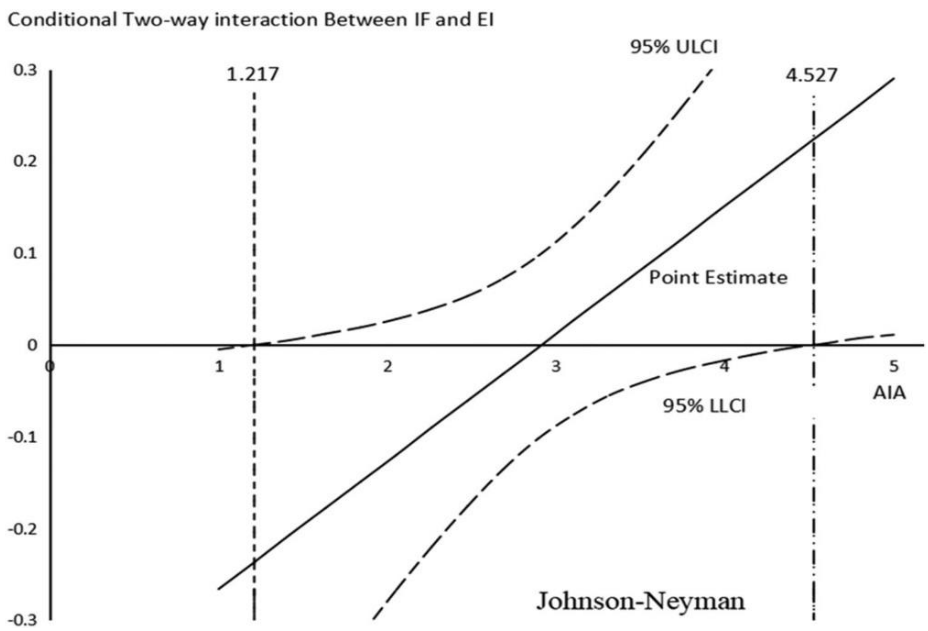

Figure 3. The conditional two-way interaction between IF and EI as a function of AIA

Analysis revealed that distributive fairness (DF), procedural fairness (PF), and interactional fairness (IF) did not directly impact task performance (TP), yet all three had significant positive indirect effects through emotional engagement (EE).

Interestingly, DF’s total effect on TP was not statistically significant due to a suppression effect: its direct effect was slightly negative while its indirect effect via EE was positive. This suggests that appropriate differences in compensation can stimulate employee effort, supporting the perspective of Tournament Theory, which argues that non-egalitarian pay structures can motivate higher performance [74]. PF, on the other hand, showed a significant total effect on TP, with EE acting as a full mediator, and its overall influence on TP exceeded that of DF and IF. These findings imply that organizations aiming to boost task performance should emphasize fair procedures and transparent compensation management, as these foster both dedication and loyalty among employees.

Although IF’s total effect on TP was not significant, its indirect effect via EE was positive, and moderated-moderated mediation was observed. Specifically, when both EI and AI adoption (AIA) reached certain levels, the positive influence of IF on TP became significant. This highlights the importance of IF in cultivating employee engagement. Historical evidence from the Hawthorne Studies further supports the idea that involving employees in discussions, listening to their concerns, and acknowledging their perspectives can enhance morale and performance [75].

Prior research has examined the role of EI in moderating the relationship between fairness and performance [76] or between job resources and engagement [14]. However, few studies have considered whether this moderating effect itself depends on contextual factors. Our study found that EI alone did not significantly moderate the influence of DF, PF, or IF on EE. When considering AIA, EI’s moderating role was still insignificant for DF and PF but became significantly positive for IF. This pattern likely arises because DF and PF relate to material outcomes and procedural transparency, which are relatively stable and less affected by individual traits or technology. In contrast, IF involves interpersonal interactions and the perceived respect from supervisors, making it more sensitive to employee characteristics and work context, such as AIA.

In environments with high AI adoption, employees with high EI experienced a stronger positive reinforcement effect, whereas those with low EI were more susceptible to negative disclosure effects. Consequently, managers can enhance EE by improving IF, particularly among employees with higher EI in AI-intensive settings. As AI continues to transform workflows and social dynamics at work, employees with strong emotional intelligence are better able to adapt, maintain engagement, and sustain loyalty. This underscores the need for organizations to account for both individual traits and technology-embedded work contexts when designing compensation interactions.

From a practical perspective, managers should prioritize IF by fostering open communication, respectful interactions, and opportunities for employees to voice concerns. Training programs and team-building initiatives can strengthen employees’ emotional regulation skills and their ability to adapt to AI-augmented work environments, thereby enhancing engagement and performance.

Theoretically, this study advances the Group Engagement Model (GEM) by empirically differentiating the effects of DF, PF, and IF on EE and TP, while demonstrating the conditional role of EI and AIA. Unlike prior research that treats compensation fairness as a single construct, our findings highlight the distinct pathways through which each dimension influences engagement and performance. Moreover, the study extends the theoretical boundaries of GEM and equity theory by incorporating higher-order moderating effects of work context, offering new insights into how personal traits and organizational technologies interact to shape employee engagement. We also observed that EI’s moderation was significant for behavioral engagement but not for cognitive engagement, indicating that AI’s impact is primarily psychological and behavioral rather than cognitive.

For future research, the framework can be extended to examine other individual differences, such as achievement motivation or personality traits, and additional work-context factors, such as leadership style or organizational climate. There remains ample opportunity to explore strategies for enhancing employee engagement and performance through a nuanced understanding of fairness, individual characteristics, and technology-driven work environments.

In practice, while DF and IF had relatively weaker effects on TP, PF emerged as the most influential. Organizations should focus on transparent, consistent, and fair procedures in compensation management, including clear performance appraisal systems and equitable decision-making processes. By prioritizing procedural fairness, companies can strengthen employee engagement, motivation, and productivity in a sustainable manner.

The moderating roles of emotional intelligence (EI) and AI adoption (AIA) in the relationship between interactional fairness (IF) and emotional engagement (EE) highlight the context-dependent nature of IF’s effects. Under specific conditions, IF can influence task performance (TP) via EE. The impact of AIA—whether it manifests as a positive reinforcement effect [52, 53] or a negative disclosure effect [17, 53, 54]—is closely tied to the interplay between EI and IF. These findings suggest that managers should adopt a differentiated approach to compensation management. In highly AI-integrated work environments, employees with high EI are more responsive to the reinforcing benefits of AIA. For such employees, managers should address individual needs, show respect, and engage in sincere discussions regarding compensation decisions, thereby enhancing understanding, motivation, and dedication to work. Conversely, employees with lower EI may be more affected by the negative disclosure aspects of AIA, making efforts to enhance IF less effective. This study illuminates the “black box” of how compensation fairness influences task performance and provides actionable insights for optimizing employee incentives in organizational practice.

This study integrates TP, EI, and AIA into the Group Engagement Model (GEM) framework to examine how the three dimensions of compensation fairness (DF, PF, and IF) influence EE and TP. The results demonstrate that all three dimensions positively affect EE, with DF exerting the strongest influence. EE, in turn, positively affects TP. PF also has a direct positive effect on TP, fully mediated by EE. Importantly, the moderating role of EI on the IF–EE relationship is positively associated with AIA, and a moderated-moderated mediation effect was observed. In other words, AIA amplifies the influence of EI on the relationship between IF and EE, which subsequently affects TP. These findings extend the theoretical boundaries of GEM and equity theory, especially in the context of increasing AI adoption in organizations, offering valuable guidance for both research and practical human resource management. Managers can leverage these insights to enhance employee performance by ensuring fairness in compensation processes and strategically emphasizing interactional fairness tailored to individual employees.

Despite these contributions, several limitations remain. This study focused on DF, PF, and IF as dimensions of compensation fairness affecting EE and TP, but future research could investigate their effects on other facets of work engagement, including cognitive and behavioral engagement, as well as the potential moderating variables in these relationships. The cross-sectional design also constrains the ability to establish causal inferences; longitudinal studies are recommended to strengthen the causal understanding. Additionally, the sample was limited to employees in Chinese media enterprises, raising questions about generalizability. Future research should examine whether these findings hold across different industries in China or among media employees in other cultural contexts, which would enhance external validity and provide a broader understanding of how compensation fairness, EI, and AIA interact to influence engagement and performance.

Acknowledgments: All authors contributed to the research concepts and design. Yingming Qiu drafted the manuscript and performed the data acquisition and analysis. Yingming Qiu and Nuttawut Rojniruttikul repeatedly revised and refined the content of the manuscript. All authors have read and agreed to the published version of the manuscript.

Conflict of interest: None

Financial support: None

Ethics statement: None

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