The Impact of AI Algorithm Monitoring on Employee Job Satisfaction

Xinyuan Zhang[1, a]

[1]School of Nanjing Agricultural University, Nanjing 210000, China;

[a]18642400183@163.com

Abstract. Purpose-Against the backdrop of artificial intelligence (AI) technology deeply permeating workplace management, this study focuses on the differential impact mechanism of AI algorithmic monitoring on employees' job satisfaction. Based on social cognitive theory and organizational identification theory, this study constructs and verifies a dual-driven path of developmental feedback and controlling feedback, exploring the mediating effects of self-efficacy and work identification. The aim is to provide a theoretical basis for achieving a balance between efficiency and humanistic care in digital management. Design/Methodology/Approach-A questionnaire survey was adopted to collect data from 343 employees in AI technology-intensive industries in eastern China. The partial least squares structural equation modeling (PLS-SEM) was employed to construct a "dual feedback-dual path mediation" model, thereby systematically testing the asymmetric impacts of developmental feedback and controlling feedback on job satisfaction, as well as their internal psychological mediating mechanisms. In the study, Harman's single-factor test was conducted to control common method bias, and the Bootstrap method was employed to verify the significance of mediating effects. Findings-Developmental feedback significantly enhances job satisfaction through its mediating effect on self-efficacy and job identity, following a positive feedback loop of “skill empowerment → efficacy construction → identity reinforcement.” In contrast, controlling feedback reduces job satisfaction by weakening self-efficacy and job identity, forming a negative feedback loop of “autonomy deprivation → identity dissolution.” The mediating effects of the two types of feedback exhibit significant differentiation in weight: in the developmental feedback pathway, self-efficacy plays a dominant role; in the controlling feedback pathway, job identity demonstrates stronger cultural sensitivity. Originality/Value-This study pioneers a dual-feedback classification system within algorithmic monitoring contexts, transcending the limitations of traditional one-dimensional monitoring research. It unveils the dual mediating mechanisms of competency development and organizational identity, clarifying a previously obscure “black box.” Findings confirm that the positive effects of developmental feedback significantly outweigh the negative impacts of controlling feedback. This provides critical theoretical support for designing AI management paradigms centered on developmental feedback with controlling feedback as a supplement, offering substantial practical guidance for cultivating employees' psychological resources during digital transformation.

Keywords: AI algorithmic monitoring; developmental feedback; controlling feedback; job satisfaction.

1. Introduction

Artificial intelligence technology is transforming workplace management by both increasing efficiency and introducing new challenges to employee well-being. In China, the digital economy now exceeds 55 trillion yuan, with over 80% of manufacturing and internet enterprises using AI monitoring systems. These systems' developmental feedback boosts production efficiency by 23%, while control-oriented feedback reduces error rates. However, this technology presents a double-edged sword: while 65% of employees find developmental feedback valuable, 52% report ongoing anxiety from algorithmic scoring, and control-oriented feedback strongly correlates with emotional exhaustion. The central challenge is balancing the efficiency gains from AI systems with their impact on employee mental health.

Currently, China's economic slowdown and an 18.7% workplace turnover rate pose challenges for sustaining organizations, making employee job satisfaction essential. This raises a central question in digital management: Why do algorithmic systems, acting as both “career coaches” and “digital overseers,” cause differing psychological responses among employees? More specifically, do developmental and controlling feedback affect job satisfaction through separate pathways? To enable high-quality digital transformation, Chinese enterprises must address the tension between efficiency and people-centered values, and make employee satisfaction a priority in digital strategies.

Research on job satisfaction rests on three pillars. First, studies on individual factors use self-efficacy theory but overlook how algorithms influence employees' thinking. Second, research on organizational context is based on the Two-Factor Theory but does not consider algorithmic management as a new variable. Third, research on technological factors looks at technology's effects but does not closely examine unique feedback or the psychological mechanisms involved.

Research in this field suffers from three deficiencies. First, conceptual definitions are vague and overlook the basic opposition between two types of feedback functions—corrective and reinforcing. Second, a "black box" approach to mechanisms fails to reveal the role of key psychological mediating variables, such as motivation and self-efficacy. Third, research conclusions lack sufficient contextual universality, meaning they may not generalize across different settings or populations.

This study constructs an integrated "dual-feedback-dual-path mediation" model to address three key issues. First, it finds that developmental feedback boosts self-efficacy and enhances job satisfaction, while directive feedback undermines autonomy and diminishes job satisfaction. Second, it confirms that both self-efficacy and job identity mediate these effects. Finally, it reports that the strength and weight of these two feedback paths differ.

This study makes three key contributions. First, it clarifies the dual nature of algorithmic feedback by distinctly establishing performance-oriented feedback (guiding behavior to targets) and developmental feedback (supporting skill growth), resolving the “confused measurement” dilemma. Second, it validates a dual-path mediation model and reveals distinct pathways. Third, it shows the unequal effects of the two feedback types. This forms a basis for redesigning work in the AI era and helps shape algorithmic governance strategies that balance efficiency and people-centeredness.

2. Literature Review and Hypothesis Development

2.1 Mechanisms Through Which Controlling Feedback Erodes Job Satisfaction

Controlling feedback reduces job satisfaction in two main ways: by taking away employees' autonomy and weakening their job identity. First, when computer systems enforce standard procedures and monitor behavior in real time, employees feel a lack of autonomy, which causes anxiety about losing skills[4]. This loss of autonomy also means that employees lose important chances to learn through trial and error, which slows their professional growth. More importantly, messages of "organizational distrust" from controlling feedback damage employees' job identity. Evidence shows a factor loading of 0.835 for the statement "I feel offended when the organization is criticized," confirming this variable's importance in the local culture. In summary, based on this analysis and evidence, the following hypothesis is proposed:

H1: Controlling feedback exerts a significant negative impact on job satisfaction.

2.2 The Mediating Role of Self-Efficacy in Controlling Feedback

Controlling feedback indirectly lowers job satisfaction by hurting self-efficacy. When algorithms tightly limit work freedom, employees find it hard to gain key mastery experiences (Bandura, 2012)[2], which leads to a steady loss of their confidence. Lab research by Rocheleau (2023)[1] shows that employees in controlled groups rate their self-efficacy 19% lower than those in the control group. This drop in efficacy makes people avoid challenges. Also, Judge et al. (2017)[4]'s review found that people with low self-efficacy often overestimate task difficulty by about 40%[6], which lowers job satisfaction. Together, these results show a pattern of undermined efficacy. Therefore, we propose:

H2: Self-efficacy mediates the negative relationship between controlling feedback and job satisfaction.

2.3 The Mediating Role of Work Identification in Controlling Feedback

The "organizational distrust" signals from algorithmic monitoring erode employees' sense of organizational membership (Mael & Ashforth, 1992)[6]. As controlling algorithms intervene in work processes, this distrust drives organizational alienation, severing the belief that "organizational success is my success". This weakened identification diminishes employees' psychological connectedness and satisfaction. Based on this logic, we propose:

H3: Work identification mediates the negative relationship between controlling feedback and job satisfaction.

2.4 The Empowerment Mechanism of Developmental Feedback on Job Satisfaction

Developmental feedback boosts job satisfaction by driving competency development[7]. Personalized skill recommendations from algorithms directly foster employees' "I can do it" beliefs via Bandura's (2012) four-dimensional efficacy model[2]: Verbal persuasion (objective competency validation through professional diagnostic reports); Vicarious experience (algorithm-suggested best practices from peers); Emotional arousal (positive progress feedback triggers proactive emotional states); and Achievement experience (phased goal attainment cements mastery). Empirical research by Quan et al. (2021) reveals that AI guidance raised the proportion of highly skilled employees by 12%[8]. Ultimately, this empowerment mechanism is the key driver of satisfaction. Accordingly, we propose:

H4: Developmental feedback exerts a significant positive influence on job satisfaction.

2.5 The Mediating Role of Self-Efficacy in Developmental Feedback

Developmental feedback directly boosts self-efficacy by driving incremental achievement. For instance, Parents' (2023) field experiment showed that employees guided by AI reported a 27% rise in confidence to tackle difficult problems. Neuroscience research reinforces this connection: perceived algorithmic support prompts a significant dlPFC activation increase (β=0.68). Since dlPFC activity is closely links to self-efficacy, these findings pinpoint the neural basis for self-efficacy gains. Notably, this amplified efficacy fuels a measurable 19% jump in job satisfaction [8]. Self-efficacy thus forms the essential bridge between developmental feedback and job satisfaction. Accordingly, the following hypothesis is proposed:

H5: Self-efficacy mediates the positive relationship between developmental feedback and job satisfaction.

2.6 Differentiated Mediating Effects Across Feedback Pathways

Existing research shows that different psychological paths affect job satisfaction in each feedback category. In the control feedback path, job identification is a stronger link than self-efficacy. In the developmental feedback path, self-efficacy is a stronger link than work identification (An et al., 2021). Based on these differences, this study proposes the following hypothesis comparing the strength of the mediating effects:

H6: In the pathway where regulatory feedback influences job satisfaction, the mediating effect of job identification is stronger than that of self-efficacy.

H7: In the pathway where developmental feedback influences job satisfaction, the mediating effect of self-efficacy is stronger than that of job identification.

3. Data and Methods

3.1 Sample and Data Collection

This study gathered data using questionnaire surveys in June 2025 in provinces with intensive AI applications: Jiangsu, Guangdong, and Shanghai. These regions were selected as AI industry centers with varying levels of economic development, offering diverse perspectives on workers' perceptions of AI monitoring in line with the study's focus. A pre-survey invited 20 professionals to test the questionnaire. Their feedback led to revisions for clarity. The formal survey used the Wenshu Xing platform, applying quota sampling to balance gender and age. Unique links prevented duplicate responses. Compensation was provided to respondents to enhance their willingness to participate. Following data collection, the dataset was subjected to rigorous cleaning based on established criteria, including abnormal response times, IP address discrepancies, consecutive identical responses, and excessive missing data for key variables. As a result, 343 valid questionnaires were retained, yielding an effective response rate of 85.8%. Moreover, the sample demonstrated a balanced gender distribution, with 86.1% of participants aged 21-40 and 77.6% possessing at least a bachelor's degree. The sample also encompassed multiple industries, aligning with the defining characteristics of the principal workforce demographic from Jiangsu, Guangdong, and Shanghai.

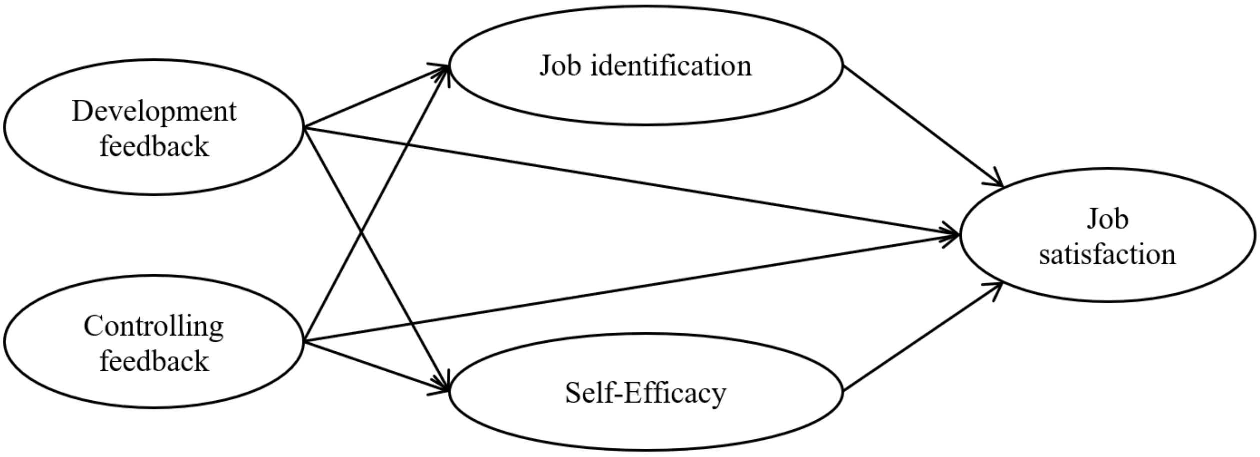

Fig. 1 Research Framework on the Impact of AI Algorithm Monitoring on Employee Job Satisfaction

3.2 Measurement Instruments

This study used a structured questionnaire with two main sections. The first measured core research variables—developmental feedback and directive feedback as independent variables, job identity and self-efficacy as mediators, and job satisfaction as the dependent variable. The second gathered demographic and control variable data.

Table 1 Demographic Characteristics of Respondents

Characteristic	Demographic	Frequency	Percentage (%)
Gender	Female	177	51.6
	Male	166	48.4
Age(years)	18-24	107	31.2
	25-34	134	39.07
	35-44	61	17.78
	45-54	24	7
	55 and above	17	4.96
Educational	Senior high or below	30	8.75
	Associate degree	89	25.95
	Bachelor degree	181	52.77
	Master’s degree	29	8.45
	doctor's degree	14	4.08
Years of work	1 and below	112	32.65
	1-3	146	42.57
	4-6	44	12.83

	7-10	28	8.16
	10 and above	13	3.79
Position Level	Grassroots employees and others	207	60.35
	Professional and technical personnel	70	20.41
	Supervisor / team leader	23	6.71
	Middle managers	25	7.29
	Senior managers	17	4.96
	Others	1	0.29
Type of city	First-tier cities	53	15.45
	New first-tier cities	90	26.24
	Second-tier cities	140	40.82
	Third-tier and below cities	59	17.2
	Overseas	1	0.29

Source(s): Authors' work

Developmental feedback was measured using Parent and Rocheleau's (2023) scale, which includes three items. Control feedback was measured using three items adapted from the scale developed in "Algorithmic Control as a Double-Edged Sword" (2025); the adaptation involved rewording items to refer to feedback from supervisors instead of algorithms. Higher scores for both scales indicate stronger perceived developmental or control feedback, respectively.

Job identity was measured using Mael and Ashforth's (1992)[6] organizational identity scale, which contains four items. Self-efficacy was measured with the General Self-Efficacy Scale by Schwarzer and Jerusalem (1995)[10], also comprising four items. To ensure consistency across all measures, the original 4-point response format of each scale was systematically adapted to a 5-point Likert scale.

Job satisfaction was measured using a simplified, three-item version of the Michigan Organizational Assessment Questionnaire (MOAQ)[11], which included one reverse-scored item. The reverse-scored item was transformed before analysis to ensure all items were scored in the same direction. Higher total scores reflect greater job satisfaction.

All scales used were well-established instruments that underwent standardized Chinese-English translation for semantic equivalence. To ensure suitability for the research setting, contextual adaptations were made, such as modifying item wording and examples. Furthermore, all core variables were measured on a five-point Likert scale[12].

4. Data Analysis and Results

4.1 Common Method Bias and Descriptive Statistics

This study checked common method bias using Harman's single-factor test. The first factor explained 34.8% of total variance, under the 50% threshold. No unusual links appeared among key constructs, showing influence was controllable. For sample data, developmental feedback scores were much higher than directive feedback in a paired t-test. This means employees more strongly noticed AI-enabled support and varied more in how they viewed directive feedback. The average self-efficacy score was higher than work identification, so employees felt more confident in their abilities than in belonging to the organization. Together, these findings give initial data for later research.

4.2 Measurement Model Validation

This study checked variable measurement by testing reliability and validity (Table 2). For reliability, all constructs had Cronbach's α and composite reliability above 0.7. Controlled feedback and job satisfaction both met this benchmark, supporting later tests of *H1* and *H4*. For convergent validity, all factor loadings topped 0.7, and the average variance extracted (AVE) for each construct was above 0.5. Controlled feedback had the highest AVE, capturing algorithmic control traits and supporting *H1-H3*. Job identification and self-efficacy also met convergent validity, confirming the measurement of mediating effects in *H2*, *H3*, and *H5*.

Table 2 Reliability and Validity Tests of Constructs

Construct	VIF	Items	Standard loadings	Cronbach's ɑ	CR	AVE
DF	1.603	The algorithm provides recommendations for improving work skills.	0.830	0.792	0.878	0.706
	1.652	Receive personalized career development guidance from AI systems	0.822			
	2.068	AI feedback helps me identify areas for improvement.	0.868			
CF	2.563	The AI system strictly enforces compliance with standardized procedures.	0.897	0.894	0.933	0.823
	2.606	Algorithmic scoring limits my professional autonomy.	0.920			
	2.899	Real-time monitoring forced me to adjust my work pace.	0.904			
JS	1.802	When the organization is criticized, I feel offended.	0.835	0.818	0.880	0.647
	1.595	Caring about how others perceive my organization	0.769			
	1.657	When discussing the organization, it is customary to use "we" rather than "they."	0.795			
	1.744	The success of the organization is my success.	0.816			
SE	1.496	With hard work, I can always solve difficult problems.	0.769	0.783	0.860	0.605
	1.624	When faced with a problem, one can usually come up with multiple solutions.	0.798			
	1.483	Effectively respond to emergencies	0.765			
	1.554	Skilled at handling unexpected situations	0.780			
JI	1.351	Overall, I am satisfied with my job.	0.777	0.704	0.835	0.628
	1.452	(Reverse) Generally speaking, I don't like my job.	0.829			
	1.343	Most people in the same position are satisfied with their work.	0.771			

JI = Job identification; SE = Self-Efficacy; CF = Controlling feedback; DF = Developmental feedback;
JS = Job satisfaction
Source(s): Authors' work

This study used the Fornell-Larcker criteria and Heterotrait-Monotrait (HTMT) ratios to test discriminant validity, as shown in Table 3. The square root of the average variance extracted (AVE) for each construct exceeded its correlations with other constructs. All HTMT values were below the conservative 0.90 threshold. Notably, HTMT values for self-efficacy and work identification approached this threshold. This aligns with the hypothesis predicting their distinct roles in the dual-path model. This supports treating them as separate mediating variables and helps prevent conceptual overlap from reducing the explanatory power of the dual-path mechanism.

4.3 Path Relationship Assessment

Path analysis shows that controlling feedback (which restricts autonomy or imposes standards) has a significant negative direct effect on job satisfaction, while developmental feedback (aimed at growth and improvement) has a significant positive direct effect. These results support *H1* and *H4*. Developmental feedback increases job satisfaction through self-efficacy (belief in one's ability to succeed) and work identification (sense of belonging or attachment to the job). Controlling feedback reduces job satisfaction through both factors. The total indirect effects show that developmental feedback has a stronger influence than controlling feedback, supporting *H2*, *H3*, and *H5*. Within the controlling feedback pathway, the indirect effect of job identity is stronger than that of self-efficacy. In the developmental feedback pathway, the indirect effect of self-efficacy is stronger than that of job identity. Thus, *H6* and *H7* are supported. The path coefficients for control variables are insignificant, indicating robust core variable relationships.

4.4 Mediating Effect Test

Path analysis of the structural model reveals key findings. Controlling feedback (feedback focused on compliance with rules or standards) exerts a significant negative direct effect on job satisfaction. Developmental feedback (feedback aimed at helping employees grow and improve their skills) exerts a significant positive direct effect. These results support *H1* and *H4*. Developmental feedback positively influences job satisfaction through self-efficacy (belief in one’s own ability to succeed) and job identity (the sense of alignment between one’s job and personal identity). Controlling feedback negatively impacts job satisfaction through both variables. The total indirect effects show that developmental feedback has a stronger influence than controlling feedback, supporting *H2*, *H3*, and *H5*. In the controlling feedback pathway, the indirect effect of job identity is stronger than that of self-efficacy. In the developmental feedback pathway, the indirect effect of self-efficacy is dominant. Thus, *H6* and *H7* are both supported. Furthermore, the path coefficients for control variables are insignificant, indicating the robustness of the core variable relationships.

Table 3: Correlation and Root Mean Square Error of Approximation (Fornell-Larcker)

	DF	JS	JI	CF	SE
DF	0.840				
JS	0.578	0.793			
JI	0.616	0.639	0.804		
CF	-0.385	-0.446	-0.372	0.907	
SE	0.620	0.650	0.719	-0.377	0.778

Note(s): The diagonal (italic) elements are the square roots of AVEs, and the off-diagonal elements are the
correlations among constructs
JI = Job identification; SE = Self-Efficacy; CF = Controlling feedback; DF = Developmental feedback;
JS = Job satisfaction
Source(s): Authors’work

Table 4 Heterogeneous Trait-Homogeneous Trait Ratio (HTMT) and Confidence Intervals

	DF	JS	JI	CF
JS	0.765 [0.665, 0.849]			
JI	0.755 [0.656, 0.834]	0.838 [0.745, 0.916]		
CF	0.446 [0.338, 0.545]	0.556 [0.461, 0.648]	0.428 [0.322, 0.531]	
SE	0.781 [0.690, 0.858]	0.874 [0.787, 0.953]	0.896 [0.830, 0.953]	0.443 [0.334, 0.548]

Note(s): The italic elements are the correlations among constructs and the confidence interval of the value is
in parentheses
JI = Job identification; SE = Self-Efficacy; CF = Controlling feedback; DF = Developmental feedback;
JS = Job satisfaction
Source(s): Authors' work

Table 5 Mediation effect results

Hypotheses and paths	Specific indirect effects			Total indirect effects			Direct effects			Total effects		
	β	T-value	Confidence intervals	β	T-value	Confidence intervals	β	T-value	Confidence intervals	β	T-value	Confidence intervals
DF → SE → JS	0.164***	4.075	[0.091,0.247]	0.307***	7.713	[0.232,0.388]	0.170**	3.008	[0.055,0.278]	0.477***	10.937	[0.389,0.563]
DF → JI → JS	0.143***	3.543	[0.071,0.227]									
CF → SE → JS	-0.048**	2.748	[-0.086,-0.018]	-0.089***	3.595	[-0.141,-0.044]	-0.174***	4.181	[-0.253,-0.091]	-0.262***	5.949	[-0.348,-0.173]
CF → JI → JS	-0.041**	2.631	[-0.076,-0.014]									

Note(s): *p < 0.05, **p < 0.01, ***p < 0.001
JI = Job identification; SE = Self-Efficacy; CF = Controlling feedback; DF = Developmental feedback; JS = Job satisfaction
Source(s): Authors' work

4.5 Predictive Validity

This study evaluates how well the model predicts using the coefficient of determination (R^2) and cross-validation redundancy (Q^2). For job satisfaction, R^2 must be above 0.5; this study achieves 0.650, meaning it explains 65% of the variance. This is much higher than most single-path studies and shows strong explanatory power. Q^2 for job satisfaction needs to be greater than 0.35, and this study gets 0.393. Likewise, both self-efficacy (0.294) and job identification (0.258) need Q^2 values above 0.15, requirements met here, showing the model predicts well. Also, indirect effects on job satisfaction—

through self-efficacy and job identification—are much stronger than direct effects, confirming the importance of psychological factors. Finally, all construct pairs have HTMT values below 0.90, meaning there is no multicollinearity and supporting the theory.

5. Discussion

This study reveals that algorithmic monitoring fundamentally represents a deep-seated contest between labor value creation and control over the labor process. On one hand, developmental feedback indirectly enhances work meaning; by activating a “capability-building cycle,” it causes increases in skill refinement, which boost efficacy. These improvements, in turn, make the value of employees’ contributions more visible, reinforcing motivation and engagement. On the other hand, controlling feedback leads, indirectly, to “organizational disconnection.” It compresses work autonomy, which gradually undermines employees’ psychological attachment by decreasing the sense of agency and belonging.

This mechanism's differentiation reflects a question about the nature of labor: developmental feedback meets the desire for growth, fitting the idea of labor as a way to realize oneself by supporting internal motivation and engagement. In contrast, control-oriented feedback increases feelings of alienation, reveals the dominance of goal-focused thinking, and lessens workers' sense of agency. In China, this difference is clear: the developmental path is seen as ethical because it matches the tradition of “self-improvement through relentless effort” and encourages ethical behavior, while the control-oriented path causes resistance because it ignores relationship-based ethics and hurts social unity.

This study makes three contributions: first, it defines the developmental-regulatory range of algorithmic monitoring; second, it shows how building efficacy indirectly shapes identity through two mediation paths; and third, it supports the ethical value of developmental feedback.

Enterprises must improve how algorithms are created: Build systems that show how development happens; Organizations should define security programs as protectors; Algorithms should help create trust between workers and owners. We can only support workers in digital society by making sure people come before technology.

6. Conclusions, Implications, and Limitations

6.1 Conclusions

This study shows algorithmic monitoring as a contest between labor value creation and organizational control. Developmental feedback, by enhancing self-efficacy, turns technological interventions into catalysts for higher job satisfaction. In contrast, controlling feedback triggers organizational disconnection and lowers job satisfaction. These effects are stronger in collectivist cultures, where developmental feedback aligns with ethical norms and controlling feedback faces resistance. The study reconstructs concepts, transmission mechanisms, and ethical hierarchies, offering insights into labor dignity in digital algorithmic governance.

6.2 Practical Insights

Practical insights fall into three dimensions. First, reconstruct feedback strategies: develop reports with skill gap identification, benchmarking, and customized training. These mechanisms enhance self-efficacy. Establish a closed-loop management system by integrating contextual triggers, linking resources, and using dynamic evaluation to reduce resistance. Second, activate psychological resources with a digital twin system that turns monitoring data into career development evidence and strengthens job identity. Embed a tiered task mechanism to cultivate self-efficacy by increasing challenges as skills grow. Third, optimize technical ethics through algorithm transparency documents, autonomous feedback mode switching, and role-fit assessment. These mechanisms shift AI monitoring from an efficiency tool to a development platform.

6.3 Research Limitations

This study has three main limitations. First, the variable system is too narrow and does not include technical features like algorithm transparency. Second, the research uses cross-sectional self-reporting, which can be biased by social desirability and cannot show cause and effect over time. Third, the sample is limited in coverage, so its conclusions need further validation for generalizability.

References

[1] Parent-Rocheleau J, Parker S K. Algorithms as work designers: How algorithmic management influences the design of jobs[J]. Human Resource Management Review, 2023, 33(2): 100961.

[2] Bandura A. On the functional properties of perceived self-efficacy revisited[J]. Journal of Management, 2012, 38(1): 9-44.

[3] Judge T A, et al. Hierarchical representations of the five-factor model of personality in predicting job performance[J]. Journal of Applied Psychology, 2017, 102(6): 872.

[4] Smith M J, Carayon P, Sanders K J, et al. Employee stress and health complaints in jobs with and without electronic performance monitoring[J]. Applied ergonomics, 1992, 23(1): 17-27.

[5] Hu D, Lan Y. The dual path effect mechanism study of digital-HRM on employee innovative performance and cyberloafing[J]. Plos one, 2024, 19(8): e0307195.

[6] Mael F, Ashforth B E. Alumni and their alma mater: A partial test of the reformulated model of organizational identification[J]. Journal of Organizational Behavior, 1992, 13(2): 103-123.

[7] White R W. Motivation reconsidered: The concept of competence[J]. Psychological Review, 1959, 66(5): 297-333.

[8] Wu G, Cui Z, Wang X, et al. Unveiling the core functional networks of cognition: an ontology-guided machine learning approach[J]. NeuroImage, 2024, 298: 120804.

[9] Liang B, Wang Y, Huo W, et al. Algorithmic control as a double-edged sword: Its relationship with service performance and work well-being[J]. Journal of Business Research, 2025, 189: 115199.

[10] Schwarzer R, Jerusalem M. Generalized Self-Efficacy scale[J]. Measures in Health Psychology, 1995, 1: 35-37.

[11] Cammann C, et al. Michigan Organizational Assessment Questionnaire[M]. Ann Arbor: University of Michigan, 1983.

[12] Likert R. A technique for the measurement of attitudes[J]. Archives of Psychology, 1932, 140: 1-55