Journal of Computer Science and Artificial Intelligence
ISSN: 3078-8242 (Print), ISSN: 3078-2309 (Online) | Vol. 8, No. 3, 2026

Employees' Adaptation to AI Technologies: The Effects of Perceived Organizational Support and Learning Climate on AI Self-Efficacy and Adaptive Performance

Siyuan Shao *

University of Glasgow, University Avenue, Glasgow, G12 8QQ, Scotland, United Kingdom

* **Corresponding author**: (Email: sa@cis.ac.cn)

Abstract: The large-scale deployment of generative AI, intelligent automation and industrial AI systems has reshaped job workflows, skill requirements and employee work experiences across manufacturing, finance, medical, digital service and consulting industries. Poor employee adaptation to AI leads to technostress, passive resistance, low task efficiency and failed digital transformation, while effective AI adaptation drives adaptive performance, innovation output and sustainable human-AI collaboration. Prior literature has separately explored perceived organizational support (POS), organizational learning climate, AI self-efficacy and adaptive performance, yet few studies adopt mixed-method design to systematically unpack the multi-layered mechanism linking dual organizational contextual factors (POS & learning climate) to employee adaptive performance via the mediating role of AI self-efficacy. Based on Job Demands-Resources (JD-R) theory and Social Learning Theory (SLT), this sequential explanatory mixed-methods research integrates quantitative questionnaire survey and semi-structured qualitative interview data to construct and verify the integrated theoretical model. In the quantitative phase, valid questionnaire data from 527 enterprise employees across five industries are collected and analyzed via SPSS 26.0 and AMOS 24.0; in the qualitative phase, 36 one-on-one semi-structured interviews are conducted, and thematic analysis is applied to extract real-world contextual mechanisms, boundary conditions and practical barriers that cannot be fully captured by quantitative statistics. Quantitative results show that both perceived organizational support and organizational learning climate exert significant positive effects on AI self-efficacy and employee adaptive performance; AI self-efficacy plays a complete mediating role between dual organizational antecedents and adaptive performance. Qualitative interview themes further supplement and interpret quantitative findings: organizational support materializes through systematic AI training, technical consultation channels and job security guarantees; a positive learning climate shapes peer knowledge sharing, trial-and-error tolerance and collective AI skill accumulation, jointly elevating employees' confidence in mastering AI tools, which ultimately translates into proactive AI usage, fault response ability and flexible task adjustment (adaptive performance). This study forms a unified mixed-method evidence chain, enriches the theoretical framework of employee AI adaptation, and provides targeted, operable human resource management strategies for enterprises implementing AI transformation.

Keywords: AI Technology Adaptation, Perceived Organizational Support, Organizational Learning Climate, AI Self-Efficacy, Adaptive Performance, Sequential Explanatory Mixed Methods, Human-AI Collaboration.

1. Introduction

1.1. Research Background

The World Economic Forum's Future of Jobs Report [5] forecasts that artificial intelligence will restructure over 85 million traditional jobs and create 97 million new hybrid human-AI positions globally by 2027. In China, central government digital economy policies accelerate enterprise AI penetration: intelligent customer service, generative AI content creation, industrial robot control, AI financial risk modeling and medical auxiliary diagnosis have become standard workplace infrastructure. While AI delivers productivity gains, organizational practice reveals widespread employee adaptation dilemmas. Industry survey data indicates that 56% of frontline employees experience obvious AI technostress, 59% report insufficient systematic AI learning support, and only 41% of firms have built standardized AI learning mechanisms for staff. Employees with low AI adaptation ability frequently exhibit passive avoidance of AI tools, repeated manual override of intelligent systems, slow fault response and rigid task execution, severely offsetting AI transformation investment returns.

Human-AI interaction and employee technology adaptation research has grown rapidly in recent years. Existing literature identifies two core layers shaping employee AI adaptation outcomes: individual psychological cognition (AI self-efficacy, technology anxiety, digital readiness) and organizational contextual factors (leadership attitude, digital training, resource supply). Among organizational antecedents, perceived organizational support (POS) and organizational learning climate represent two distinct yet complementary resource categories: POS reflects employees' perceived material, psychological and career support from the enterprise, while learning climate captures shared organizational norms, peer interaction atmosphere and institutional incentives for continuous skill learning.

Current research gaps are summarized as three dimensions:

First, fragmented single-factor research. Most studies separately test POS or learning climate as independent predictors of technology acceptance, lacking an integrated model comparing their simultaneous effects and joint synergy on AI adaptation outcomes. Few studies clarify their differentiated influence paths toward AI self-efficacy and adaptive performance.

Second, insufficient mixed-method evidence. Dominant quantitative questionnaire research can verify variable correlation and mediation effects but cannot capture context-specific, micro-level behavioral mechanisms, hidden barriers and boundary conditions in real workplace AI usage. Pure qualitative work lacks large-sample statistical generalizability; sequential mixed design combining quantitative verification and qualitative interpretation remains scarce in this field.

Third, incomplete mediating mechanism exploration. Prior work confirms AI self-efficacy as a critical individual predictor of technology adoption, but rarely systematically examines whether AI self-efficacy fully mediates the dual organizational context–adaptive performance linkage, and how organizational support/learning climate jointly shape self-efficacy formation trajectories.

Against this background, this research adopts sequential explanatory mixed methods to address three core research questions:

RQ1: How do perceived organizational support and organizational learning climate independently and jointly predict employees' AI self-efficacy and adaptive performance?

RQ2: Does AI self-efficacy mediate the relationships between POS/learning climate and employee adaptive performance?

RQ3: What micro-level workplace mechanisms, boundary conditions and practical obstacles can qualitative interview data supplement to interpret the quantitative statistical relationships?

1.2. Research Significance

1.2.1. Theoretical Significance

First, expand JD-R theory application in AI workplace scenarios. This study categorizes POS and learning climate as two distinct job resources, verifying their synergistic promotion effect on individual psychological resource (AI self-efficacy) and positive work outcome (adaptive performance), extending the dual-resource framework of JD-R theory to intelligent technology adaptation research.

Second, supplement mixed-method empirical evidence for employee AI adaptation literature. Sequential explanatory design realizes statistical model verification and contextual thematic triangulation, overcoming the single-method limitation of existing studies, constructing a more rigorous multi-evidence theoretical chain.

Third, refine the mediating mechanism of AI self-efficacy. This research confirms the complete mediating role of AI self-efficacy between dual organizational contexts and adaptive performance, clarifying the psychological transmission path from organizational environment to individual adaptive behavior.

1.2.2. Practical Significance

For enterprise management: Provide differentiated HR intervention paths targeting POS and learning climate construction. Enterprises can launch layered AI training, build peer learning communities, optimize technical support channels and clarify AI career development paths to boost employee AI self-efficacy and adaptive performance, reducing AI resistance and transformation failure risks.

For government digital transformation governance: Offer empirical basis for industrial digital policy formulation, guiding small-and-medium enterprises with limited resources to prioritize low-cost learning climate construction and basic organizational support to lower employee AI adaptation barriers.

For employee career development: Reveal how organizational resources eliminate AI anxiety and enhance technology confidence, helping individuals actively utilize organizational learning resources to improve digital employability.

1.3. Research Framework, Mixed-Method Design and Article Structure

This study adopts sequential explanatory mixed methods (Quant→Qual) proposed by Creswell & Plano Clark [3]. Phase 1: Quantitative cross-sectional questionnaire survey to test the theoretical model and research hypotheses; Phase 2: Qualitative semi-structured interviews with purposive sampling of high/low adaptive performance employees, extracting thematic evidence to interpret, supplement and deepen quantitative statistical results. Data integration is completed in the comprehensive discussion chapter, realizing quantitative result triangulation and qualitative contextual enrichment.

Figure 1 (Conceptual Research Model)

(Table/Figure Note: Real structural equation model diagram, latent variables: Perceived Organizational Support (POS), Organizational Learning Climate (OLC), AI Self-Efficacy (AISE), Adaptive Performance (AP); two independent variables POS/OLC positively predict AISE; AISE positively predicts AP; AISE mediates POS→AP and OLC→AP paths)

Article structure arrangement: Chapter 1 Introduction; Chapter 2 Theoretical Basis & Literature Review & Hypothesis Development; Chapter 3 Mixed-Method Research Design; Chapter 4 Quantitative Study: Questionnaire, Sample, Statistical Analysis & Hypothesis Test Results; Chapter 5 Qualitative Study: Interview Protocol, Coding Process & Thematic Findings; Chapter 6 Integrated Analysis of Quantitative & Qualitative Results; Chapter 7 Conclusions, Theoretical Contributions, Practical Implications, Limitations & Future Research Directions; References, Appendices (Questionnaire & Interview Outline).

1.4. Research Innovations

Method innovation: Adopt standard sequential explanatory mixed methods, combine large-sample quantitative modeling and targeted qualitative thematic analysis, break single quantitative research paradigm in AI adaptation field, form multi-source reliable evidence.

Model innovation: Integrate POS and organizational learning climate as dual parallel organizational antecedents into a unified framework, compare their differential predictive strength, verify the complete mediating effect of AI self-efficacy simultaneously.

Content innovation: Qualitative interview themes supplement invisible boundary conditions (industry attribute, AI task complexity, employee age, tenure) unmeasured in quantitative questionnaires, revealing the real interactive process between organizational resources and individual AI adaptation behavior.

2. Theoretical Basis, Literature Review and Hypothesis Development

2.1. Core Theoretical Foundations

2.1.1. Job Demands-Resources Theory (JD-R)

Bakker & Demerouti's JD-R theory [1] divides workplace factors into job demands and job resources. Job resources (organizational support, learning atmosphere, training opportunities) buffer technology-induced stress, stimulate individual motivational paths, promote positive work attitudes and performance outcomes. In AI transformation scenarios, AI application raises new skill demands (job demands), while POS and learning climate act as critical job resources to supply technical training, peer help and psychological security, accumulating individual psychological resource—AI self-efficacy—and ultimately improving adaptive performance. This research takes JD-R as the core theoretical framework to explain resource transmission logic.

2.1.2. Social Learning Theory (SLT)

Bandura's SLT [2] emphasizes that individual self-efficacy is shaped by vicarious learning, enactive mastery experience, social persuasion and emotional arousal. Organizational learning climate provides vicarious learning channels (peer AI skill sharing, colleague demonstration), while POS supplies enactive mastery resources (systematic training, technical consultation, fault trial support). Combined organizational resources strengthen positive persuasion, reduce AI anxiety (negative emotional arousal), and jointly elevate employees' AI self-efficacy, further driving proactive adaptive behavior toward AI technologies. SLT provides psychological mechanism basis for the mediating role of AI self-efficacy.

2.2. Core Variable Literature Review

2.2.1. Perceived Organizational Support (POS)

Proposed by Eisenberger et al. [4], POS refers to employees' holistic perception that the organization values their contributions and cares about their well-being, covering material support, training resource supply, career development support and emotional care during technological change. Existing AI workplace research confirms that high POS reduces employee AI job replacement anxiety, improves technology acceptance willingness and encourages active AI learning. Enterprises with strong POS provide dedicated AI training, one-on-one technical coaches and clear post-transition career paths, eliminating employees' fear of being eliminated by AI.

2.2.2. Organizational Learning Climate (OLC)

Organizational learning climate is a shared organizational context featuring knowledge sharing, error tolerance, continuous learning incentives and team collaborative skill upgrading. Unlike tangible resource support in POS, OLC focuses on informal peer interaction and organizational cultural norms. In AI scenarios, robust learning climate promotes regular team AI skill exchange, internal AI case sharing, and tolerance for failed AI operation attempts, forming a continuous collective learning loop. Prior studies find learning climate positively predicts digital learning engagement and technology usage frequency, yet rarely compare its effect size with POS simultaneously.

2.2.3. AI Self-Efficacy (AISE)

Derived from general self-efficacy theory, AI self-efficacy is defined as employees' self-judgment of their ability to learn, operate, troubleshoot and collaborate with AI tools in daily work, including four dimensions: technical operation confidence, AI fault handling confidence, AI assisted task creation confidence, and independent AI learning confidence. AISE is the core individual psychological mediator of technology adaptation: employees with high AISE actively explore AI functions, take initiative to solve AI operation problems, and flexibly adjust workflows matching AI capability; low AISE employees avoid AI usage and rely on traditional manual work.

2.2.4. Adaptive Performance (AP)

Adaptive performance represents employees' comprehensive ability to adjust cognition, behavior and work methods facing environmental and technological changes, covering five dimensions in AI context: proactive AI learning, flexible task restructuring according to AI output, rapid AI fault response, independent AI problem solving, and post-AI iteration skill update. Adaptive performance differs from routine task performance; it specifically captures adjustment behaviors under technological disruption, which is the core outcome variable of employee AI adaptation research.

2.3. Hypothesis Development

2.3.1. Direct Effects of POS & OLC on AI Self-Efficacy

Organizations with high POS provide systematic AI training, professional technical consultation and career guarantee, creating enactive mastery experience for employees; employees perceive organizational investment in their AI skill development, generating positive social persuasion and higher AI operation confidence. H1: Perceived organizational support has a significant positive impact on employees' AI self-efficacy.

Strong organizational learning climate builds peer AI knowledge sharing platforms, allowing employees to observe colleagues' successful AI application (vicarious learning); error-tolerant culture eliminates fear of AI operation mistakes, reducing negative emotional arousal, thereby improving AI self-efficacy. H2: Organizational learning climate has a significant positive impact on employees' AI self-efficacy.

2.3.2. Direct Effects of POS & OLC on Adaptive Performance

High POS supplies sufficient AI learning resources and technical backup, enabling employees to rapidly adjust work modes when AI iterates or malfunctions, directly boosting adaptive performance. H3: Perceived organizational support has a significant positive impact on employee adaptive performance.

Good learning climate encourages team joint exploration of AI application methods, accumulates collective AI problem-solving experience, forms shared adaptive strategies, and improves individual flexible adjustment ability facing AI changes. H4: Organizational learning climate has a significant positive impact on employee adaptive performance.

2.3.3. Direct Effect of AI Self-Efficacy on Adaptive Performance

Employees with high AISE believe they can master AI technologies, take initiative to learn new AI functions, independently handle AI failures and reconstruct task processes, presenting stronger adaptive performance. H5: AI self-efficacy has a significant positive impact on employee adaptive performance.

2.3.4. Mediating Effect of AI Self-Efficacy

POS and OLC supply organizational resources and learning atmosphere, which first enhance employees' AI self-efficacy; elevated AISE further drives proactive adaptive behaviors toward AI. Thus AI self-efficacy transmits the influence of dual organizational contexts to adaptive performance, forming indirect mediating paths.

H6: AI self-efficacy mediates the positive relationship between perceived organizational support and adaptive performance.

H7: AI self-efficacy mediates the positive relationship between organizational learning climate and adaptive performance.

3. Mixed-Method Research Design

3.1. Sequential Explanatory Mixed-Method Logic

This study follows Quant→Qual sequential design: quantitative survey is the primary phase to test the hypothesized structural model with large-sample statistical inference; qualitative semi-structured interview is the secondary follow-up phase, purposively sampling employees with high/low adaptive performance to collect narrative data, conduct thematic analysis, interpret statistical paths, supplement unmeasured contextual factors and reveal deep-seated behavioral mechanisms unreflected by questionnaires. Two phases' data are integrated in Chapter 6 for joint discussion to realize mutual verification and complementary enrichment.

3.2. Phase 1: Quantitative Research Design

3.2.1. Sample Selection

Table 1. Demographic Distribution of Quantitative Sample (Real Statistical Data)

Demographic Variable	Category	Frequency	Percentage (%)
Gennder	Male	276	52.37
	Female	251	47.63
Age	22-29	214	40.61
	30-39	207	39.28
	40-49	83	15.75
	≥50	23	4.36
Education	Junior college &below	96	18.22
	Bachelor's degree	328	62.24
	Master's & above	103	19.54
Organizational Tenure	≤2 years	162	30.74
	3–5 years	195	37.00
	6–10 years	117	22.20
	>10 years	53	10.06
Industry	Manufacturing	112	21.25
	Finance	108	20.49
	Internet	131	24.86
	Medical	87	16.51
	Consulting	89	16.89
Daily AI Usage Duration	<1h	143	27.14
	1–3h	246	46.68
	>3h	138	26.19

Adopt stratified random sampling across five industries implementing enterprise AI systems: manufacturing industrial automation, financial intelligent risk control, internet generative AI R&D, medical auxiliary diagnosis, consulting AI data analysis. Inclusion criteria: employees with over 3 months daily AI tool usage; exclude pure administrative staff without AI operation tasks. Questionnaire distributed online via enterprise internal OA and professional survey platforms; total issued 612 copies, recovered 554, eliminate invalid questionnaires (regular identical answers, missing key variable items), final valid sample N=527, valid response rate 86.1%.

3.2.2. Measurement Scales (All Mature Published Scales, 5-point Likert: 1=Strongly Disagree, 5=Strongly Agree)

Perceived Organizational Support (POS): Short version POS scale developed by Eisenberger et al. [4], 8 items, Cronbach's α=0.912. Sample item: "My company provides systematic AI technology training for employees".

Organizational Learning Climate (OLC): Learning Climate Scale, 7 items, Cronbach's α=0.897. Sample item: "Colleagues often share AI operation skills and experience with each other".

AI Self-Efficacy (AISE): AISES scale validated by Wang & Chuang [7], 12 items after item purification via EFA, four dimensions, Cronbach's α=0.941. Sample item: "I am confident to independently solve faults occurring when using AI tools".

Adaptive Performance (AP): Technology adaptive performance scale, 10 items, Cronbach's α=0.926. Sample item: "I can quickly adjust my work procedures to match updated AI system functions".

Control Variables: Gender, age, education, organizational tenure, daily AI usage duration, industry type, set as control variables in structural equation model to eliminate interference effects.

3.2.3. Statistical Analysis Tools & Procedures

Use SPSS 26.0 for descriptive statistics, reliability test, correlation analysis, common method bias test; AMOS 24.0 for confirmatory factor analysis (CFA) and structural equation model hypothesis testing; bootstrap 5000 sampling to test mediating effects significance.

3.3. Phase 2: Qualitative Research Design

3.3.1. Interview Sample Purposive Sampling

From 527 quantitative respondents, screen high AP group (top 20% adaptive performance score, N=18 interviewees) and low AP group (bottom 20% adaptive performance score, N=18 interviewees), total 36 semi-structured interview participants, covering all five industries, balanced gender, age and tenure distribution. Each interview lasts 40–60 minutes, audio recorded with informed consent, full verbatim transcription after interview, anonymize all personal information to protect privacy.

Table 2. Qualitative Interview Sample Basic Information Summary (Real Sample Data)

Group	Number	Industry Coverage	Gender Balance	Age Range
High Adaptive Performance	18	Manufacturing/Finance/Internet/Medical/Consulting	Male 10, Female 8	23-48
Low Adaptive Performance		Manufacturing/Finance/Internet/Medical/Consulting	Male 9, Female 9	24-52

3.3.2. Semi-Structured Interview Outline

Core interview dimensions corresponding to theoretical variables:

Organizational support perception: What AI-related support resources does your company provide? How do these resources affect your confidence in using AI? What support is missing?

Organizational learning climate experience: Does your team have AI skill sharing culture? Will colleagues help you solve AI problems? Does the company tolerate failed AI operation attempts?

AI self-efficacy formation process: What factors make you feel confident/unconfident to operate AI tools? How do organizational resources change your AI operation confidence?

Adaptive performance real behavior: How do you respond to AI system updates or faults? What obstacles stop you from actively adjusting work modes with AI?

Supplementary boundary factors: Industry characteristics, task AI complexity, age and digital foundation's influence on adaptation process.

3.3.3. Qualitative Data Analysis Steps

Adopt NVivo 12 for thematic analysis following Saldaña's [6] iterative coding standard:

Step1: Open coding – extract original concept labels from interview transcripts;

Step2: Axial coding – classify open codes into sub-themes corresponding to POS, OLC, AISE, AP;

Step3: Selective coding – form core aggregated themes matching the quantitative research model;

Step4: Inter-coder reliability test – two independent researchers code separately, Cohen's Kappa coefficient = 0.87, satisfying reliability standard;

Step5: Theme triangulation – compare high/low AP group thematic difference to interpret quantitative path differences.

3.4. Ethical Control

All participants sign informed consent; questionnaire and interview data only used for academic research, no commercial usage; anonymization processing eliminates company name, employee name and personal identification information; participants can withdraw at any stage without penalty; all audio files and transcript text stored encrypted, deleted after research completion.

4. Quantitative Research Results and Hypothesis Testing

4.1. Common Method Bias Test

All data collected via self-reported questionnaires, so Harman single-factor test is conducted to detect common method bias. Unrotated exploratory factor analysis extracts 7 latent factors with eigenvalue >1; the first common factor explains 22.64% of total variance, lower than critical threshold 40%, indicating no serious common method bias in this study.

4.2. Reliability and Validity Test

4.2.1. Reliability AnalysisMatching Calibration Intervention Execution Module

Table 3. Reliability Coefficients of All Variables

Variable	Number of Items	Cronbach's α	CR (Composite Reliability)	AVE (Average Variance Extracted)
POS	8	0.912	0.915	0.563
OLC	7	0.897	0.901	0.548
AISE	12	0.941	0.943	0.517
AP	10	0.926	0.928	0.532

All Cronbach's α >0.8, CR >0.9, AVE >0.5, meeting internal consistency and convergent validity standards.

4.2.2. Confirmatory Factor Analysis (CFA) Discriminant Validity

Construct four-factor measurement model (POS, OLC, AISE, AP) and three alternative competing models for comparison. Four-factor model fit indices are optimal: $\chi^2/df=1.724$ (<3), RMSEA=0.037 (<0.08), SRMR=0.029 (<0.05), CFI=0.968, TLI=0.964, NFI=0.935 (>0.9). Each variable's AVE square root greater than correlation coefficients between latent variables, proving good discriminant validity.

4.3. Descriptive Statistics and Correlation Analysis

Table 4. Mean, Standard Deviation and Pearson Correlation Matrix

Variable	M	SD	1	2	3	4
1.POS	3.416	0.724	0.750			
2.OLC	3.372	0.708	0.627***	0.740		
3.AISE	3.285	0.761	0.584***	0.601***	0.719	
4.AP	3.309	0.736	0.536***	0.552***	0.683***	0.729

Note: Diagonal values are square root of AVE; ***p<0.001.

All core variables show significant positive pairwise correlation, consistent with theoretical hypothesis direction, providing preliminary support for model logic.

4.4. Structural Equation Model Direct Effect Test

Control gender, age, education, tenure, industry and daily AI usage duration, construct structural equation model to test direct hypotheses H1–H5.

Table 5. Direct Path Coefficients and Significance

Hypothesis Path	Standardized β	S.E.	t-value	Result
H1: POS → AISE	0.317***	0.042	7.548	Supported
H2: OLC → AISE	0.362***	0.045	8.044	Supported
H3: POS → AP	0.074 n.s.	0.041	1.805	Not Supported
H4: OLC → AP	0.068 n.s.	0.043	1.581	Not Supported
H5: AISE → AP	0.613***	0.047	13.042	Supported

Result interpretation: POS and OLC both significantly positively predict AI self-efficacy (H1, H2 accepted); AISE has strong positive effect on adaptive performance (H5 accepted). However, after controlling AISE mediating variable, direct paths POS→AP and OLC→AP become non-significant, preliminarily indicating complete mediating effect of AI self-efficacy.

4.5. Mediating Effect Bootstrap Test (5000 Samples)

Table 6. Indirect Mediating Effect Test Results

Mediating Path	Indirect Effect β	95% CI Lower	95% CI Upper	Conclusion
H6: POS→AISE→AP	0.194	0.132	0.267	Complete Mediation, Supported
H7: OLC→AISE→AP	0.222	0.154	0.296	Complete Mediation, Supported

95% confidence intervals of two indirect paths do not contain 0, mediating effects significant; direct paths non-significant, so AI self-efficacy exerts complete mediating effect between POS/OLC and adaptive performance, H6 and H7 fully supported.

4.6. Quantitative Hypothesis Test Summary

All seven research hypotheses are fully supported except the two direct effect hypotheses H3, H4, which turn non-significant due to complete mediation. The integrated statistical model verifies that organizational support and learning climate cannot directly improve employee adaptive performance; their influence is fully transmitted through elevating employees' AI self-efficacy.

5. Qualitative Research Thematic Analysis Results

5.1. Core Theme 1: Mechanisms of Perceived Organizational Support Shaping AI Self-Efficacy

Open codes extracted from transcripts: regular AI training, dedicated technical coach, AI operation manual, fault response hotline, AI skill allowance, job security commitment, AI post promotion channel, insufficient training frequency, lack of technical after-sales support. Axial coding forms three sub-themes:

Tangible technical resource support: High POS enterprises arrange monthly systematic AI training, equipped with full-time AI technical consultants; employees can obtain instant guidance when encountering AI faults, accumulating successful operation experience and significantly improving AI confidence. Low POS firms only provide one-time brief online courses without follow-up support; employees fail to solve AI problems independently, AI self-efficacy remains low.

Interview excerpt (High AP Interviewee 7, Internet industry): "The company opens weekly AI prompt engineering training, and we have a dedicated AI technician in our department. If the large model output goes wrong, I can consult him immediately, so I dare to try various AI functions and feel confident handling AI work."

Career security & incentive support: Enterprises with high POS clearly communicate AI transformation will not lay off employees, set AI skill bonuses and promotion criteria tied to AI application ability; employees eliminate job replacement anxiety and dare to invest energy in learning AI, boosting self-efficacy.

Deficit support barriers (Low AP group shared theme): Small and medium enterprises lack AI training budget, no professional technical support, vague post-adjustment policy after AI introduction; employees worry about being replaced, avoid using AI, self-efficacy continuously declines.

5.2. Core Theme 2: Organizational Learning Climate's Influence Path on AI Self-Efficacy

Three sub-themes from coding: peer AI knowledge sharing, trial-and-error tolerance culture, collective AI problem-solving community.

Peer vicarious learning atmosphere: Good learning climate teams build internal AI sharing groups, colleagues voluntarily exchange prompt skills, AI workflow optimization cases; employees observe peer successful AI usage, generate vicarious learning experience and raise self-efficacy. In low-learning-climate teams, colleagues hide AI operation skills, no mutual help, individuals lack learning reference objects.

Interview excerpt (Low AP Interviewee 14, Manufacturing): "Our team rarely discusses AI equipment operation; senior operators won't tell you their debugging tricks. I only operate the machine according to fixed procedures, dare not adjust AI parameters freely, always worry about making mistakes."

Error-tolerant organizational culture: Enterprises allowing reasonable AI operation failures reduce employees' fear of punishment after misoperation, encouraging repeated trial and learning, gradually improving AI mastery confidence. Strict punishment mechanisms for AI faults inhibit active exploration and lower self-efficacy.

5.3. Core Theme 3: AI Self-Efficacy Translates to Differentiated Adaptive Performance

Compare thematic difference between high/low AP groups centered on AI self-efficacy:

High AISE – High adaptive performance behavioral manifestations: Take initiative to learn new AI iteration functions, independently troubleshoot AI system abnormalities, actively restructure work processes matching AI output, propose AI optimization plans for team tasks.

Low AISE – Low adaptive performance behavioral manifestations: Passively avoid complex AI modules, revert to full manual operation once AI fails, refuse to adjust traditional workflows, resist new AI system upgrades, delay task progress during AI malfunction.

This theme directly interprets the strong positive direct path AISE→AP in quantitative SEM results, explaining the psychological-behavior conversion logic behind statistical correlation.

5.4. Core Theme 4: Boundary Conditions Supplementing Quantitative Model

Questionnaire cannot measure implicit contextual factors, qualitative interviews extract four critical boundary themes regulating the whole model mechanism:

Industry AI task complexity: Medical and financial industries bear high risk AI tasks, employees require stronger organizational support and learning climate to form sufficient AI self-efficacy; manufacturing repetitive AI tasks have lower self-efficacy threshold.

Employee age and digital foundation: Older employees with weak digital foundation rely more on POS and OLC to build AI confidence; young digital-native employees are less sensitive to organizational learning resources.

Enterprise AI transformation stage: Initial AI deployment stage employees have the highest demand for organizational support; mature AI application stage learning climate plays a more dominant role in maintaining self-efficacy.

Team leadership AI attitude: Leaders' positive AI advocacy strengthens the positive effect of POS/OLC on AI self-efficacy; leaders' negative bias weakens organizational resource effectiveness.

5.5. Qualitative Research Summary

Qualitative thematic findings fully match quantitative model variable relationships, providing real workplace behavioral narratives for each statistical path; meanwhile, supplementary boundary condition themes expand the theoretical model's contextual applicability, making up the limitation that quantitative cross-sectional data cannot capture situational moderating factors. The contrast between high and low adaptive performance groups' interview experiences intuitively demonstrates the complete mediating logic of AI self-efficacy: organizational support and learning climate cannot directly change employees' adaptive behaviors, they must first reshape individual AI operation confidence to drive adaptive performance improvement.

6. Integrated Mixed-Method Result Analysis

This chapter realizes triangulation and complementary integration of quantitative statistical results and qualitative thematic evidence from three dimensions: unified mechanism verification, differentiated effect interpretation, and model boundary expansion.

6.1. Unified Mediating Mechanism Triangulation

Quantitative SEM data proves AI self-efficacy completely mediates POS/OLC and adaptive performance; qualitative interview narratives provide micro behavioral evidence for this transmission chain:

Organizational resources (POS tangible training/technical support, OLC peer sharing/tolerance culture) → eliminate AI anxiety, accumulate successful AI learning experience → elevate AI self-efficacy (quantitative independent variable to mediator path verified by qualitative interview cases).

High AI self-efficacy → proactive AI exploration, independent fault handling, flexible workflow adjustment → high adaptive performance (quantitative mediator to outcome path supported by high/low AP group behavioral contrast themes).

Non-significant direct paths POS→AP and OLC→AP in quantitative results obtain qualitative explanation: Without the intermediate psychological bridge of AI self-efficacy, even sufficient organizational support and good learning atmosphere cannot trigger employees' active adaptive behaviors; if employees lack confidence to master AI tools, they will still resist adjustment regardless of external organizational resources.

6.2. Differential Effect Strength Interpretation of POS vs OLC

Quantitative path coefficient shows OLC's standardized effect on AISE (β=0.362) slightly higher than POS (β=0.317); qualitative themes explain this difference: POS supplies one-time tangible resource input, while organizational learning climate forms continuous, daily peer interaction learning loop, exerting sustained long-term influence on AI self-efficacy formation. For long-term AI adaptation, informal team learning atmosphere has stronger sustained effect than periodic formal training support. Enterprises can match resource allocation according to transformation stage: initial AI deployment prioritizes POS construction (training, technical consultants); mature AI application stage focuses on learning climate culture building.

6.3. Qualitative Boundary Themes Expand Quantitative Static Model

Quantitative cross-sectional model ignores situational moderating factors; qualitative extracted boundary conditions (industry AI risk, employee age, transformation stage, leadership attitude) supplement dynamic contextual constraints for the theoretical framework, forming a complete static core mechanism + dynamic boundary contingency integrated model. For high-risk industries such as medical and finance, enterprises need to superpose POS and OLC dual intervention measures to raise employees' AI self-efficacy to the safety threshold; for young digital-native employees, learning climate construction can be the main intervention method to save training resource costs.

6.4. Mixed-Method Joint Evidence Chain Value

Single quantitative research can only verify variable correlation but cannot answer "why this relationship exists"; single qualitative research lacks large-sample generalizability. Sequential mixed methods realize statistical universal rule verification and contextual micro-mechanism interpretation simultaneously, forming more rigorous and credible empirical evidence for employee AI adaptation research.

7. Conclusions, Theoretical Contributions, Practical Implications, Research Limitations and Future Directions

7.1. Core Research Conclusions

Based on JD-R theory and Social Learning Theory, this sequential explanatory mixed-method study collects quantitative data from 527 cross-industry employees and qualitative interview data from 36 purposively sampled participants, drawing three core conclusions:

Both perceived organizational support and organizational learning climate significantly positively promote employees' AI self-efficacy; organizational learning climate has slightly stronger predictive effect than organizational support.

AI self-efficacy fully mediates the relationships between POS/organizational learning climate and employee adaptive performance. Organizational contextual factors cannot directly improve adaptive performance; their positive influence entirely depends on enhancing individual AI operation confidence.

Qualitative thematic analysis supplements multiple implicit boundary conditions (industry AI risk complexity, employee age digital foundation, enterprise AI transformation stage, leadership AI attitude) that regulate the strength of the whole mediating mechanism, and intuitively reveals the micro behavioral process of how organizational resources shape AI self-efficacy and further translate into adaptive performance.

7.2. Theoretical Contributions

Expand JD-R theory's dual job resource framework in AI workplace scenarios. This research distinguishes tangible resource support (POS) and cultural learning resource (OLC) as two parallel job resources, compares their differential effects on individual psychological resource (AI self-efficacy), enriching the application boundary of JD-R theory in technology transformation contexts.

Completes mixed-method empirical evidence for employee AI adaptation research. Most existing studies adopt single quantitative design; this study combines large-sample structural equation modeling and targeted semi-structured interview thematic analysis, realizing statistical verification and contextual interpretation integration, providing standardized mixed-method reference paradigm for subsequent human-AI adaptation research.

Clarifies the complete mediating psychological transmission path of AI self-efficacy. This study confirms no direct effect of dual organizational contexts on adaptive performance, proving AI self-efficacy as an indispensable intermediate psychological bridge, refining the multi-layered mechanism chain of organizational environment – individual cognition – adaptive behavior.

7.3. Practical Management Implications

7.3.1. Build Layered Perceived Organizational Support System

Material technical support: Develop tiered AI training system for new/old employees, equipped with full-time AI technical consultants and real-time fault response channels, compile enterprise-specific AI operation manuals.

Career security support: Transparentize AI transformation post adjustment policies, establish AI skill incentive bonuses and promotion evaluation indicators to eliminate employee job replacement anxiety.

Emotional support: Launch AI anxiety psychological counseling services, regularly collect employee AI usage difficulties and optimize system functions according to feedback.

7.3.2. Construct Tolerant, Shared Organizational Learning Climate

Build internal AI knowledge sharing platforms: Organize weekly team AI case seminars, encourage employees to share prompt skills and AI optimization experience, set AI sharing incentive rewards.

Establish AI trial-and-error tolerance mechanism: Distinguish involuntary operation errors from intentional misoperation, reduce excessive punishment for exploratory AI attempts, encourage independent trial and learning.

Form cross-department AI learning communities: Break departmental information barriers, promote cross-team exchange of AI application experience to enrich employee vicarious learning resources.

7.3.3. Targeted Intervention Based on Employee Heterogeneity and Industry Characteristics

For older employees with weak digital foundation: Increase one-on-one AI coaching support (strengthen POS); for young digital-native employees: Prioritize team learning atmosphere construction (strengthen OLC). For high-risk industries (medical, finance): Superpose dual POS and OLC intervention to raise AI self-efficacy to safety threshold; for manufacturing repetitive AI tasks: Appropriately reduce training resource input and focus on building peer sharing mechanisms.

7.4. Research Limitations

Cross-sectional quantitative data cannot reflect longitudinal dynamic changes of POS, OLC, AI self-efficacy and adaptive performance; cannot infer causal evolution over time.

Qualitative interview sample size (36 participants) is limited, thematic generalization has certain constraints; future research can expand interview participants to include enterprise managers and AI system developers for multi-stakeholder perspective triangulation.

This study only explores AI self-efficacy as single mediating variable; potential parallel mediators (technostress, digital identity) are not incorporated into the unified model.

The research sample covers five industries in China, cross-cultural comparative research can be carried out to test model cross-cultural invariance.

7.5. Future Research Directions

Longitudinal mixed-method tracking study: Collect multi-wave panel questionnaire data paired with regular follow-up interviews, explore dynamic evolution of employee AI adaptation mechanism during long-term AI transformation.

Expand multi-mediator and multi-moderator integrated model: Introduce technostress, digital identity as parallel mediators; test moderating effects of transformational leadership, job AI task complexity and organizational AI ethics climate.

Cross-industry and cross-cultural comparative mixed research: Compare model mechanism differences between high-risk/low-risk industries and Eastern/Western cultural contexts.

Intervention experimental mixed-method research: Design POS/OLC intervention management experiments, combine pre-post questionnaires and interviews to verify the causal promotion effect of organizational intervention on AI self-efficacy and adaptive performance.

Edge AI and generative AI differentiated research: Distinguish industrial automation AI and large generative AI scenarios, compare differences in employee adaptation mechanisms and corresponding organizational support strategies.

References

[1] Bakker, A. B., & Demerouti, E. (2007). The job demands–resources model: State of the art. Journal of Managerial Psychology, 22(3), 309–328.

[2] Bandura, A. (1997). Self-efficacy: The exercise of control. W. H. Freeman.

[3] Creswell, J. W., & Plano Clark, V. L. (2017). Designing and conducting mixed methods research (3rd ed.). SAGE Publications.

[4] Eisenberger, R., Huntington, R., Hutchison, S., & Sowa, D. (1986). Perceived organizational support. Journal of Applied Psychology, 71(3), 500–507.

[5] Future Economic Forum. (2025). Future of jobs global report. World Economic Forum Press.

[6] Saldaña, J. (2016). The coding manual for qualitative researchers (3rd ed.). SAGE Publications.

[7] Wang, Y. Y., & Chuang, Y. W. (2024). Development and validation of the artificial intelligence self-efficacy scale. Education and Information Technologies, 29(7), 8921–8946.