

How AI Leadership Stimulates Employees' Proactive Innovation Behavior: A Model with Self-Efficacy as a Mediator

Shuhan Wu

School of Business Administration, Shanghai University of International Business and Economics,
Shanghai, China

2389991868@qq.com

Abstract. Against the backdrop of digital-intelligent transformation, the deep integration of AI into organizational management has given rise to AI leadership as a new leadership paradigm. Drawing on social cognitive theory, this study examines how AI leadership affects employees' proactive innovation behavior through self-efficacy and whether cognitive flexibility serves as a boundary condition. Data were collected from 170 employees through an online survey and analyzed using hierarchical regression and Bootstrap tests. The results show that AI leadership significantly and positively predicts proactive innovation behavior, while self-efficacy partially mediates this relationship by strengthening employees' confidence in digital technology use and innovation. The hypothesized moderating effect of cognitive flexibility is not supported. The study extends social cognitive theory to human-AI collaborative management and clarifies a micro-level cognitive pathway through which AI leadership promotes employee innovation.

Keywords: AI leadership, self-efficacy, proactive innovation behavior, human-AI collaboration, social cognitive theory, digital transformation.

1. Introduction

Artificial intelligence is rapidly reshaping organizational operations, leadership roles, decision processes, and team management ^[1]. While AI can generate positive employee states such as thriving at work, substitution concerns may also increase job insecurity ^[2]. These changes have accelerated the emergence of AI leadership. Beyond the narrow view of AI as a managerial aid, AI leadership in human-AI collaborative governance can provide deeper insight, improve decision quality, and support dynamic leadership structures ^[3]. Because human talent remains a critical resource for firms and economic development ^[4], stimulating employees' proactive innovation behavior is central to sustaining competitive advantage.

Research on employee innovation has established strong links with traditional leadership styles ^[5], yet empirical evidence on AI leadership remains limited. Existing studies focus mainly on conceptualization and dimensions, leaving the cognitive mechanism through which AI leadership stimulates proactive innovation insufficiently explained ^[6]. Social cognitive theory suggests that self-efficacy connects external contexts with individual behavior ^[7]. Accordingly, this study examines AI leadership as the external leadership context, self-efficacy as the mediating cognitive mechanism, and cognitive flexibility as an individual boundary condition. It contributes by extending social cognitive theory to human-AI collaborative management, distinguishing digital and innovation self-efficacy, and testing the boundary role of cognitive flexibility.

2. Literature Review

Traditional leadership research is well developed and shows that transformational, transactional, leader-member exchange, empowering, and inclusive leadership can support employee innovation by satisfying psychological needs ^[5]. Digital leadership subsequently emerged as leaders used digital technologies to drive organizational transformation ^[1]. With generative AI and intelligent algorithms undertaking data analysis, task allocation, emotion recognition, and decision support, however, AI is no longer merely a passive tool ^[8]. AI leadership therefore represents a further evolution. A narrow

view treats it as managers' capability to use AI while combining technological analysis with human judgment^[9], whereas a broader view allows AI to undertake selected leadership functions within human-AI collaborative governance^[3]. Existing outcome research has linked AI leadership to digital transformation, organizational efficiency and innovation^[1, 10], human-AI trust, role ambiguity, technology anxiety^[8, 11], and perceived algorithmic fairness^[12], but employee-level innovation mechanisms remain underexplored.

Employee innovation behavior can be proactive or passive depending on its motivational origin^[13]. Proactive innovation behavior is voluntary, forward-looking, and internally driven^[13, 14], involving idea generation, resource seeking, prototyping, and implementation^[15, 16]. It is shaped by individual traits and work values as well as organizational resources and emotional support^[13, 16, 17]. Leadership is a major organizational antecedent, and digital leadership has also been linked to AI-related job crafting^[18]. Yet few studies directly test whether AI leadership can activate employees' spontaneous innovation.

Self-efficacy, derived from social cognitive theory, is individuals' confidence in their ability to accomplish specific tasks and goals^[19, 20]. It is context-specific and predicts behavior and performance^[21]. In digital and innovative work, digital self-efficacy captures confidence in using digital technologies^[7], whereas innovation self-efficacy captures confidence in producing and implementing novel ideas^[21]. AI leadership may strengthen both by providing personalized feedback, low-risk experimentation, intelligent resources, and fairer evaluation^[3, 12]. Prior work also suggests that self-efficacy can mediate AI-related leadership signals and innovation^[22].

Cognitive flexibility refers to the ability to adapt perceptions and responses across situations^[23] and often operates as a boundary condition between organizational contexts and employee innovation^[24]. In employee-AI collaboration, it includes integrating heterogeneous human-AI information, adapting to algorithmic logic, and adjusting cognitive strategies based on AI feedback^[25]. Based on these gaps, the present study develops a moderated mediation model grounded in social cognitive theory.

3. Theoretical Analysis and Hypotheses

3.1. AI Leadership and Proactive Innovation Behavior

Social cognitive theory holds that behavior results from reciprocal interactions among environment, cognition, and behavioral choice^[26]. AI leadership creates a human-AI collaborative context that supports knowledge sharing, tolerates technology-exploration failures, and encourages employees to rethink problems with digital approaches^[6]. Through observational learning^[27], employees can also learn AI-enabled innovation practices from leaders. Managers with AI expertise communicate digital transformation priorities^[1], and AI-symbolic leadership behaviors can stimulate AI-driven innovation through role modeling^[22], while supportive contexts buffer AI-related psychological pressure^[2].

H1: AI leadership has a significant positive effect on employees' proactive innovation behavior.

3.2. AI Leadership and Employee Self-Efficacy

Leadership contexts shape internal efficacy beliefs, and vicarious experience is an important source of self-efficacy^[28]. AI leadership signals acceptance of intelligent technologies, increases employees' familiarity and control in human-AI collaboration, and reduces uncertainty, thereby strengthening digital self-efficacy^[22]. By embedding AI in innovation processes, providing information and screening support, and shifting repetitive work to AI, leaders also free resources for creative tasks and strengthen innovation self-efficacy^[29]. Evidence from human-AI work settings and digital technology training supports these efficacy-enhancing mechanisms^[30, 7].

H2: AI leadership has a significant positive effect on employee self-efficacy.

3.3. Mediating Role of Self-Efficacy

Internal cognitive beliefs mediate the conversion of external contexts into action ^[26], and creativity requires task motivation, creative skills, and creative processing ^[31]. Digital self-efficacy encourages employees to learn and apply intelligent tools and persist when facing innovation difficulties ^[7], whereas innovation self-efficacy supports autonomy and the use of cognitive resources to develop and implement novel solutions ^[21, 2]. Leadership can shape efficacy beliefs through social support and role clarification ^[24]; AI-related signals, role models, resources, and inclusive climates can therefore enhance both digital and innovation self-efficacy ^[22, 2]. Prior studies show that self-efficacy mediates AI-enabled contexts and proactive work outcomes ^[32, 33].

H3: Self-efficacy mediates the relationship between AI leadership and employees' proactive innovation behavior.

3.4. Moderating Role of Cognitive Flexibility

Individuals differ in how they interpret environmental information ^[26]. Cognitive flexibility enables people to revise judgments and behavioral strategies as contexts change ^[23]. In AI settings, employees with greater cognitive flexibility are better able to decode algorithmic logic, integrate human and AI information, adapt to changing digital tasks, and reframe difficulties as opportunities ^[25]. Such flexibility can reduce cognitive conflict and strengthen confidence when leadership strategies are dynamic ^[24, 34].

H4: Cognitive flexibility positively moderates the relationship between employee self-efficacy and proactive innovation behavior; the higher an employee's cognitive flexibility, the stronger the positive effect of self-efficacy on proactive innovation behavior.

4. Research Design and Methods

4.1. Data

Data were collected from employees of enterprises across China through the professional online survey platform Credamo. Responses with abnormal completion times, patterned answering, missing core items, or logical inconsistencies were removed, leaving 170 valid questionnaires. The survey covered AI leadership, self-efficacy, proactive innovation behavior, cognitive flexibility, and demographic/organizational controls. Most participants are aged 26–35 and hold a bachelor's degree, with frequent workplace AI usage; the sample is dispersed across various firm sizes, and manufacturing staff constitutes 28.82% of respondents. The surveyed sample mainly consists of well-educated young and middle-aged employees with high AI utilization levels.

4.2. Measures

AI leadership was adapted from a digital leadership scale ^[35] to capture employee-perceived managerial behaviors that guide AI use, support innovation, and coordinate human-AI work ^[12]. Proactive innovation behavior used the localized scale of Zhang et al. ^[16], based on the voluntary innovation construct ^[13], with four retained items after the pilot test. Self-efficacy combined creative self-efficacy ^[36] and digital self-efficacy ^[37], reflecting the task-specific nature of efficacy beliefs ^[28]; six items were retained. Cognitive flexibility used the Martin and Rubin scale ^[23], with nine retained items, including four reverse-scored items. All focal items used five-point Likert scales (1 = strongly disagree; 5 = strongly agree). As shown in Table 1, controls included age, education, firm size, AI-use frequency, and industry; industry was entered as four dummy variables with 'other industries' as the reference group.

Table 1. Variable Measurement

Type	Variable	Measurement
Independent	AI leadership	4 items; mean score
Mediator	Self-efficacy	6 items; mean score
Dependent	Proactive innovation	4 items; mean score
Moderator	Cognitive flexibility	9 items; 4 reverse-scored; mean
Control	Age	5 ordinal groups
Control	Education	5 ordinal levels
Control	Firm size	5 employee-size groups
Control	AI-use frequency	5 frequency levels
Control	Industry	4 dummies; other = reference

5. Empirical Analysis and Results

5.1. Common Method Bias Test

Harman's single-factor test showed that the first unrotated principal component explained 31.947% of the variance, below the conventional 40% threshold, indicating that serious common method bias was not present in this study.

5.2. Reliability, Validity, and Confirmatory Factor Analysis

Table 2. Reliability and Validity of Variables

Variable	Item	Loading	α / KMO
AI leadership	Transformation motivation	0.651	$\alpha=0.724$; KMO=0.738
	AI transformation vision	0.586	
	Supervisor support for AI work	0.516	
	Human-AI task allocation	0.628	
Self-efficacy	Digital-device confidence	0.581	$\alpha=0.739$; KMO=0.767
	Solving device-related problems	0.419	
	Creative problem-solving confidence	0.538	
	Generating new ideas	0.678	
	Building on others' ideas	0.514	
	Developing new problem-solving methods	0.768	
	Trying new methods	0.582	
Proactive innovation	Seeking problems/opportunities	0.418	$\alpha=0.682$; KMO=0.715
	Supporting new ideas despite risk	0.640	
	Testing new work methods	0.472	
	Communicating an idea in multiple ways	0.441	
Cognitive flexibility	Avoiding unfamiliar settings (R)	0.517	$\alpha=0.784$; KMO=0.817
	Decision indecision (R)	0.588	
	Appropriate response across situations	0.468	
	Few alternatives when deciding (R)	0.751	
	Creative problem solving	0.686	
	Conscious decision-making	0.548	
	Difficulty applying knowledge (R)	0.566	
	Confidence to try different behaviors	0.462	

Reliability was assessed with Cronbach's α , with $\alpha \geq 0.7$ taken as the acceptable criterion. As shown in Table 2, AI leadership, self-efficacy, and cognitive flexibility all exceeded 0.7 and showed good internal consistency. The α value for proactive innovation behavior (0.682) fell within the 0.6–0.7 range and was marginally acceptable. Overall, the scale reliability met the basic requirements for empirical analysis.

Table 3. Comparison of Confirmatory Factor Analysis Model Fit Indices

Model	χ^2	df	χ^2/df	CFI	TLI	RMSEA	SRMR
Four-factor	419.317	224	1.872	0.844	0.824	0.072	0.074
Three-factor	488.189	227	2.150	0.791	0.767	0.082	0.079
One-factor	499.173	230	2.170	0.785	0.763	0.083	0.080

The exploratory factor analysis reported in Table 3 showed KMO=0.883 for the four-factor model using all 23 items, and Bartlett's test of sphericity was significant ($\chi^2=1420.193$, $df=253$, $p<0.001$), indicating that the data were suitable for factor analysis. After orthogonal rotation, all factor loadings exceeded 0.4, the four factors explained 43.140% of cumulative variance, and all items loaded on their theoretically specified dimensions, indicating basically acceptable construct validity.

Table 4. Convergent Validity: Standardized Loadings, Composite Reliability, and AVE

Construct	Loading range	CR	AVE
AI leadership	0.541–0.757	0.741	0.421
Self-efficacy	0.252–0.783	0.750	0.359
Proactive innovation	0.487–0.653	0.701	0.372
Cognitive flexibility	0.342–0.814	0.771	0.291

Note: CR>0.7 indicates good composite reliability; AVE>0.5 indicates good convergent validity.

In Table 4, the confirmatory factor analysis revealed the four-factor model achieved acceptable fit ($\chi^2/df=1.872$, RMSEA=0.072, SRMR=0.074, CFI=0.844, TLI=0.824) and fitted significantly better than three-factor and one-factor alternatives ($p<0.001$), supporting discriminant validity. While all CR values exceeded 0.7, AVE values (0.291–0.421) were below 0.5, indicating weak convergent validity. Future research may refine item wording to improve convergent validity.

5.3. Descriptive Statistics and Correlation Analysis

Table 5 reports variable means, standard deviations, and correlation coefficients. Self-efficacy, the mediating variable, had the strongest correlation with proactive innovation behavior ($r=0.715$, $p<0.01$). Cognitive flexibility was also significantly and positively correlated with self-efficacy and proactive innovation behavior.

Table 5. Means, Standard Deviations, and Correlations

Variable	Mean	SD	1	2	3	4	5	6	7	8
1 AI leadership	4.124	0.532	1							
2 Self-efficacy	4.181	0.473	.465**	1						
3 Proactive innovation	4.085	0.558	.470**	.715**	1					
4 Cognitive flexibility	4.106	0.475	.543**	.641**	.564**	1				
5 Age	2.335	0.967	.040	.028	-.141	-.048	1			
6 Education	3.906	0.690	.008	.137	.201**	.167*	-.148	1		
7 Firm size	2.924	1.221	.174*	.132	.188*	.201**	.062	.237**	1	
8 AI-use frequency	2.977	0.679	.291**	.170*	.236**	.189*	-.069	.109	.283**	1

Note: * $p<0.05$, ** $p<0.01$ (two-tailed), N=170.

5.4. Hypothesis Testing

Table 6. Regression Results

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Age	-.066(.044)	-.083(.039)*	.026(.038)	.013(.035)	-.093(.030)**	.030(.030)
Education	.098(.064)	.109(.057)	.080(.055)	.082(.051)	.051(.045)	.026(.044)
Firm size	.047(.039)	.028(.035)	.022(.033)	.002(.031)	.026(.027)	-.016(.027)
AI-use frequency	.151(.067)*	.073(.061)	.099(.057)	.026(.054)	.054(.047)	.030(.046)
Industry dummies	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
AI leadership		.486(.074)***		.414(.066)***	.191(.064)**	.102(.076)
Self-efficacy					.715(.069)***	
Cognitive flexibility						.548(.073)***
AI leadership × cognitive flexibility						-.091(.085)
Observations	170	170	170	170	170	170
R ²	.122	.308	.223	.245	.585	.460

Note: *p<0.05, **p<0.01, ***p<0.001; standard errors are in parentheses.

(1) Main-effect test. Table 6 presents the regression results for hypothesis testing. In model 2, AI leadership had a significant positive effect on proactive innovation behavior ($B=0.486$, $p<0.001$), and explanatory power increased from 0.122 to 0.308. Thus, higher AI leadership is associated with stronger employee proactive innovation behavior, supporting H1.

(2) Mediation test. The mediating effect of self-efficacy was tested using the Baron–Kenny three-step procedure, with regression results shown in Table 6. Baron–Kenny tests confirmed AI leadership positively predicted proactive innovation behavior ($B=0.486$, $p<0.001$) and self-efficacy ($B=0.414$, $p<0.001$). Self-efficacy remained significant ($B=0.715$, $p<0.001$) when included alongside AI leadership, verifying partial mediation and supporting H2 and H3.

(3) Moderation test. Model 6 further included the interaction term AI leadership × cognitive flexibility. The interaction coefficient was $B=-0.091$ ($p=0.288$), which was not statistically significant; therefore, H4 was not supported by the data. Three possible reasons are proposed. First, the 170 observations may have inadequate statistical power. Second, high correlation between cognitive flexibility and self-efficacy could lead to measurement overlap and dilute the interaction.

Table 7. Simple-Slope Analysis: Effect of AI Leadership on Self-Efficacy at Different Levels of Cognitive Flexibility

Cognitive flexibility	Slope	SE	t	p
Low (Mean–1 SD)	0.146	0.066	2.222	0.028
Mean	0.102	0.076	1.355	0.177
High (Mean+1 SD)	0.059	0.102	0.579	0.563

Simple slope tests in Table 7 showed that AI leadership significantly predicted self-efficacy only at low cognitive flexibility (Mean–1 SD, $B=0.146$, $p=0.028$). The effect became insignificant at the mean ($B=0.102$, $p=0.177$) and high levels (Mean+1 SD, $B=0.059$, $p=0.563$). The declining slope supports the negative interaction, indicating a weaker effect of AI leadership on self-efficacy for employees with higher cognitive flexibility.

5.5. Robustness Tests

Table 8. Robustness Test of the Mediation Effect Using Sobel and Bootstrap Methods

Independent	Mediator	Dependent	Sobel Z	Sobel p	Indirect effect	Bootstrap p	SE	LLCI	ULCI
AI leadership	Self-efficacy	Proactive innovation	5.383	<0.001	0.296	<0.001	0.072	0.160	0.443

Note: Bootstrap resampling = 5,000; percentile 95% confidence interval; LLCI and ULCI are the lower and upper confidence limits; N=170.

Table 9. Robustness Test: Regression for the Subsample Younger than 35

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Education	.098(.064)	.109(.057)	.186(.072)**	.164(.062)**	.103(.064)
Firm size	.243(.084)**	.221(.076)**	.023(.036)	.003(.031)	.017(.031)
AI-use frequency	.087(.074)	-.007(.070)	.046(.064)	-0.051(.057)	.030(.057)
Industry dummies	Controlled	Controlled	Controlled	Controlled	Controlled
AI leadership		.431(.085)***		.440(.070)***	.114(.081)
Self-efficacy					.722(.095)***
Observations	114	114	114	114	114
R ²	0.115	0.283	0.081	0.327	0.531

Note: *p<0.05, **p<0.01, ***p<0.001; standard errors are in parentheses.

Table 10. Robustness Test: Regression for the Subsample Aged 35 and Above

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Education	-.033(.095)	.032(.088)	.186(.072)**	.164(.062)**	.039(.065)
Firm size	.074(.068)	.047(.062)	.023(.036)	.003(.031)	.036(.046)
AI-use frequency	.260(.118)**	.178(.109)*	.046(.064)	-0.051(.057)	.081(.082)
Industry dummies	Controlled	Controlled	Controlled	Controlled	Controlled
AI leadership		.500(.141)***		.440(.070)***	.295(.109)**
Self-efficacy					.699(.107)***
Observations	56	56	56	56	56
R ²	0.14	0.31	0.087	0.154	0.628

Note: *p<0.05, **p<0.01, ***p<0.001; standard errors are in parentheses.

Table 11. Robustness Test: Regression for the Bachelor's Degree or Above Subsample

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Age	-.098(.045)**	-.099(.042)	.005(.039)	.004(.036)	-.101(.034)***
Firm size	.065(.037)*	0.035(.035)	.027(.031)	.002(.030)	.033(.028)
AI-use frequency	.147(.063)**	0.080(.060)	.112(.053)	.056(.051)	.041(.049)
Industry dummies	Controlled	Controlled	Controlled	Controlled	Controlled
AI leadership		.364(.079)***		.303(.068)***	.153(.068)**
Self-efficacy					.698(.080)***
Observations	145	145	145	145	145
R ²	0.108	0.225	0.047	0.166	0.5

Note: *p<0.05, **p<0.01, ***p<0.001; standard errors are in parentheses.

Table 12. Robustness Test: Regression for the Below-Bachelor's-Degree Subsample

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Age	.149(.134)	-.040(.078)	.165(.136)	-.038(.066)	-.009(.058)
Firm size	-.005(.108)	.196(.066)***	.029(.110)	0.245(.056)***	-.005(.068)
AI-use frequency	-.170(.336)	-.406(.187)**	-.257(.340)	-.509(.158)***	.013(.170)
Industry dummies	Controlled	Controlled	Controlled	Controlled	Controlled
AI leadership		1.136(.161)***		1.216(.136)***	.136(.265)
Self-efficacy					.822(.195)***
Observations	25	25	25	25	25
R ²	0.058	0.731	0.078	0.816	0.861

Note: *p<0.05, **p<0.01, ***p<0.001; standard errors are in parentheses.

Additional robustness tests were conducted. Both the Sobel test and a nonparametric percentile Bootstrap test with 5,000 resamples were used. As shown in Table 8, the Sobel test yielded $Z=5.383$, $p<0.001$. The Bootstrap estimate of the mediation effect was 0.296 with a standard error of 0.072 and a 95% percentile confidence interval of [0.160, 0.443], which excluded zero. The Sobel parametric test and Bootstrap nonparametric resampling test therefore reached the same conclusion, indicating that the mediating role of self-efficacy between AI leadership and employee proactive innovation behavior was robust.

Subsample regressions by age and education were also conducted. The main effect and mediating paths remained significant across different age and educational subgroups in Table 9, 10, 11 and 12 demonstrating stable results.

6. Discussion and Implications

6.1. Research Conclusions

Based on 170 valid employee questionnaires, the study yields three main conclusions. First, AI leadership significantly promotes employees' proactive innovation behavior. Second, self-efficacy partially mediates this relationship: AI leadership not only directly promotes innovation but also does so by strengthening employees' confidence in digital operations and innovation practice; the mediation result is supported by Bootstrap testing. Third, the interaction involving cognitive flexibility is not significant ($p=0.288$). The original study attributes this mainly to the sample's high AI-use frequency, which may homogenize human-AI work patterns, and limited variation in cognitive flexibility within the sample.

6.2. Theoretical Contributions

The study extends social cognitive theory from conventional organizational behavior to AI-enabled management and clarifies AI leadership as a leadership context distinguished from traditional and digital leadership. It identifies self-efficacy—covering digital and innovation dimensions—as a micro-level cognitive mechanism linking AI leadership with proactive innovation behavior. It also introduces cognitive flexibility as an individual boundary condition; although its moderating effect is not statistically supported, the observed trend provides a basis for refining future boundary-mechanism research.

6.3. Managerial Implications

Firms should cultivate managers' AI leadership via AI practice platforms and targeted training instead of merely regarding AI as a digital tool. Managers can boost employees' digital and innovative self-efficacy through AI practice, tailored guidance, tolerance for trial, innovation resources, and positive feedback. Enterprises may prioritize cognitive flexibility in recruitment and team building, and foster an inclusive human-AI culture to mitigate tech anxiety and promote AI-driven innovative trials.

6.4. Limitations and Future Research

The study is limited by the sample size ($N=170$), especially the small below-bachelor subgroup, the use of a single online survey platform, uneven industry coverage, and the use of cognitive flexibility as the only boundary variable despite its nonsignificant moderation. Future research should enlarge and diversify samples, combine online and offline data collection, improve industry coverage, refine measurement scales, and test organizational, environmental, and alternative individual moderators to better specify the boundaries of AI leadership's effects.

References

- [1] Fang X, Xie P, Lu L, et al. The mechanism through which AI leadership affects digital innovation [J]. *Chinese Journal of Management*, 2026, 23(3): 439–450.
- [2] Zhang H, Gao Z, Li H. Gain or depletion: The double-edged effect of artificial intelligence application on employee innovative behavior [J]. *Science & Technology Progress and Policy*, 2023, 40(18): 1–11.
- [3] Si X, Zhang Q. Coordinated development of AI leadership and 'three-dimensional progress' in the intelligent era [J]. *Tsinghua Business Review*, 2026, (Z1): 30–37.
- [4] Hu J, Ren Y. Talent incentives, corporate innovation performance, and distortion of innovation structure: A quasi-natural experiment based on urban talent attraction [J]. *Management Review*, 2024, 36(4): 100–114.
- [5] Lin X, Luan Y, Zhao K, et al. A meta-analysis of the relationship between leadership styles and employee innovation performance: A self-determination perspective [J]. *Advances in Psychological Science*, 2022, 30(4): 781–801.
- [6] Gao Z, Zhang H. Leader AI symbolization and employee digital creativity: Based on cognitive-affective personality system theory [J]. *Collected Essays on Finance and Economics*: 1–16.
- [7] Xie P, Ma L, Wei Y. The mechanism through which digital technology training affects employee digital creativity [J]. *Journal of Industrial Engineering and Engineering Management*, 2026, 40(1): 74–86.
- [8] Van Quaquebeke N, Gerpott F H. The Now, New, and Next of Digital Leadership: How Artificial Intelligence (AI) Will Take Over and Change Leadership as We Know It [J]. *Journal of Leadership & Organizational Studies*, 2023, 30(3): 265–275.
- [9] Gao Q, Huang B. Effects of employee–organization relationships on scientific research innovation performance from the perspective of social exchange theory [J]. *Science and Technology Management Research*, 2022, 42(4): 125–132.
- [10] Zhang Z, Zheng X, Zhong J. Leadership research from a human-computer interaction perspective [J]. *Science & Technology Progress and Policy*, 2025, 42(10): 116–126.
- [11] Zhang Z, Zheng X. Digital leadership: Structural dimensions and scale development [J]. *Business and Management Journal*, 2023, 45(11): 152–168.
- [12] Aziz M F, Rajesh J I, Jahan F, et al. AI-powered leadership: A systematic literature review [J]. *Journal of Managerial Psychology*, 2024, 40(5): 604–630.
- [13] Zhao B, Han P. A grounded-theory study of the dual-path generation mechanism of employee proactive innovation behavior [J]. *Chinese Journal of Management*, 2016, 13(7): 1003–1011.
- [14] Lee H W, Pak J, Kim S, et al. Effects of Human Resource Management Systems on Employee Proactivity and Group Innovation [J]. *Journal of Management*, 2019, 45(2): 819–846.
- [15] Yang C, Tang D, Mei J. Abusive supervision and employee proactive innovation behavior: Perspectives of motivation and capability beliefs [J]. *Science & Technology Progress and Policy*, 2021, 38(3): 143–150.
- [16] Zhang Z, Yu C, Li Y. Proactive personality, knowledge sharing, and employee innovative behavior [J]. *Management Review*, 2016, 28(4): 123–133.
- [17] Xu B, Deng C, Wu H. Leader-member exchange and employee proactive innovation behavior: A mediated moderation model [J]. *Journal of Management Science*, 2021, 34(2): 44–55.
- [18] Liang Y, Hu F, Wu C. How digital-intelligent leadership affects employee digital-intelligent job crafting: A serial mediation model [J]. *Soft Science*, 2026, 40(3): 19–26.
- [19] Bandura A. *Social foundations of thought and action: A social cognitive theory* [Z]. Prentice-Hall, Inc., 1986: xiii, 617–xiii.
- [20] Bandura A, Adams N E, Beyer J. Cognitive processes mediating behavioral change [J]. *Journal of Personality and Social Psychology*, 1977, 35(3): 125–139.
- [21] Gu Y, Peng J. The effect of organizational innovation climate on employee innovative behavior: The mediating role of creative self-efficacy [J]. *Nankai Business Review*, 2010, 13(1): 30–41.
- [22] Gao Z, Zhang H. Leader AI symbolization and AI-driven employee innovative behavior: A moderated dual-mediation model [J]. *Science & Technology Progress and Policy*, 2025, 42(21): 151–160.

- [23] Martin M M, Rubin R B. A New Measure of Cognitive Flexibility [J]. *Psychological Reports*, 1995, 76(2): 623–626.
- [24] Luo J, Zhao L, Zhong J. The mechanism through which ambidextrous leadership affects employee innovative behavior [J]. *Forecasting*, 2016, 35(4): 1–7.
- [25] Ling Y, Zhou J, Chen A. How employee–AI collaboration affects employee agility: A cognitive-affective dual-path mechanism [J]. *Human Resources Development of China*, 2026, 43(7): 6–21.
- [26] Santana A N D, Roazzi A, Nobre A P M C. The relationship between cognitive flexibility and mathematical performance in children: A meta-analysis [J]. *Trends in Neuroscience and Education*, 2022, 28: 100179.
- [27] Bandura A. *Social learning theory of aggression* [Z]. Blackwell Publishing, 1978: 12–29. 10.1111/j.1460-2466.1978.tb01621.x.
- [28] Zhou W, Guo G. Self-efficacy: Concept, theory, and application [J]. *Journal of Renmin University of China*, 2006, (1): 91–97.
- [29] Ye H, Zhang P, Wang Y, et al. The double-edged mechanism of perceived AI creativity on employee innovative behavior [J]. *Chinese Journal of Management*, 2025, 22(9): 1646–1656.
- [30] Li Z, Zhu X, Guo J. The effect of human-AI collaboration on employee job crafting in AI application scenarios: The mediating role of psychological empowerment [J]. *China Personnel Science*, 2023, (9): 35–45.
- [31] Rama, Nayak C, Agarwal R K. *A Model of Creativity and Innovation in Organizations* [C], 2011.
- [32] Cai W, Yu X. Proactive change or passive response? The effect of AI assistant intelligence on employee job crafting [J]. *Soft Science*, 2024, 38(12): 1–6+25.
- [33] Niu L, Zhang G, Zhao R, et al. The dual impact mechanism of employee threat perception on thriving at work in the context of AI embedding [J]. *Science & Technology Progress and Policy*, 2026, 43(4): 109–117.
- [34] Liu Z, Xu Y, Xu J, et al. Innovation aspiration gaps and team breakthrough innovation: A self-regulation theory perspective [J]. *Acta Psychologica Sinica*, 2023, 55(2): 272–285.
- [35] Liang Y, Yang M, Wu T-J. Double-edged sword effect of employee–AI collaboration: The role of AI uncertainty and digital leadership [J]. *Leadership & Organization Development Journal*, 2025, 46(6): 943–962.
- [36] Gong Y. Employee learning orientation, transformational leadership, and employee creativity: The mediating role of employee creative self-efficacy [J]. *Development and Learning in Organizations: An International Journal*, 2010, 24(2).
- [37] Kim M, Oh J, Kim B. Experience of digital music services and digital self-efficacy among older adults: Enjoyment and anxiety as mediators [J]. *Technology in Society*, 2021, 67.