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AI LEARNING ANXIETY, JOB INSECURITY, AND INNOVATION: A MEDIATION MODEL IN ASIAN FIRMS

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Abstract

The rapid adoption of Artificial Intelligence (AI) presents a critical challenge for organizations, particularly in dynamic Asian economies where institutional pressures for innovation are high. While AI promises efficiency, it also heightens employee anxiety and concerns about job stability. This study investigates the intricate relationship between AI learning anxiety and employees' innovative work behavior, focusing on the mediating role of job insecurity within Asian firms. Drawing on Threat-Rigidity Theory, we hypothesized that AI learning anxiety would increase job insecurity, which, in turn, would dampen innovative work behavior. Using a quantitative approach, data were collected from 403 employees at Chinese internet companies with at least 1 year of experience with AI tools. Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed for data analysis. The findings reveal that AI learning anxiety significantly heightens job insecurity. Importantly, job insecurity significantly undermined employees' innovative work behavior. Crucially, AI learning anxiety did not directly influence innovation; instead, its negative effect was fully mediated through job insecurity. This demonstrates that employees' emotional responses to AI are transmuted into tangible resource threats, driving defensive rather than innovative behaviors. This study extends Threat-Rigidity Theory to the context of AI. It offers vital insights for management, emphasizing the critical need to address employees' psychological security to foster innovation during AI-driven transformations in Asia.
Keywords: AI Learning Anxiety, Job Insecurity, Employee Innovation, Threat-Rigidity Theory, Asian Firms

Introduction

The rapid advancement of large language models such as ChatGPT and Claude has accelerated the penetration of artificial intelligence (AI) into the core task domains of knowledge-intensive industries at an unprecedented pace. Recent estimates from the McKinsey Global Institute suggest that, under moderate adoption scenarios, up to 30% of current work hours could be automated by 2030. The development of generative AI is expected to intensify this trend further, potentially resulting in as many as 12 million occupational transitions (Hazan et al., 2024). Against this transformative backdrop, employee responses to AI have become increasingly polarized: while some employees actively embrace AI technologies, others experience anxiety and resistance, driven by fears of skill obsolescence and job displacement (Brougham & Haar, 2018; Chen & Zhao, 2025; He et al., 2024). In Asian economies such as China, the rapid adoption of AI is deeply intertwined with institutional pressures for continuous innovation, rendering the tension between upskilling and job security particularly acute compared with many Western contexts (Khanal et al., 2025; Wang et al., 2024; Xu et al., 2024). This raises a critical question: how do employees adapt to AI while sustaining the innovative behavior that organizations need to remain competitive?

Compared with traditional information technologies, AI exhibits distinctive characteristics, including autonomous decision-making, continuous evolution, cognitive task execution, and opacity in its decision-making processes. Although these features significantly enhance organizational efficiency, they also amplify perceptions of uncertainty and loss of control, thereby triggering career concerns and psychological strain among employees. Within this context, the psychological stress associated with learning and adapting to AI, commonly referred to as AI learning anxiety, has emerged as a critical focus of scholarly inquiry (Huang & Rust, 2018).

Extant research indicates that AI learning anxiety, as a salient psychological factor, can significantly influence job-related outcomes such as burnout, job satisfaction, and organizational commitment (Huang & Rust, 2018; Brougham & Haar, 2018). It may also alter employees' self-perceived competence, shaping their ability to adapt to new technologies. However, despite these insights, important gaps remain in understanding how AI learning anxiety affects employees' specific behavioral responses, particularly innovative work behavior. Most studies have concentrated on the direct effects of AI learning anxiety on attitudes and emotions, with limited attention to its indirect effects via psychological mediators (Wu et al., 2024; Yuangngoen et al., 2025). Specifically, in an era of rapid technological change, employees often face heightened job mobility pressures and demands for skill renewal. However, potential mediating variables, such as job insecurity, have received insufficient empirical attention.

Moreover, most of these frameworks were originally developed in Western contexts. In collectivist and high power-distance cultures that characterize many Asian organizations, employees may respond to threat and uncertainty not only with withdrawal but also with conformity and silence, raising questions about the direct applicability of Threat-Rigidity Theory without contextual refinement (Gustiawan et al., 2023; Toufighi et al., 2024).

Addressing this gap is of considerable theoretical and practical significance. Theoretically, this study advances understanding of how technology-induced stressors influence employee innovation by unpacking the mediating role of job insecurity, thereby extending Threat Rigidity Theory to the context of AI adoption. Practically, clarifying this mechanism provides actionable insights for organizations seeking to mitigate psychological barriers and sustain innovation during digital transformation. Specifically, this study aims to (1) investigate the relationship between AI learning anxiety and employees' innovative work behavior; (2) examine the mediating role of job insecurity in this relationship; and (3) explore the contextual

boundaries of this influence mechanism to enrich the application of Threat Rigidity Theory in AI contexts.

Literature Review

This study draws on Threat-Rigidity Theory (Staw et al., 1981) as the overarching framework to explain how AI learning anxiety influences employees' innovative work behavior. The theory posits that when individuals perceive environmental threats, they exhibit rigid responses characterized by restricted information processing, conservative behavioral strategies, and reduced exploratory activities. In the context of rapid AI development, employees face not traditional work stressors but novel and complex technological learning requirements. Whether these requirements are interpreted as opportunities for skill enhancement or as threats to job security largely depends on the intensity of employees' threat perceptions.

AI learning anxiety is conceptualized as a psychological response rooted in such threat perceptions. It reflects employees' subjective evaluation of the difficulty of AI-related learning and their confidence in their ability to cope with these demands. Prior research suggests that individuals differ considerably in their threat appraisals, which directly shape subsequent behaviors and innovative performance (Brougham & Haar, 2018; Kim et al., 2024). Recent studies in China and other Asian economies show that employees often interpret AI-related learning demands as threats to job stability rather than as opportunities for reskilling, reflecting the strong institutional pressures for continuous innovation in these contexts (Wang et al., 2024; Xu et al., 2024). Building on this logic, we argue that AI learning anxiety may not only directly suppress innovative work behavior but also indirectly influence it through job insecurity. Specifically, employees who perceive AI learning as threatening are more likely to experience heightened job insecurity, which in turn reduces their willingness to engage in innovation.

In sum, the proposed framework highlights the mechanism of threat rigidity: identical AI learning requirements can lead to divergent behavioral outcomes depending on employees' threat perceptions. Through processes of threat amplification and behavioral rigidity, AI learning anxiety constrains innovative behavior both directly and via job insecurity (Ngamcharoen et al., 2024). In collectivist, high power-distance cultures, employees may respond to threats with conformity and silence rather than withdrawal, underscoring the need to validate Threat-Rigidity Theory in Asian organizations (Gustiawan et al., 2023; Toufighi et al., 2024). The following sections elaborate on the theoretical foundations and develop specific hypotheses.

The Impact of AI Learning Anxiety on Job Insecurity

Innovative work behavior refers to employees' actions to generate, promote, and implement novel ideas that enhance organizational performance, relying on proactive risk-taking, resource investment, and adaptive thinking, all of which are undermined by threat perceptions and defensive cognition.

From the lens of Threat-Rigidity Theory (Staw et al., 1981), AI learning anxiety (as a perceived threat) triggers rigid cognitive patterns: employees narrow their focus to mitigating learning failures or job loss, reducing exploration of new possibilities, and avoiding the trial-and-error essential for innovation (He et al., 2024).

Empirical studies support this link: AI learning anxiety reduces employees' willingness to experiment with new workflows (Sharif et al., 2025), while stress from technology adaptation diminishes the cognitive flexibility needed for creative solutions (Brougham & Haar, 2018). Moreover, it fosters a "threat avoidance" mindset, employees may avoid proposing innovative ideas for fear of diverting energy from AI skill learning, or worry that innovation could be devalued if AI replaces their role (Kim et al., 2024).

Additionally, AI learning anxiety erodes the psychological safety critical for innovation: employees anxious about adapting to AI are less likely to share untested ideas or challenge

status quos, key to innovation, for fear of revealing incompetence or risking job security (de Witte et al., 2016). Based on this reasoning, we hypothesize the following:

H1: AI learning anxiety positively influences job insecurity.

The Impact of AI Learning Anxiety on Employee Innovative Work Behavior

According to Threat-Rigidity Theory (Staw et al., 1981), when individuals perceive environmental changes as uncontrollable and harmful, they display threat responses characterized by negative psychological states and conservative behaviors. In the AI context, learning anxiety reflects employees' negative evaluations of the demands, challenges, and risks associated with AI technologies. Such threat appraisals can suppress innovative intentions and reduce motivation (Kim et al., 2024).

AI learning anxiety affects innovation through several mechanisms. It depletes cognitive resources, diverting attention from creative efforts to coping with the pressure of learning. It increases risk aversion, leading employees to adopt conservative strategies and avoid innovation that might expose capability gaps. It also weakens self-efficacy, reducing confidence in completing innovative tasks (He et al., 2024; Sharif et al., 2025).

Empirical studies support this view. Brougham & Haar (2018) found that AI-related anxiety was negatively related to innovative work behavior, while Kim et al. (2024) showed that technological anxiety suppresses exploratory activities and performance. Accordingly, we propose:

H2: AI learning anxiety negatively influences employees' innovative work behavior.

The Impact of Job Insecurity on Employee Innovative Work Behavior

Job insecurity refers to employees' perceptions of uncertainty about the continuity and stability of their current employment (de Witte et al., 2016). It acts as a core threat to work resources, undermining the psychological conditions for innovative work behavior. Per Threat-Rigidity Theory (Staw et al., 1981), when employees feel job insecurity, they prioritize "resource protection" over "resource exploration", a shift that conflicts with innovation's risk-taking and experimental nature.

Job insecurity inhibits innovative work behavior via three interrelated mechanisms. First, it diverts cognitive-emotional resources: rather than focusing on novel ideas or new workflows, employees prioritize defensive actions (e.g., adhering to routines, avoiding mistakes) to secure their positions (Sharif et al., 2025). Second, it erodes psychological safety, key to innovation. Employees fearing job loss are less likely to share untested ideas or challenge processes, fearing "innovation failure" could risk dismissal (de Witte et al., 2016). Third, it triggers emotional exhaustion: persistent employment anxiety diminishes motivation for time-consuming iterative innovation work (Brougham & Haar, 2018).

Empirical evidence supports this: Sharif et al. (2025) found that higher job insecurity was associated with a 32% drop in employees' participation in innovation projects. De Witte et al. (2016) further showed that job insecurity reduces risk-taking in innovation, as employees view such risks as "unnecessary threats" to retention. Therefore, we hypothesize:

H3: Job insecurity negatively influences employees' innovative work behavior.

**The Mediating Role of Job Insecurity**

According to Threat-Rigidity Theory (Staw et al., 1981), AI learning anxiety may not directly reduce employees' innovative behavior but rather operates through a threat-amplification process. Anxiety about learning AI intensifies concerns over job stability, creating perceptions of job insecurity that trigger conservative responses (Kim et al., 2024).

From a process view, initial anxiety about AI learning develops into job insecurity, which then reduces employees' willingness to innovate to avoid perceived risks. From a functional view, job insecurity acts as an amplifier, turning abstract learning concerns into concrete threats to core resources, thereby activating rigid responses (He et al., 2024; de Witte et al., 2016).

Empirical studies support this mechanism. Kim et al. (2024) showed that job insecurity mediates the link between technological threats and employee behavior, while Brougham & Haar (2018) found that negative reactions to AI learning foster conservative strategies through job insecurity. Likewise, Staw et al. (1981) and He et al. (2024) confirmed that perceived threats influence behavior via cognitive amplification. Therefore, we hypothesize:

H4: Job insecurity mediates the relationship between AI learning anxiety and employees' innovative work behavior.

Based on the literature review, the conceptual framework can be presented as shown in Figure 1.
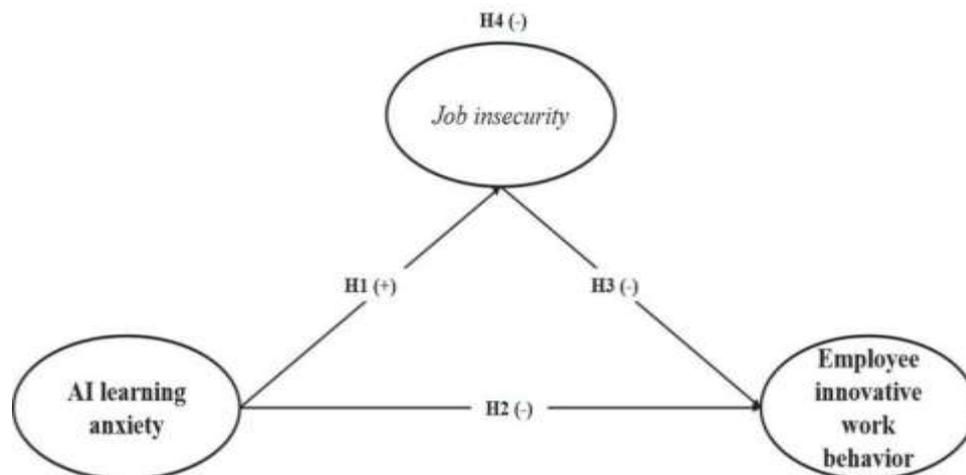
Figure 1 Conceptual Framework

Research Methodology

This study adopts a quantitative design to examine how AI learning anxiety influences innovative work behavior through job insecurity in China's internet industry. The target population consisted of employees at internet companies who frequently engage with artificial intelligence technologies in their daily work.

Data were collected through an online questionnaire administered via Credamo between May and July 2025, using purposive sampling with screening criteria to ensure that participants had direct experience with AI usage at work. A total of 403 valid responses were obtained, exceeding the minimum sample size estimated via Monte Carlo simulation for structural equation modeling, ensuring sufficient statistical power for hypothesis testing (Muthén & Muthén, 2002).

The measurement instrument was adapted from well-established scales in prior research. Content validity was ensured through literature-based item selection and expert review. To ensure semantic equivalence in the Chinese context, a standard translation-back-translation procedure was conducted. Minor linguistic adjustments were made to enhance contextual relevance for employees in the internet industry.

AI learning anxiety was measured with three items adapted from Wang & Wang (2022). Job insecurity was assessed using five items from de Witte et al. (2016). Innovative work behavior was measured with six items from Scott & Bruce (1994). All items were rated on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree).

Partial Least Squares Structural Equation Modeling (PLS-SEM) was conducted using SmartPLS 4.0. The measurement model was evaluated using standard criteria: indicator loadings (≥ 0.70), average variance extracted (AVE ≥ 0.50), Cronbach's alpha (≥ 0.70), composite reliability (CR ≥ 0.70), and Dijkstra-Henseler's rho_A (≥ 0.70). Discriminant validity was assessed using both the Fornell-Larcker criterion and the Heterotrait-Monotrait

ratio (HTMT). The structural model was then evaluated by analyzing path coefficients (β), t-values, p-values, R^2 values, and effect sizes (f^2) to test the proposed hypotheses.

Common method bias (CMB) was considered a potential concern given the single-source, self-reported nature of the data. To mitigate this risk, both procedural and statistical remedies were applied. Procedurally, anonymity was guaranteed, attention checks were included, question order was randomized, and a brief time lag was introduced between the measurement of predictors and outcomes. Statistically, the marker variable technique was employed (Kock, 2015), using an unrelated construct ("blue preference") as a marker. The results revealed non-significant paths and acceptable VIF values, indicating no serious multicollinearity (Simmering et al., 2014). Collectively, these results suggest that CMB is not a major issue in this study (Podsakoff et al., 2003).

Research Results
Respondents' Profiles and Studied Variables
Gender distribution was relatively balanced (male 55.6%). The sample was young, with 72% aged 26-40 (the industry's core working age). Education level was high: bachelor's degrees (64.8%) and doctoral degrees (21.8%) dominated. Work experience concentrated in the growth stage (1-5 years, 74%), with 17.6% having ≥10 years and 8.4% 6-9 years. AI usage was frequent, with daily use (40.5%) and 5-6 days/week (31%), aligning with the study's focus on AI-related variables.

Overall, the sample was relatively young and well-educated, with substantial exposure to AI, consistent with the profile of employees in China's internet industry.

AI Learning Anxiety, Job Insecurity, and Employee Innovative Work Behavior
Table 1 presents descriptive statistics for the individual variables, including means and standard deviations. The mean values range from 2.63 to 5.95, while the standard deviations range from 1.13 to 1.58. Detailed results are provided in the table.

Model Development, Convergent Validity, and Discriminant Validity
The measurement model was assessed by evaluating the standardized loadings of the indicators for each latent variable to determine whether they exceeded the recommended threshold of 0.70. As shown in Table 1, all item loadings were greater than 0.826, indicating adequate indicator reliability. In addition, the average variance extracted (AVE) for each construct exceeded the cutoff value of 0.50 (ranging from 0.743 to 0.797), supporting convergent validity.

Composite reliability was assessed using Cronbach's alpha (α), Dijkstra-Henseler's rho (ρA), and composite reliability (CR). All values were above the recommended threshold of 0.70 (α: 0.874-0.931; ρA: 0.891-0.934; CR: 0.922-0.946), indicating satisfactory internal consistency (Dijkstra & Henseler, 2015).

Discriminant validity was examined using both the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio (HTMT). As reported in Table 1, the square root of the AVE for each construct (shown on the diagonal) was greater than its correlations with other constructs (off-diagonal values), thus satisfying the Fornell-Larcker criterion. Additionally, all HTMT values were below the conservative threshold of 0.85, further confirming the discriminant validity of the constructs and indicating no multicollinearity problems (Henseler, Ringle, & Sarstedt, 2015).
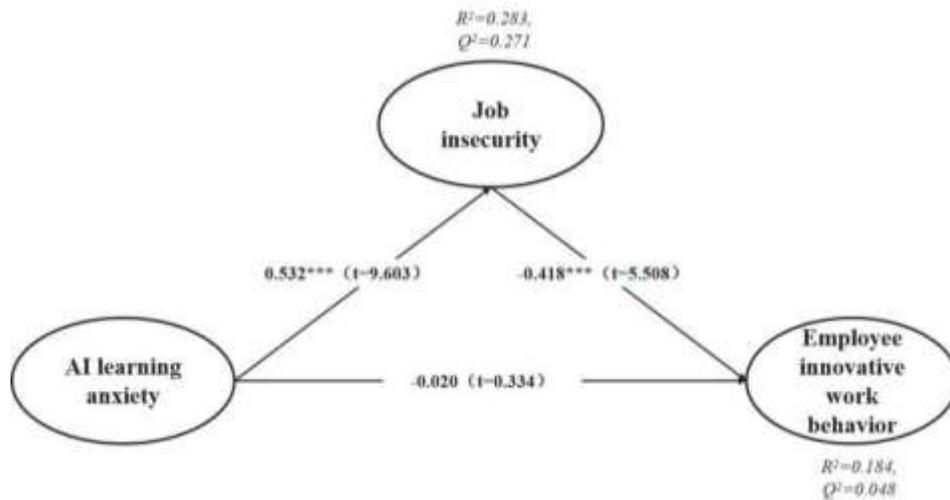
Note: ***p < 0.001; **p < 0.01; *p < 0.05
Figure 2 Estimated Relationships of the Structural Model

Finalized Model and Hypothesis Analysis

After confirming the measurement model's reliability and validity, the structural model was evaluated using PLS-SEM (Figure 2; Table 2). The results show that AI learning anxiety significantly increased job insecurity, and job insecurity significantly reduced innovative behavior, supporting H1 and H3. The direct effect of AI learning anxiety on innovative behavior was non-significant, indicating full mediation through job insecurity, which supports H4 but not H2.

Table 1 The descriptive statistics, as well as the construct reliability and validity values

Construct	Items	Descriptive				Convergent Validity				Discriminant Validity		
		Mean	Deviation	Loadings	VIF	Alpha	Rho_A	CR	AVE	1	2	3
Employee's	EIWB1	5.86	1.15	0.881	3.331	0.931	0.934	0.945	0.743	**0.862**	-0.243	-0.429
innovative	EIWB2	5.82	1.20	0.856	2.689							
work behavior	EIWB3	5.66	1.22	0.826	2.292							
	EIWB4	5.94	1.16	0.854	2.817							
	EIWB5	6.00	1.13	0.875	3.375							
	EIWB6	5.95	1.17	0.878	3.104							

Construct	Items	Descriptive				Convergent Validity				Discriminant Validity		
		Mean	Deviation	Loadings	VIF	Alpha	Rho_A	CR	AVE	1	2	3
AI learning anxiety	AILA1	2.63	1.58	0.912	2.635	0.874	0.891	0.922	0.797	0.263	**0.893**	0.532
	AILA2	2.54	1.52	0.869	2.344							
	AILA3	2.77	1.56	0.897	2.189							
Job insecurity	JI1	2.69	1.43	0.887	3.066	0.929	0.930	0.946	0.779	0.456	0.580	**0.883**
	JI2	2.55	1.51	0.894	3.323							
	JI3	2.45	1.17	0.851	2.495							
	JI4	2.49	1.44	0.880	3.078							
	JI5	2.44	1.40	0.902	3.408							

Table 2 Estimated structural model

Hypothesis	Structural Path	β(O)	mean (M)	SD	T-value	intervals bias corrected			Confidence intervals		Conclusion
						Bias	2.5%	97.5%	2.50%	97.50%	
H1	AILA -> JI	0.532	0.534	0.055	9.603***	0.002	0.422	0.639	0.425	0.643	Supported
H2	AILA-> EIWB	-0.020	-0.021	0.061	0.334	-0.001	-0.139	0.098	-0.139	0.098	Not supported
H3	JI -> EIWB	-0.418	-0.417	0.076	5.508***	0.001	-0.558	-0.257	-0.560	-0.261	Supported
H4	AILA -> JI -> EIWB	-0.222	-0.222	0.042	5.238***	0.001	-0.313	-0.144	-0.309	-0.141	Supported

Note: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

The model demonstrated acceptable explanatory power (R^2 for job insecurity = 0.283; innovative behavior = 0.184) and predictive relevance ($Q^2 > 0$). Overall, these findings highlight that the psychological effects of AI learning anxiety on innovation operate primarily through job insecurity. The mediating effect of job insecurity was tested using a bias-corrected bootstrapping procedure with 5,000 resamples (Hair et al., 2013; Preacher & Hayes, 2008). The indirect effect of AI learning anxiety on innovative behavior via job insecurity was significant, while the direct effect was non-significant, indicating full mediation (Zhao et al., 2010). This suggests that AI learning anxiety does not directly inhibit innovation but exerts its influence through heightened job insecurity, forming a cognitive-emotional-behavioral transmission mechanism.

Conclusion and Discussion

This study investigated how anxiety about learning AI shapes employees' innovative behavior through perceptions of job insecurity, drawing on threat-rigidity theory. The findings point to a clear threat-based pathway: anxiety about AI learning significantly heightens job insecurity, which, in turn, critically reduces employees' willingness to innovate. Our results confirm that AI learning anxiety amplifies employees' sense of insecurity, echoing prior research (Wu et al., 2024), where AI-related skill demands are often perceived not as challenges but as threats to job stability, transforming learning pressure into a cognitive appraisal of risk that subsequently shapes workplace emotions.

Interestingly, AI learning anxiety does not directly suppress innovation. Unlike earlier studies that treated technology-related anxiety as a straightforward inhibitor (Wu et al., 2024), our results suggest that anxiety becomes behaviorally significant only when it translates into perceived job insecurity. This supports the view that emotional responses influence behavior mainly when filtered through cognitive evaluations. Moreover, job insecurity clearly undermines innovation, consistent with prior evidence (Kim et al., 2024). Employees who perceive their jobs to be at risk tend to conserve resources and avoid uncertainty, making them less willing to take risks associated with innovation. Crucially, job insecurity fully mediates the link between AI learning anxiety and innovation, meaning innovation declines only when anxiety evolves into a perceived job threat. This aligns precisely with threat-rigidity theory, which posits that threats to valued resources trigger defensive, risk-averse behavior (Staw et al., 1981).

Overall, these findings demonstrate that the impact of AI learning anxiety is not automatic but critically depends on whether employees interpret it as a signal of job loss; once that happens, defensive strategies dominate and innovation suffers. For organizations, this underscores the importance of reducing perceived insecurity during AI transitions to prevent anxiety from escalating into withdrawal. These insights offer three significant contributions at the intersection of organizational behavior, technology management, and innovation research. First, this study clarifies the indirect nature of AI learning anxiety's effect on innovation, challenging the conventional assumption that such anxiety directly suppresses creativity (e.g., Brougham & Haar, 2018). Our findings unequivocally show that its impact is fully mediated by job insecurity, thereby revealing a previously overlooked cognitive pathway.

Second, this research advances Threat-Rigidity Theory by positioning job insecurity as a critical amplifier of threat. It demonstrates how job insecurity transforms abstract learning anxiety into a tangible resource threat, triggering defensive responses and reducing exploratory behaviors—an amplification mechanism largely ignored in prior research. Third, the study articulates a comprehensive threat-cognition-behavior chain that explains why anxiety alone does not automatically reduce innovation. By integrating threat perception, cognitive appraisal, and behavioral rigidity into a single explanatory process, this study addresses the lack of clarity in psychological mechanisms within innovation research.

The central insight that AI learning anxiety inhibits innovation only through job insecurity offers actionable guidance for organizations navigating AI-driven change. Firms should move beyond mere skill-focused strategies to emphasize psychological security. Managers need to ensure that learning anxiety does not escalate into perceived job threats by communicating transparently about roles and career prospects, thereby fostering a sense of stability and reassurance among employees.

Furthermore, AI change initiatives should strategically combine anxiety management with job stability interventions. Creating a culture that tolerates mistakes, encourages experimentation, and provides consistent psychological support can effectively buffer insecurity and sustain innovation. Talent strategies, therefore, must balance technical training with the development of psychological resilience. Monitoring perceptions of stability and role clarity, alongside

capability development, is essential to maintaining innovative behavior during AI transformation processes.

Although this study offers valuable insights into the complex interplay of AI learning anxiety, job insecurity, and innovation, several limitations should be acknowledged, which in turn highlight promising avenues for future research. Primarily, the cross-sectional, single-source, self-reported design of this study inherently limits the ability to draw definitive causal inferences and raises potential concerns about common method bias and social desirability. Future research would benefit significantly from employing longitudinal or experimental approaches, for example, by tracking employees before and after AI-related training interventions, and from utilizing multi-source data such as supervisor ratings, organizational records, or objective innovation outputs to enhance validity and robustness.

Moreover, the sample was limited to Chinese internet firms, a sector characterized by high digitalization and rapid AI integration. While this context provided a rich environment for our study, it may limit the generalizability of the findings. Comparative studies across other industries and diverse cultural settings would be beneficial to determine whether the mechanisms observed here hold more broadly. Additionally, this study focused on a single mediating pathway. Future work could fruitfully examine additional mechanisms, such as the influence of organizational support, AI governance policies, and technological self-efficacy, and consider cultural and institutional factors, such as collectivism and power distance, as potential moderators. This would further enrich our understanding of the specific conditions under which AI learning anxiety leads to job insecurity and consequently to reduced innovation.

Finally, it is important to note that the model's explanatory power, while significant, was moderate, suggesting that other unexamined factors may also play a role in shaping innovative behavior. Future studies should therefore adopt multi-level and cross-contextual designs that integrate broader variables like leadership styles, team climate, and institutional pressures. Such comprehensive accounts are crucial for providing a more holistic understanding of employee adaptation in AI-driven transformations.

In conclusion, within the rapidly evolving landscape of AI development and organizational change, this study clarifies how AI learning anxiety shapes innovation through an indirect and fully mediated pathway, significantly advancing our understanding of technology-related anxiety. Rather than exerting an immediate negative effect, AI learning anxiety influences innovative behavior primarily through the heightened perception of job insecurity. This finding challenges conventional assumptions of a direct inhibitory effect and underscores the intricate complexity of employee responses in AI-driven environments. Theoretically, this research enriches Threat-Rigidity Theory by specifying job insecurity as a key transmission mechanism, moving beyond the assumption of a direct behavioral constraint, and by integrating cognitive appraisal into this process, offering a nuanced view of psychological mechanisms in digital transformation contexts. In practice, these insights suggest that reducing anxiety or enhancing technical skills alone may be insufficient to sustain innovation. Instead, organizations should prioritize building psychological security through transparent career paths, supportive cultures, and open communication to prevent anxiety from escalating into perceived threats. This strategic shift from 'anxiety reduction' to 'security construction' offers a vital blueprint for fostering sustainable innovation in the era of AI.

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