Education Science and Management
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The Dual-Edged Effect of Artificial Intelligence Anxiety on University Students' Proactive Skill Development

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Received: 05-02-2025 **Revised:** 06-17-2025 **Accepted:** 06-23-2025

Citation: Liu, W. Y. (2025). The dual-edged effect of artificial intelligence anxiety on university students' proactive skill development. *Educ Sci. Manag., 3*(2), 128–141. https://doi.org/10.56578/esm030205.

Abstract: Artificial intelligence (AI) changes the way university students learn and improve skills. A total of 476 valid responses were received. This study examined AI anxiety's dual effect on university students' proactive skill development and the related mechanisms. The results show that AI anxiety promotes proactive skill development through challenge appraisal and inhibits it through threat appraisal. AI literacy strengthens the positive challenge appraisal and weakens the negative threat appraisal. A high self-driven profile and other profiles driven by resource management, crisis response, and competence are conducive to developing skills proactively. AI anxiety has a complex influence on students' proactive skill development. At the same time, this provides guidance for universities' digital transformation and talent cultivation, underscoring the importance of improving AI literacy and fostering constructive mindsets.

Keywords: University students; AI anxiety; Cognitive appraisal; Proactive skill development; AI literacy

1. Introduction

University students utilize AI to enhance their learning efficiency, refine their practice and stimulate innovation. However, AI exerts both beneficial and adverse influences on their proactive skill development theoretically and practically. For instance, the limitations of AI may motivate their proactive skill development. However, the convenience of robots and algorithms may raise their sense of being replaced, enabling those students to consider AI as a threat, thereby hindering their willingness in proactive skill enhancement. Therefore, this exerts far-reaching impacts on proactive skill development in terms of the challenges for traditional capabilities and the redefined skill requirements arising from opportunities. AI's rapid development and widespread adoption make university students uneasy and afraid in learning and daily life. These emotional reactions are AI anxiety (Ge et al., 2025; Russo et al., 2025), which is the concern, understanding, or psychological resistance regarding careers, social roles, ethical and security implications, and personal capabilities in the world with rapid AI development.

AI anxiety adversely affects individuals' readiness for change (Yuan & Liu, 2024), possibly causing psychological and physiological health issues and self-depletion during proactive skill development. It may affect their innovative learning using AI and cause deviant behaviors, affecting their development (Zhang & Chen, 2024). Conversely, AI anxiety also makes some individuals vigilant, competitive, and more willing to address work-related challenges (Li & Xue, 2025). Through stronger internal and external motivation, AI anxiety may promote students to learn using AI and generate a positive understanding of AI utilization. This, in turn, may further motivate them and make them proactive, contributing to proactive skill development. Specifically, proactive skill development refers to the process where individuals improve their core competencies to adapt to complex environments through self-driven, goal-oriented, and dynamically adjusted activities, ultimately substituting anxiety with learning (Xiao, 2025). Its core is to emphasize individuals' abilities in identifying the demand, designing the learning method, and innovating practice, instead of traditional passive knowledge acquisition. Self-motivation and continuous learning improve competency even within relatively stable knowledge systems and occupational structures (Bao et al., 2024).

AI literacy is a personal attribute. It affects individual behavior, competence and confidence in using digital technologies, thereby influencing their cognitive appraisal (Kong et al., 2021). Students with high AI literacy tend to believe they can exceed expectations and overcome obstacles, often with a greater sense of responsibility. In contrast, those with low AI literacy often focus on potential failures. This fosters a fear of AI and makes them more sensitive to it. Therefore, AI literacy was introduced as moderation to explore its regulatory role between AI anxiety and proactive skill development.

AI anxiety is an emotional response elicited by AI development (Xu, 2023). However, existing research has not yet systematically explained whether, and in what ways, AI anxiety influences proactive skill development among university students, particularly with respect to its positive and negative effects. Consequently, a comprehensive and dialectical investigation is required to examine AI anxiety's facilitative and inhibiting dimensions and its underlying mechanisms during students' proactive skill development. Guided by the cognitive appraisal theory of stress, this study focuses on university students undergoing digital transformation and aims to reveal the influence of AI anxiety on proactive skill development. Structural Equation Modeling (SEM) was employed to validate the causal relationships among the variables and deal with complex multiple concurrent causal conditions and latent associations among antecedent factors. By responding to these questions, the study contributes to revealing the influence of AI anxiety on university students' proactive skill development and the triggering pathways of proactive skill development in AI-mediated learning environments, thereby extending the application of the cognitive appraisal theory of stress to AI.

2. Theoretical Foundations and Research Hypotheses

2.1 University Students' AI Anxiety and Their Proactive Skill Development

AI development provides personalized support and efficient tools for education, significantly reducing the time to learn knowledge and innovate research while accelerating the intelligent education transformation (Adabor et al., 2025). AI adoption also affects labor markets and competency demands, requiring higher-standard skills for university students. While low-skill, repetitive roles may be replaced, interdisciplinary competence, AI literacy, and innovative thinking are core competitive strengths to make them proactively adapt to career transitions driven by technology (Zhu et al., 2025a). AI anxiety's effect on learning outcomes has been examined. High-level AI anxiety reduces positive emotions and self-efficacy, tends to increase depression, weakens the understanding of disciplinary value, and increases uncertainty in career decision-making among university students (Zhao, 2025). However, the influence of AI anxiety is not universally negative. AI anxiety has been shown to improve students' technological literacy, interdisciplinary integration capability, and sense of social responsibility. Challenge-oriented AI anxiety improves students' learning competitiveness, whereas hindrance-oriented AI anxiety has minimal influence, indicating that AI anxiety is not exclusively detrimental. As the limitations of single-method research methods become apparent, it is necessary to further investigate the relationship between AI anxiety and proactive skill development and the mechanisms.

According to the learning demands and resources model, learning behaviors depend on the balance between a student's resources and the demands they face. AI anxiety depletes their resources for self-regulation and affects their ability to develop new skills proactively. Conversely, in terms of resource acquisition, AI anxiety may prompt them to seek external resources more actively to improve their digital skills and learn more knowledge. Additional resources can be obtained, potentially promoting their proactive skill development. Proactive skill development is a specific form of proactive career behavior and reflects that students are willing to learn to improve their skills and personal capabilities in digital learning. For university students, proactive skill development is a forward-looking investment of resources. Students tend to adjust their behaviors and attitudes based on resource depletion and gain. As individuals acquire new skills and knowledge, their critical thinking and problem-solving capabilities are strengthened at the same time. The effect of AI anxiety on proactive skill development ultimately depends on whether the former is considered a challenge associated with resource gain or a threat associated with resource depletion.

2.2 The Mediating Role of Cognitive Appraisal

According to the cognitive appraisal theory of stress, cognitive appraisal is the process to classify stressors based on individuals perceived stakes, and it shows how stressors influence university students' attitudes and behaviors (Glassman et al., 2015). When faced with external stimulus events, university students tend to form challenge appraisal or threat appraisal (Wang & Che, 2024). The two-dimensional appraisal structure has been extensively supported (Chen et al., 2019). Academic demands, learning standards, pressure for self-improvement, employment anxiety, and academic or time management requirements all elicit challenge appraisal and threat appraisal. As for individuals adopting challenge appraisal, they tend to believe that they have sufficient confidence to manage high-pressure situations. They utilize opportunities to show competence, motivation for exploration and learning, and proactive attitudes. This indicates that appropriate stress helps them realize the goal and potentially motivates them to obtain resources. If individuals consider the stressor as a threat, they are likely to believe that a certain stress peak prevents them from realizing goals and career plans. This makes them have fear and avoidance and other negative psychological responses. This sense of oppression makes them lose resources and affects their growth. Stress formation and related response involve primary appraisal and secondary appraisal. The former refers to the judgment of beneficial or harmful implications of an event based on existing resources, whereas the latter involves evaluating options available for event management (Zhu et al., 2025b). The dynamic appraisal interaction produces fluctuating emotional experiences, influencing attitudes and behaviors (Kammeyer-Mueller et al., 2009). Furthermore, cognitive stressor appraisals (i.e., challenge appraisal and threat appraisal) may coexist.

During digital transformation, AI is a form of technological cognition and prompts university students to cognitively appraise based on their skills, institutional support, and anticipated job market changes. AI's impact is dual for university students. Positive experiences make students view digital transformation as a chance for resource gain, leading to challenge appraisal. Contrarily, AI causes anxiety and resource loss, students will generate threat appraisal and adopt protective measures (Feng & Xing, 2021). Challenge appraisal leads to high expectations and positive results, while based on potential failure and injury, threat appraisal usually yields adverse effects (Li, 2021). Moderate academic pressure may facilitate proactive skill development. Individuals adopting challenge appraisal treat skill development as a resource investment and actively learn new skills and knowledge. However, those with threat appraisal tend to preserve their resources. Therefore, the following hypotheses can be derived:

H_{1a}: AI anxiety has a significant positive effect on challenge appraisal.

H_{1b}: AI anxiety has a significant positive effect on threat appraisal.

Challenge appraisal and threat appraisal affect student behavior differently. The former fosters motivation and proactive learning and skill development. Conversely, the latter leads to negative emotions (e.g., fear and anxiety), and students may avoid proactive learning to conserve their resources, affecting their skill development. Therefore, the following hypotheses can be derived:

H_{2a}: Challenge appraisal has a significant positive effect on proactive skill development.

H_{2b}: Threat appraisal has a significant negative effect on proactive skill development.

Thus, AI anxiety indirectly influences proactive skill development through these two pathways: challenge appraisal facilitates learning resource investment, while threat appraisal triggers resource conservation. Therefore, the following hypotheses can be derived:

H_{3a}: AI anxiety indirectly influences proactive skill development through challenge appraisal.

H_{3b}: AI anxiety indirectly influences proactive skill development through threat appraisal.

2.3 AI Literacy's Moderating Role

Drawing on information and digital literacy theories, AI literacy is the comprehensive capacity to understand, utilize, and evaluate AI (Long & Magerko, 2020). It emphasizes individuals' understanding of AI design, development, and use principles, their algorithmic decision-making thinking and self-efficacy for technological change brought by AI. Specifically, AI literacy encompasses technical, ethical, and developmental metacognitive abilities. They are reflected in machine learning system operation, identification of data privacy and algorithmic bias and other issues, and continuous learning and adaptation to AI. While self-efficacy is related to confidence in one's comprehensive capabilities, AI literacy emphasizes understanding technological complexity and the ability to make ethical decisions. According to social cognitive theory, individuals are agents of their own behaviors. Thus, AI literacy is expected to predict students' behavioral responses. As a critical personal resource, AI literacy enables individuals to mobilize and transform other resources better and determines their resilience under stress (Maran et al., 2022). In addition, consistent with the learning demands–resources model, individuals have different views of the same learning resource due to differences in AI literacy. Students with higher AI literacy are more capable of adjusting resource allocation and their behaviors. Therefore, AI literacy is considered a key boundary condition influencing how AI anxiety affects proactive skill development.

AI literacy is influenced by AI anxiety. University students with higher-level AI literacy are more interested in skill development and more competent in using intelligent devices (Zhang et al., 2025). Accordingly, AI literacy is critical in affecting individual interactions with AI. In this study, AI literacy influences individuals' focus during AI transformation, meaning that AI literacy affects cognitive appraisal. Individuals with high AI literacy think highly of their competence, complete digital tasks beyond their responsibilities and manage potential barriers, thereby reducing their negative responses. Higher AI literacy leads to a better environmental assessment and a stronger interest in AI use. This makes students view new competencies as opportunities. AI anxiety's positive influence possibly leads to challenge appraisal. Low literacy, however, may cause resource depletion, amplifying sensitivity to AI anxiety and leading to threat appraisal. The following hypotheses can be derived, with the model presented in Figure 1:

H_{4a}: AI literacy moderates the relationship between AI anxiety and challenge appraisal.

H_{4b}: AI literacy moderates the relationship between AI anxiety and threat appraisal.

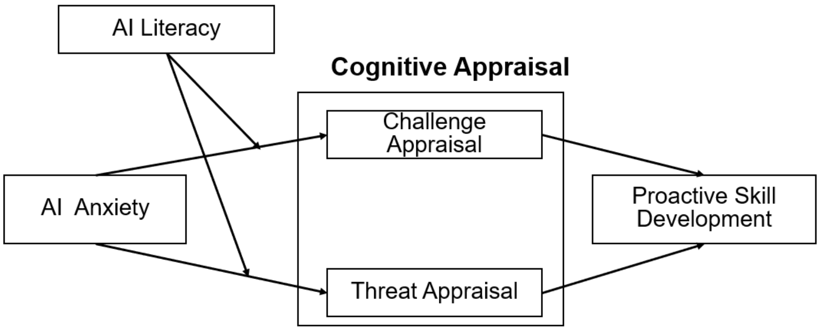

Figure 1. Theoretical model

3. Results Design

3.1 Survey Participants

An offline questionnaire was administered, which measures AI anxiety, challenge appraisal, threat appraisal, proactive skill development, and AI literacy. 476 valid responses were received, with a response rate of 93.70%. As shown in Table 1, the sample is well-balanced in terms of gender and academic year. Management students represent the largest group (31.09%), followed by engineering, law, science, literature, and others. This diversity supports the investigation into AI anxiety and its impact on proactive skill development.

Table 1. Demographic statistics

Category	Option	Frequency	Percentage
Gender	Male	221	46.43%
	Female	255	53.57%
Academic year	First year	121	25.42%
	Second year	121	25.42%
	Third year	125	26.26%
	Fourth year	109	22.90%
Major	Science	82	17.23%
	Engineering	87	18.28%
	Literature	61	12.82%
	Management	148	31.09%
	Law	84	17.65%
	Other	14	2.94%
Total		476	100%

3.2 Variable Measurement

All constructs were measured using established and validated scales (Drach-Zahavy & Erez, 2002; Kim et al., 2025; Liu et al., 2024; Ren & Chadee, 2017; Wang & Wang, 2019; Xu & Wang, 2022) on a seven-point Likert scale. The AI anxiety scale captures AI anxiety and uncertainty. The challenge appraisal scale evaluates the degree of AI as a positive challenge. The threat appraisal scale, grounded in stress theories, assesses the understanding of AI threats. The proactive skill development scale measures how people learn new skills to overcome AI-related professional challenges. The AI literacy scale measures the confidence in learning and using AI. Control variables include gender, academic major, and academic year.

3.2.1 Reliability analysis of the questionnaire

Cronbach's α was calculated using SPSS to assess the measurement consistency and data reliability. All constructs in Table 2 demonstrate high to excellent reliability. These values exceed the accepted threshold of 0.70 for attitude and opinion questionnaires, confirming the data's reliability.

3.2.2 Validity analysis of the questionnaire

Table 3 shows the results of the Kaiser–Meyer–Olkin (KMO) test conducted. The KMO value was 0.922 and exceeded 0.60. In addition, a p-value of <0.001 in Bartlett's test of sphericity indicates high data quality and good validity, demonstrating data suitability for further factor analysis.

Table 2. Reliability assessment

Construct	Number of Items	Cronbach's α
AI anxiety	6	0.891
Challenge appraisal	4	0.848
Threat appraisal	4	0.844
Proactive skill development	4	0.841
AI literacy	9	0.927

Table 3. KMO and Bartlett's sphericity test results

KMO Statistic		0.922
Bartlett's test of sphericity	Approx. chi-square	7013.103
	df	351
	p-value	0.000

All factor loadings in Table 4 have absolute values greater than 0.40, indicating that the items and their respective factors are strongly associated. All measurement items loaded appropriately onto their corresponding factors.

Table 4. Rotated factor loadings and communalities

	Factor Loading					Communality
	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	
AI anxiety 1	0.198	**0.757**	0.076	0.12	0.108	0.644
AI anxiety 2	0.179	**0.737**	0.084	0.118	0.178	0.627
AI anxiety 3	0.253	**0.726**	0.073	0.053	0.181	0.632
AI anxiety 4	0.176	**0.777**	0.041	0.141	0.082	0.663
AI anxiety 5	0.212	**0.751**	0.038	0.191	0.148	0.669
AI anxiety 6	0.169	**0.787**	0.032	0.131	0.091	0.674
Challenge appraisal 1	0.199	0.149	-0.03	**0.797**	0.039	0.7
Challenge appraisal 2	0.187	0.13	-0.043	**0.775**	0.158	0.679
Challenge appraisal 3	0.221	0.146	-0.046	**0.788**	0.105	0.704
Challenge appraisal 4	0.212	0.221	-0.06	**0.745**	0.143	0.672
Threat appraisal 1	-0.129	0.056	**0.767**	-0.01	-0.032	0.609
Threat appraisal 2	-0.075	0.065	**0.84**	-0.046	-0.011	0.718
Threat appraisal 3	-0.082	0.087	**0.829**	-0.014	-0.038	0.703
Threat appraisal 4	-0.077	0.054	**0.827**	-0.084	-0.029	0.7
Proactive skill development 1	0.201	0.203	-0.061	0.158	**0.697**	0.596
Proactive skill development 2	0.184	0.155	0.017	0.098	**0.788**	0.689
Proactive skill development 3	0.148	0.121	-0.059	0.096	**0.815**	0.713
Proactive skill development 4	0.198	0.17	-0.026	0.081	**0.805**	0.723
AI literacy 1	**0.756**	0.188	0.052	0.101	0.154	0.643
AI literacy 2	**0.776**	0.102	-0.097	0.148	0.084	0.651
AI literacy 3	**0.783**	0.152	-0.027	0.105	0.125	0.663
AI literacy 4	**0.75**	0.208	-0.097	0.12	0.135	0.648
AI literacy 5	**0.782**	0.132	-0.012	0.161	0.086	0.662
AI literacy 6	**0.741**	0.179	-0.109	0.172	0.119	0.636
AI literacy 7	**0.711**	0.172	-0.148	0.143	0.15	0.599
AI literacy 8	**0.739**	0.197	-0.084	0.106	0.128	0.62
AI literacy 9	**0.734**	0.169	-0.1	0.165	0.148	0.626

Five factors were extracted, each with an eigenvalue greater than 1. The first factor accounted for 33.546% of the total variance, below 40%, indicating no severe common method bias. After rotation, the variance explained by the extracted factors was 21.027%, 14.535%, 10.288%, 10.174%, and 10.147%, respectively, as presented in Table 5.

Table 5. Rotated factor loadings and variance explained

Factor No.	Eigenvalue			Variance Explained Before Rotation			Variance Explained After Rotation		
	Eigenvalue	Variance explained (%)	Cumulative (%)	Eigenvalue	Variance explained (%)	Cumulative (%)	Eigenvalue	Variance explained (%)	Cumulative (%)
1	9.057	33.546	33.546	9.057	33.546	33.546	5.677	21.027	21.027

2	3.268	12.102	45.649	3.268	12.102	45.649	3.924	14.535	35.561
3	2.073	7.677	53.325	2.073	7.677	53.325	2.778	10.288	45.849
4	1.815	6.721	60.046	1.815	6.721	60.046	2.747	10.174	56.023
5	1.654	6.125	66.17	1.654	6.125	66.17	2.74	10.147	66.17
6	0.685	2.537	68.708						
7	0.604	2.237	70.944						
8	0.572	2.12	73.064						
9	0.564	2.088	75.152						
10	0.546	2.022	77.174						
11	0.515	1.909	79.083						
12	0.477	1.766	80.849						
13	0.446	1.651	82.5						
14	0.439	1.625	84.126						
15	0.408	1.509	85.635						
16	0.402	1.488	87.123						
17	0.395	1.462	88.585						
18	0.38	1.409	89.994						
19	0.364	1.347	91.341						
20	0.35	1.298	92.638						
21	0.333	1.232	93.87						
22	0.314	1.164	95.034						
23	0.304	1.125	96.16						
24	0.286	1.061	97.22						
25	0.277	1.026	98.246						
26	0.257	0.95	99.196						
27	0.217	0.804	100						

4. Data Analysis and Results

4.1 Descriptive Statistical Analysis

As presented in Table 6, AI anxiety, challenge appraisal, threat appraisal, proactive skill development, and AI literacy were employed to comprehensively understand respondents' attitudes, cognitions, and behavioral inclinations toward AI, with all items rated on a seven-point Likert scale. Descriptive statistics were computed to examine variables' central tendencies and dispersion across for full sample.

Table 6. Descriptive statistics

Construct	Minimum	Maximum	Mean	Standard Deviation (SD)
AI anxiety			4.336	1.619
Challenge appraisal			4.340	1.646
Threat appraisal	1	7	3.584	1.592
Proactive skill development			4.245	1.632
AI literacy			4.448	1.577

The highest mean score (4.448) of AI literacy shows that most respondents think highly of their ability to adapt to and use AI possibly because they grow along with widespread digital and intelligent technologies, making AI a familiar and accessible tool rather than an abstract concept. This is followed by challenge appraisal (4.340) and AI anxiety (4.336), recognizing AI challenges and moderate anxiety. Respondents believe that difficulties can be overcome because of their capability and prior learning success. However, they are concerned about AI's unpredictability and potential risks. The mean score for proactive skill development (4.245) shows their tendency to learn AI knowledge and skills. In contrast, as for the lowest mean value (3.584) in threat appraisal, stress or concern regarding AI enables certain individuals not to consider AI a direct or imminent threat. Instead, AI is viewed as a powerful auxiliary tool with a relatively optimistic outlook toward future human–AI collaboration.

Taken together, the mean scores for all dimensions (exceeding the scale midpoint of 3.5) indicate the general positive attitudes toward AI. Respondents demonstrate particularly strong performance in AI literacy and adaptability with varying degrees of anxiety, challenge, and skill enhancement.

4.2 Common Method Bias and Multicollinearity Diagnostics

Harman's single-factor test was employed to assess potential common method bias. The variance explained by the first factor was 33.546%, below 40%, indicating no serious common method bias in the dataset. Multicollinearity diagnostics were conducted. The variance inflation factor (VIF) values for all variables ranged from 1.102 to 1.604, substantially lower than 5. As shown in Table 7, multicollinearity is not a concern, and the research model has robust explanatory power.

Table 7. Multicollinearity diagnostics

Construct	VIF
AI anxiety	1.54
Challenge appraisal	1.379
Threat appraisal	1.102
Proactive skill development	1.337
AI literacy	1.604

4.3 Correlation Analysis

According to the correlation analysis in Table 8, AI anxiety demonstrates significant positive correlations with challenge appraisal ($r = 0.408$, $p < 0.01$), proactive skill development ($r = 0.411$, $p < 0.01$), and AI literacy ($r = 0.475$, $p < 0.01$). Individuals with higher AI anxiety tend to improve their skills more actively. Those who view AI as an opportunity feel more competent in using it, as shown in the relatively strong positive correlation between challenge appraisal and AI literacy. Conversely, those who view AI as a threat have lower confidence in their adaption and are less likely to view it as constructive because threat appraisal is correlated negatively with AI literacy and challenge appraisal. AI literacy is significantly correlated with all other variables, particularly with challenge appraisal and proactive skill development. It plays a central role in facilitating adaptation during AI transformation.

Table 8. Correlation analysis

	AI anxiety	Challenge Appraisal	Threat Appraisal	Proactive Skill Development	AI Literacy
AI anxiety	1				
Challenge appraisal	0.408**	1			
Threat appraisal	0.104*	-0.114*	1		
Proactive skill development	0.411**	0.343**	-0.084	1	
AI literacy	0.475**	0.459**	-0.185**	0.425**	1

Note: * indicates $p < 0.05$, and ** indicates $p < 0.01$.

4.4 Confirmatory Factor Analysis (CFA)

In CFA, common reliability indicators include factor loading (λ), item reliability, measurement error, and composite reliability (CR). Frequently used validity indicators include convergent validity (AVE) and discriminant validity. After organizing and calculating the model results, the reliability and validity outcomes were summarized in Table 9. The average variance extracted (AVE) values for all five factors exceed 0.5, and all CR values are greater than 0.7, indicating that the data demonstrate good convergent validity.

Table 9. Reliability and validity assessment of the model

Latent Variable	Item	Factor Loading (λ)	Item Reliability (λ^2)	Measurement Error	AVE	CR
AI anxiety	AI anxiety 1	0.753	0.567	-	0.577	0.891
	AI anxiety 2	0.745	0.555	0.063		
	AI anxiety 3	0.748	0.560	0.062		
	AI anxiety 4	0.763	0.582	0.061		
	AI anxiety 5	0.783	0.613	0.062		
	AI anxiety 6	0.766	0.587	0.061		
Challenge appraisal	Challenge appraisal 1	0.754	0.569	-	0.582	0.848
	Challenge appraisal 2	0.75	0.563	0.063		
	Challenge appraisal 3	0.774	0.599	0.064		
	Challenge appraisal 4	0.773	0.598	0.063		
Threat appraisal	Threat appraisal 1	0.687	0.472	-	0.579	0.846
	Threat appraisal 2	0.803	0.645	0.076		
	Threat appraisal 3	0.785	0.616	0.077		
	Threat appraisal 4	0.765	0.585	0.076		
Proactive skill	Proactive skill development 1	0.699	0.489	-	0.573	0.842

development	Proactive skill development 2	0.76	0.578	0.077		
	Proactive skill development 3	0.761	0.579	0.074		
	Proactive skill development 4	0.803	0.645	0.078		
AI literacy	AI literacy 1	0.758	0.575	-	0.587	0.928
	AI literacy 2	0.766	0.587	0.058		
	AI literacy 3	0.781	0.610	0.06		
	AI literacy 4	0.78	0.608	0.057		
	AI literacy 5	0.777	0.604	0.061		
	AI literacy 6	0.77	0.593	0.058		
	AI literacy 7	0.742	0.551	0.057		
	AI literacy 8	0.756	0.572	0.058		
	AI literacy 9	0.766	0.587	0.06		

As shown in Table 10, in terms of discriminant validity, the square roots of the AVE values for the five latent constructs are as follows: AI anxiety (0.760), challenge appraisal (0.763), threat appraisal (0.761), proactive skill development (0.757), and AI literacy (0.766). Each AVE square root exceeds the highest absolute correlation coefficient associated with the corresponding construct, indicating that all five measurement dimensions exhibit strong discriminant validity.

Table 10. Discriminant validity assessment

	AI anxiety	**Challenge Appraisal**	**Threat Appraisal**	**Proactive Skill Development**	**AI Literacy**
AI anxiety	0.760				
Challenge appraisal	0.408	0.763			
Threat appraisal	0.104	-0.114	0.761		
Proactive skill development	0.411	0.343	-0.084	0.757	
AI literacy	0.475	0.459	-0.185	0.425	0.766

The chi-square to degrees of freedom ratio (χ^2/df) is 1.644 in Table 11, below 3, indicating a good model fit. The Comparative Fit Index (CFI), Normed Fit Index (NFI), and Tucker-Lewis Index (TLI) are 0.97, 0.928, and 0.967, all exceeding 0.90. Therefore, the model fit is satisfactory. The Root Mean Square Error of Approximation (RMSEA) (0.037), which is below 0.10 and indicates a low-level model error and strong overall fit. The model exhibits a good fit and adequately reflects the structural relationships within the data.

Table 11. Model fit indices

Fit Index	**χ2/df**	**Goodness-of-Fit Index (GFI)**	**RMSEA**	**CFI**	**NFI**	**TLI**
Criterion	<3	>0.9	<0.10	>0.9	>0.9	>0.9
Value	1.644	0.927	0.037	0.97	0.928	0.967

4.5 Direct Effect Hypothesis Testing

The relationships among AI anxiety, challenge appraisal, threat appraisal, and proactive skill development were investigated using SEM. As a multivariate analytical technique, SEM examines multiple causal relationships at the same time and reveals the underlying structure among variables using the pathways linking latent constructs. Using AMOS 24.0, the paths among the variables were estimated and tested to deeply understand the interaction mechanisms and relative effects. Figure 2 shows the proposed SEM.

As presented in Table 12, the path estimation results obtained from SEM indicate the significant positive effect of AI anxiety on challenge appraisal (B = 0.464, β = 0.471, S.E. = 0.054, C.R. = 8.592, p < 0.001). This finding suggests that the anxiety induced by AI is likely to be cognitively reframed as a challenge with potential value, leading to a more positive cognitive appraisal. Sometimes, AI anxiety also has a significant positive effect on threat appraisal (B = 0.104, β = 0.11, S.E. = 0.05, C.R. = 2.079, p = 0.038). It suggesting that if the cognition of the threat consequences of AI anxiety, it will form a strong threat appraisal. Challenge appraisal has a significant positive effect on proactive skill development (B = 0.188, β = 0.208, S.E. = 0.053, C.R. = 3.562, p < 0.001), showing that viewing AI as an opportunity drives learning. Threat appraisal significantly affects skill development, as viewing AI as a risk suppresses the motivation to learn new skills (B = -0.108, β = -0.116, S.E. = 0.046, C.R. = -2.351, p = 0.019). In addition, AI anxiety exhibits a significant positive effect on proactive skill development (B = 0.342, β = 0.384, S.E. = 0.054, C.R. = 6.326, p < 0.001), suggesting that moderate AI anxiety motivates individuals to manage uncertainties.

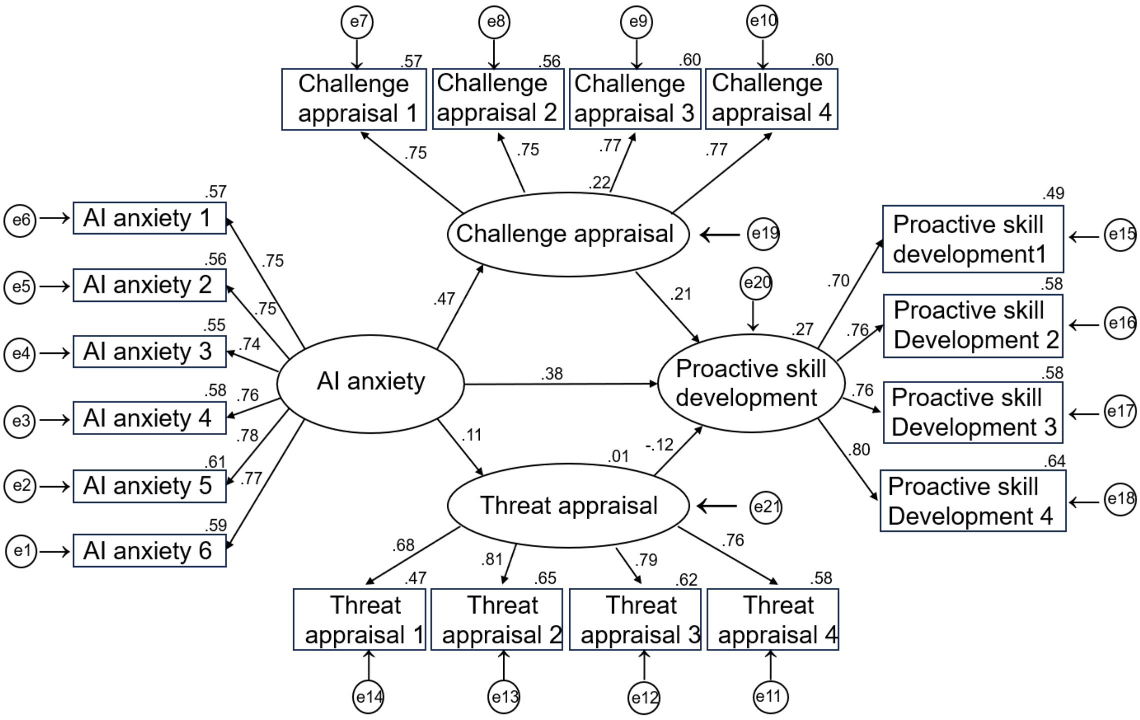

Figure 2. SEM

Table 12. Direct effect

Y	←	X	*B*	*β*	S.E.	C.R.	*p*
Challenge appraisal	←	AI anxiety	0.464	0.471	0.054	8.592	***
Threat appraisal	←	AI anxiety	0.104	0.11	0.05	2.079	0.038
Proactive skill development	←	Challenge appraisal	0.188	0.208	0.053	3.562	***
Proactive skill development	←	Threat appraisal	-0.108	-0.116	0.046	-2.351	0.019
Proactive skill development	←	AI anxiety	0.342	0.384	0.054	6.326	***

4.6 Mediation Effect Hypothesis Testing

A bootstrapping approach with 5000 resamples was employed to test the significant indirect effect of AI anxiety on proactive skill development, mediated through challenge appraisal and threat appraisal. The results, using bias-corrected confidence intervals (CIs), confirm a significant indirect effect of AI anxiety. As shown in Table 13, challenge appraisal and threat appraisal are positive and negative mediators, respectively. The significance of both pathways is confirmed by their CIs excluding zero.

Table 13. Mediation effect analysis

Mediating Pathway	Estimate	S.E.	Lower CI	Upper CI	*p*
AI anxiety → challenge appraisal → proactive skill development	0.087	0.028	0.039	0.149	0.000
AI anxiety → threat appraisal → proactive skill development	-0.011	0.007	-0.033	-0.001	0.032

Taken together, these results indicate that the influence of AI anxiety on proactive skill development is exerted not only through a direct effect but also indirectly through cognitive appraisals of AI in both the challenge and threat dimensions. These results provide mechanism-level support for the applicability and extensibility of stress–cognitive appraisal within the context of AI.

4.7 Moderation Effect Hypothesis Testing

The moderation effect was examined using three models. Model 1 included the effect of the independent variable on the dependent variable. Model 2 added the moderator. Model 3 further incorporated the interaction term. The moderation effect can be assessed in two ways: first, by examining the significance of the change in the F-value from Model 2 to Model 3; and second, by evaluating the significance of the interaction term in Model 3. In this study, the second approach was used to assess the moderation effect, as presented in Table 14.

Table 14. Analysis of the moderation effect

	M1: Challenge Appraisal		M2: Challenge Appraisal		M3: Challenge Appraisal	
	B	***t***	***B***	***t***	***B***	***t***
Constant	4.768**	14.971	4.744**	15.767	5.28**	20.079
Gender	-0.005	-0.033	-0.001	-0.011	-0.048	-0.424
Grade	-0.077	-1.232	-0.066	-1.11	-0.111*	-2.178
Major	-0.071	-1.502	-0.074	-1.653	-0.076	-1.95
AI anxiety	0.416**	9.744	0.25**	5.461	0.248**	6.27
AI literacy			0.357**	7.602	0.328**	8.08
AI anxiety × AI literacy					0.288**	12.742
R^2	0.173		0.263		0.453	
Adjusted R^2	0.166		0.256		0.446	
F	24.610**		33.622**		64.699**	
ΔR^2	0.173		0.091		0.189	
ΔF	24.610**		57.797**		162.369**	

Note: * indicates $p < 0.05$, and ** indicates $p < 0.01$.

As shown in the table, AI anxiety has a significant positive effect on challenge appraisal in Model 1. The model's R^2 value shows 17.3% of the variance explained in challenge appraisal, and the overall model is significant (F = 24.610). AI literacy introduced is an independent variable in Model 2, and an increase in R^2 (0.263) demonstrates improved explanatory power. The added interaction term between AI anxiety and AI literacy in Model 3 is 0.288, indicating that AI literacy significantly moderates the relationship between AI anxiety and challenge appraisal (Figure 3). Individuals with higher AI literacy mitigate AI anxiety' negative effects. Therefore, they have more positive and optimistic responses in challenge appraisal. When facing AI-related tasks, AI literacy can effectively regulate individuals' anxiety levels and improve their challenge appraisal.

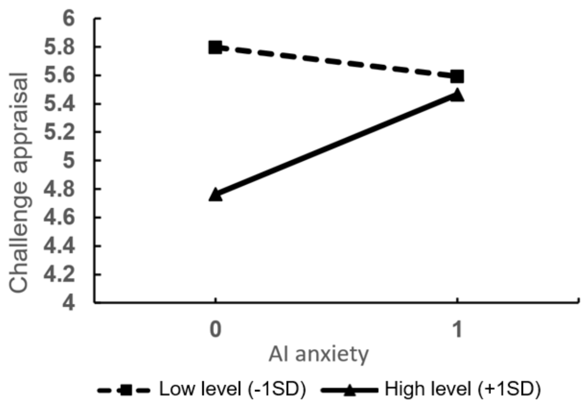

Figure 3. AI literacy's moderation between AI anxiety and challenge appraisal

The incorporated interaction term (AI anxiety × AI literacy) in Model 6 is positive and statistically significant, indicating AI literacy's significant moderation between AI anxiety and threat appraisal (Table 15). Model 6's R^2 increased to 0.142, with F = 12.930. The interaction term significantly improved explanatory power ($\Delta R^2 = 0.036$; $\Delta F = 19.610$, $p < 0.01$) (Figure 4).

Table 15. Analysis of the moderation

	M4: Threat Appraisal		M5: Threat Appraisal		M6: Threat Appraisal	
	B	***t***	***B***	***t***	***B***	***t***
Constant	4.438**	13.324	4.459**	13.907	4.233**	13.288
Gender	-0.28	-1.936	-0.283*	-2.031	-0.263	-1.927
Grade	-0.172**	-2.621	-0.182**	-2.879	-0.162**	-2.618
Major	0	-0.003	0.002	0.049	0.003	0.061
AI anxiety	0.108*	2.43	0.252**	5.165	0.253**	5.287

AI literacy			-0.31**	-6.195	-0.298**	-6.057
AI anxiety × AI literacy					0.121**	4.428
R^2	0.033		0.106		0.142	
Adjusted R^2	0.025		0.097		0.131	
F	4.028**		11.152**		12.930**	
ΔR^2	0.033		0.073		0.036	
ΔF	4.028**		38.372**		19.610**	

Note: * indicates $p < 0.05$, and ** indicates $p < 0.01$.

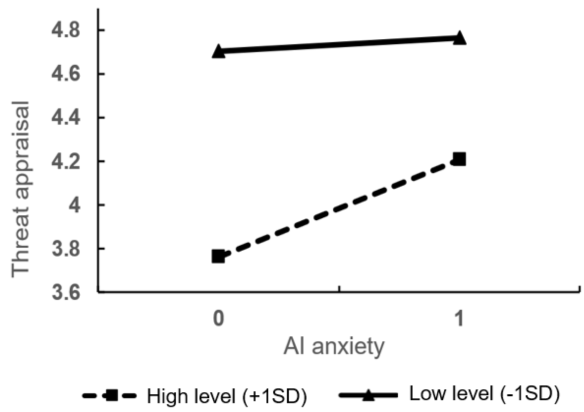

Figure 4. AI literacy's moderation between AI anxiety and threat appraisal

Higher AI literacy effectively mitigates AI anxiety's negative influence, enabling university students to positively respond to challenge appraisal. AI literacy moderates the relationship between AI anxiety and threat appraisal. Highly AI-literate students use their anxiety to learn proactively and overcome the challenge. Those with lower literacy perceive the same anxiety as a threat, which negatively impacts their skill development. AI's moderating role shapes students' cognitive appraisals and behaviors under AI anxiety (Table 16).

Table 16. Summary of hypothesis testing results for the effects of AI anxiety on related factors

No.	Hypothesis	Supported or Not
H_{1a}	AI anxiety has a significant positive effect on challenge appraisal.	Supported
H_{1b}	AI anxiety has a significant positive effect on threat appraisal.	
H_{2a}	Challenge appraisal has a significant positive effect on proactive skill development.	
H_{2b}	Threat appraisal has a significant negative effect on proactive skill development.	
H_{3a}	AI anxiety indirectly influences proactive skill development through challenge appraisal.	
H_{3b}	AI anxiety indirectly influences proactive skill development through threat appraisal.	
H_{4a}	AI literacy moderates the relationship between AI anxiety and challenge appraisal.	
H_{4b}	AI literacy moderates the relationship between AI anxiety and threat appraisal.	

5. Conclusions

5.1 Research Findings

Grounded in the cognitive appraisal theory of stress and the learning demands–learning resources model, this study examined the dual-edged effects of AI anxiety on proactive skill development among university students. A moderated mediation model was constructed in which challenge appraisal and threat appraisal functioned as mediating mechanisms, and AI literacy operated as a moderator.

(a) AI anxiety promotes university students to improve their skills proactively, with cognitive appraisal serving as mediation. Current research has investigated the detrimental consequences of AI anxiety. However, this study thinks that the stressor enables students to respond differently based on their cognitive appraisal. When AI anxiety is viewed as a challenge, AI as a tool improves efficiency and creates value, which motivates students to learn new skills proactively. Conversely, when viewed as a threat, AI disrupts current learning and may replace their capabilities, affecting skill development. Therefore, multidisciplinary, practice-oriented digital education platforms should be established to broaden students' perspectives, solve complex problems, and innovate by integrating knowledge across disciplines.

(b) AI anxiety and literacy affect how students appraise and respond to AI. Specifically, AI literacy amplifies the positive link between AI anxiety and challenge appraisal while weakening the link to threat appraisal.

Consequently, highly literate students probably change their anxiety into proactive skill development, whereas less literate ones probably adopt threat appraisal that affects their growth. These findings confirm the two-dimensional nature of learning stress. Therefore, universities should collaborate with AI experts to create substantive training courses for professional skills and AI literacy, along with intelligent recommendation systems and similar technologies used for obtaining relevant knowledge.

(c) Proactive skill development is driven by a complex mechanism, and AI anxiety's influence on proactive skill development is the result of several factors. Specifically, in the high self-driven mechanism, high AI literacy and challenge appraisal greatly promote students to learn proactively. Individuals with higher AI literacy are more inclined to view AI stressors as opportunities to improve their skills. The resource-management-driven mechanism highlights the importance of AI literacy and practical resources. Adequate external resources effectively support students with AI anxiety in improving their skills. Resource support is critical in alleviating anxiety and promoting proactive learning. In the crisis-response-driven mechanism, when threat appraisal coexists with strong achievement motivation, students tend to learn skills proactively under pressure, a potential pathway of transforming threat appraisal into learning motivation under specific conditions. In the competence-driven mechanism, when students clearly recognize the gap between their existing abilities and the future-career skill requirements brought by AI, they improve their skills to be more competitive. This mechanism reflects that students are forward-looking in career planning and the emphasis on capability development.

5.2 Theoretical Contributions

(a) This study contributes to the research on university students' proactive skill development. Although the antecedents of proactive skill development have been examined from an organizational perspective, the attention to the influence of individual cognitions on skill development is relatively limited. Digital transformation poses more skill requirements for university students, and AI anxiety is key technological cognition, reflecting concerns about career replacement, skill obsolescence, and creativity loss. Therefore, using AI anxiety as a primary antecedent variable, this study supplements and extends the research on students' proactive behaviors.

(b) This study reveals the dual-edged effect of AI anxiety on proactive skill development, as well as its underlying mechanisms and boundary conditions. AI literacy is a moderating variable, and AI anxiety's challenge and threat appraisal mechanisms have been examined in terms of resource gain and depletion. Instead of adopting a single analytical lens to explore AI anxiety, this study verifies cognitive stress appraisal's mediation between AI anxiety and proactive skill development. This explains in theory how AI influences proactive skill development and interprets the cognitive appraisal theory of stress in a new way.

5.3 Practical Implications

During digital transformation, regarding how AI anxiety affects university students' proactive skill development, the following practical implications can be proposed through theoretical reasoning and empirical analysis:

(a) It is necessary to establish diversified talent development programs for universities. Digital transformation relies on both technology and human capital, with higher requirements for high-level talent education and human–machine collaboration within traditional curricula. Instructors should fully recognize AI's dual effect and promote students to learn new knowledge for adaptation because those students have different views of AI. Universities should guide students in understanding AI for learning adaptation. This helps maximize AI's positive effects while reducing AI anxiety's risks. Revised talent programs and challenge-based courses reduce students' AI anxiety and psychological threats.

(b) Students should use AI to improve their capabilities and change their views. Learning new skills adapts to digital transformation characterized by information sharing and interconnectivity. Students must strengthen their human-machine collaboration and utilize diverse learning sources for their competencies. They should consider moderate stress as a challenge to accurately understand technological progress and proactively integrate into the digital environment.

5.4 Limitations and Future Directions

Several limitations exist. First, the reliance on self-reported, cross-sectional data from university students offers an individual-level view of AI anxiety. Longitudinal or multi-wave designs could be employed to track the evolution of cognitive responses to AI. External evaluations could diversify the sample and better capture the impact of digital transformation. Second, since proactive skill development and AI anxiety are likely influenced by career planning, how AI affects students with different career trajectories could be explored. Finally, due to the diversity of influencing factors, a multidimensional perspective could be adopted by incorporating factors like the scale of targeted occupations and regional characteristics. This will help clarify the pathways to proactive skill development and better support university students for the digital economy.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The author declares no conflict of interest.

References

Adabor, E. S., Addy, E., Assyne, N., & Antwi-Boasiako, E. (2025). Enhancing sustainable academic course delivery using AI in technical universities: An empirical analysis using adaptive learning theory. *Sustain. Futures*, *10*, 100828. https://doi.org/10.1016/J.SFTR.2025.100828.

Bao, C., Wang, X., & Zhang, Y. (2024). The effect of self-leadership on college students' career adaptability: An empirical analysis based on mediating effect and moderating effect. *Mod. Educ. Manag.*, *2024*(6), 61–72. https://doi.org/10.16697/j.1674-5485.2024.06.007.

Chen, C., Zhang, Z., & Jia, M. (2019). An empirical study of the influencing mechanism of stretch goals over emotional exhaustion: Based on transactional theory of stress. *J. Ind. Eng./Eng. Manag.*, *33*(3), 1–8. https://doi.org/10.13587/j.cnki.jieem.2019.03.001.

Drach-Zahavy, A. & Erez, M. (2002). Challenge versus threat effects on the goal–performance relationship. *Organ. Behav. Hum. Decis. Process.*, *88*(2), 667–682. https://doi.org/10.1016/S0749-5978(02)00004-3.

Feng, Y. & Xing, Z. (2021). Research on impacts of destructive leadership on safety performance based on conditional process analysis. *China Saf. Sci. J.*, *31*(8), 14–21. https://doi.org/10.16265/j.cnki.issn1003-3033.2021.08.003.

Ge, Z., Lu, K., & Li, G. (2025). A study on generative artificial intelligence anxiety and its influencing factors among information resource management students. *Libr. Inf. Serv.*, *69*(6), 72–84. https://doi.org/10.13266/j.issn.0252-3116.2025.06.006.

Glassman, J., Prosch, M., & Shao, B. B. M. (2015). To monitor or not to monitor: Effectiveness of a cyberloafing countermeasure. *Inf. Manag.*, *52*(2), 170–182. https://doi.org/10.1016/j.im.2014.08.001.

Kammeyer-Mueller, J. D., Judge, T. A., & Scott, B. A. (2009). The role of core self-evaluations in the coping process. *J. Appl. Psychol.*, *94*(1), 177–195. https://doi.org/10.1037/a0013214.

Kim, S. K., Kim, T. Y., & Kim, K. (2025). Development and effectiveness verification of AI education data sets based on constructivist learning principles for enhancing AI literacy. *Sci. Rep.*, *15*(1), 10725. https://doi.org/10.1038/S41598-025-95802-4.

Kong, S. C., Cheung, W. M. Y., & Zhang, G. (2021). Evaluation of an artificial intelligence literacy course for university students with diverse study backgrounds. Comput. *Educ. Artif. Intell.*, *2*, 100026. https://doi.org/10.1016/J.CAEAI.2021.100026.

Li, D. (2021). Employees' challenge-hindrance appraisals toward STARA awareness and competitive productivity: A micro-level case. International *J. Contemp. Hosp. Manag.*, *33*(9), 2950–2969. https://doi.org/10.1108/IJCHM-09-2020-1038.

Li, H. & Xue, L. (2025). Enabling-oriented risk regulation for the early application of generative AI: A case study of higher education. *Tsinghua J. Educ.*, *46*(1), 68–78. https://doi.org/10.14138/j.1001-4519.2025.01.006811.

Liu, Y., Liu, Y., Zhang, F., Zhang, F., Chu, F. (2024). Threat or challenge: The double-edged sword effect of artificial intelligence usage on employee innovation performance. *Collect. Essays Finance Econ.*, *2024*(9), 91–102. https://doi.org/10.13762/j.cnki.cjlc.2024.09.003.

Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. *In Proceedings of the 2020 ACM SIGCSE Technical Symposium on Computer Science Education, Georgia Institute of Technology, Atlanta, GA, USA*, 1–6. https://doi.org/10.1145/3313831.3376727.

Maran, T. K., Liegl, S., Davila, A., Moder, S., Kraus, S., Mahto, R. V. (2022). Who fits into the digital workplace? Mapping digital self-efficacy and agility onto psychological traits. *Technol. Forecast. Soc. Change*, *175*, 121352. https://doi.org/10.1016/J.TECHFORE.2021.121352.

Ren, S. & Chadee, D. (2017). Influence of work pressure on proactive skill development in China: The role of career networking behavior and Guanxi HRM. *J. Vocat. Behav.*, *98*, 152–162. https://doi.org/10.1016/j.jvb.2016.11.004.

Russo, C., Romano, L., Clemente, D., Iacovone, L., Gladwin, T. E., & Panno, A. (2025). Gender differences in artificial intelligence: The role of artificial intelligence anxiety. *Front. Psychol.*, *16*, 1559457. https://doi.org/10.3389/FPSYG.2025.1559457.

Wang, D. & Che, W. (2024). Research on the influence mechanism of work stress on the active work behavior of millennial employees. *J. Entrep. Sci. Technol.*, *37*(10), 152–158. https://doi.org/10.3969/j.issn.1672-2272.202406091.

Wang, Y. & Wang, Y. (2019). Development and validation of an artificial intelligence anxiety scale: An initial application in predicting motivated learning behavior. *Interact. Learn. Environ*., *30*(4), 619–634. https://doi.org/10.1080/10494820.2019.1674887.

Xiao, F. (2025). The internal mechanism, risks, challenges and countermeasures of AI-driven teaching reform in ideological and political theory courses in universities. *e-Educ. Res*., 46(5), 103-107+115. https://doi.org/10.13811/j.cnki.eer.2025.05.014.

Xu, G. (2023). The impact of artificial intelligence anxiety on employee deviant behavior: A moderated mediation model. *East China Econ. Manag*., *37*(11): 120–128. https://doi.org/10.19629/j.cnki.34-1014/f.221129012.

Xu, G. & Wang, H. (2022). Research on the influence of technological disruption awareness on employees' intentions to engage in change-supportive behaviors: With the development of artificial intelligence as the background. *East China Econ. Manag*., *36*(6), 119–128. https://doi.org/10.19629/j.cnki.34-1014/f.210803004.

Yuan, L. & Liu, W. (2024). Technology anxiety and cognitive misunderstandings in the field of education in the intelligent era: Present reflections based on Merleau-Ponty's perspective of embodied cognition. *Mod. Distance Educ*., *2024*(1), 14–20. https://doi.org/10.13927/j.cnki.yuan.20240202.002.

Zhang, S., Meng, L., Liu, J., Wang, Y., Yan, H. (2025). Integrating DeepSeek into the classroom: Exploration and reflection on the application of AI agents assistant teaching in organ-system based curriculum. *China Med. Educ. Technol.*, *39*(4), 432–436. https://doi.org/10.13566/j.cnki.cmet.cn61-1317/g4.202504002.

Zhang, Y. & Chen, X. (2024). The double-edged sword effect of artificial intelligence anxiety on employees' innovative work behavior. *J. Manage*., *37*(6), 127–142. https://doi.org/10.19808/j.cnki.41-1408/F.2024.0058.

Zhao, W. (2025). The impact and implementation strategies of career planning education on college students' employment. *Guide Sci. Educ.*, *2025*(12), 133–135. https://doi.org/10.16400/j.cnki.kjdk.2025.12.044.

Zhu, C., Wang, Z., Zhang, K. (2025a). How can the new quality productive forces empower high -quality employment of workers? *J. Cap. Univ. Econ. Bus*., *27*(3), 3–19. https://doi.org/10.13504 j.cnki. issn1008-2700.2025.03.001.

Zhu, D., Guo, S., & Yu, X. (2025b). Why does professional interest decline among top-notch students in basic disciplines: An analysis based on the cognitive appraisal theory of emotion. *Mod. Distance Educ. Res*., *37*(2), 73–82. https://doi.org/10.3969/j.issn.1009-5195.2025.02.008.