The Hidden Cost of AI-Supported Learning Collaboration: How It Undermines Self-Efficacy and Amplifies Anxiety in Unaided Tasks

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Manuscript received August 14, 2025; revised September 22, 2025; accepted October 28, 2025; published March 17, 2026

***Abstract*—This study examines the relationship between Artificial Intelligence (AI)-supported learning collaboration and students' experiences in unaided contexts, clarifying the underlying psychological mechanism. A survey was conducted with students from two comprehensive universities in central China (*n* = 212). The extent of AI participation in learning was measured, with reduced learning self-efficacy modeled as a mediating variable. Data analysis employed Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4.0. Findings reveal that greater AI participation correlates with lower learning self-efficacy, which subsequently relates to heightened anxiety in both unaided reading and writing contexts. The mediation analysis suggests that shifts in self-appraisal constitute a key pathway linking AI participation to domain-specific anxieties. This study extends self-efficacy theory to contexts involving learner-AI collaboration and differentiates reading anxiety from writing anxiety as distinct constructs. Implications suggest that instruction should integrate supported phases with AI-free tasks and ensure learners' contributions remain visible to maintain mastery experiences and preserve confidence.**

***Keywords*—learning-Artificial Intelligence (AI) collaboration, learning self-efficacy, unaided reading anxiety, unaided writing anxiety, AI-supported learning**

I. Introduction

Artificial Intelligence (AI) integration in higher education has reshaped learning paradigms, with AI learning collaboration emerging as a particularly influential development [1]. A growing number of university faculty and students now use AI tools for collaborative learning and problem-solving in reading and writing tasks, including text analysis, vocabulary support during independent study, grammar correction, and content generation assistance for coursework [2–5]. Yet students must still complete many academic tasks without AI, such as examinations, in-class exercises, and independent assessments, creating situations where they move between AI-supported and unaided learning environments [6, 7]. This development suggests that learning-AI collaboration is becoming a standard learning mode for college students, bringing both opportunities and challenges to educational practice [8].

Research demonstrates substantial benefits of AI integration in higher education [9, 10]. A systematic review of 148 studies shows that AI tools significantly improve personalized learning, boost student engagement, and provide effective scaffolding for academic performance [11]. In collaborative settings, AI acts as a virtual assistant, offering prompts, feedback, and alternative perspectives that support knowledge construction and deeper discussion [12]. Brod [13] also showed that AI-powered adaptive tutoring systems can produce learning gains comparable to one-on-one human tutoring by adjusting instructional strategies in real-time, improving both efficiency and outcomes.

Beyond collaboration, AI has proven valuable in self-directed learning by providing adaptive resources and guidance matched to individual student levels [14]. These tools help maintain motivation and self-regulation when students work independently [15]. When students gain efficiency and confidence through AI support, they tend to continue using these tools for self-directed tasks [16].

The psychological effects of technology in learning have drawn increasing attention in educational research [17–19]. Learning anxiety, the emotional distress and apprehension students feel during academic tasks, significantly affects performance and engagement across educational settings [20, 21]. Reading anxiety and writing anxiety are distinct psychological constructs within this category that influence students' confidence and performance in language-related tasks [22]. Reading anxiety appears as cognitive and emotional barriers to text comprehension and information processing, while writing anxiety involves apprehension and avoidance of written expression and composition [23, 24]. Self-efficacy, meaning students' beliefs about their ability to complete learning tasks successfully, acts as an important mediator between educational interventions and learning outcomes [25, 26]. Educational technology research suggests that although digital tools can initially increase student confidence, extended reliance may alter how learners view their own competence [27].

Concerns about student overdependence on AI have grown in recent educational technology literature, with studies showing patterns of excessive reliance and cognitive skill decline [28–32], yet theoretical understanding remains limited of the underlying psychological mechanisms. Three critical theoretical gaps remain.

First, self-efficacy theory assumes that competence beliefs grow through mastery experiences with clear personal attribution [33, 34]. Yet in AI-collaborative contexts, students may have difficulty separating their contributions from AI assistance [35].

Second, although research has established links between self-efficacy and academic anxiety, little is known about the psychological effects of moving from AI-supported to

doi: 10.18178/ijiet.2026.16.3.2544

unaided learning [36, 37].

Third, existing studies treat learning anxiety as a single construct [38–40]. But reading and writing use different cognitive processes that likely trigger different anxiety responses [41].

Most importantly, no theoretical model currently explains how AI collaboration might systematically weaken students' confidence in completing tasks independently. This study fills these gaps by extending self-efficacy theory to AI-assisted learning and testing learning self-efficacy as a mediating mechanism between AI collaboration and domain-specific learning anxieties.

The present study investigates how learning-AI collaboration affects students' anxiety in unaided contexts, with learning self-efficacy as the key mediating mechanism. It examines whether frequent AI collaboration systematically reduces students' confidence in working independently, raising anxiety when AI support becomes unavailable.

This study contributes in two ways: it extends self-efficacy theory to AI-assisted learning environments and builds a theoretical foundation for domain-specific anxiety research by separating reading and writing contexts. The findings can help educational institutions develop AI integration strategies that maintain student autonomy while capturing technological benefits.

II. Hypothesis Development

As AI technology has advanced rapidly in education, growing attention has focused on its potential negative psychological effects on students. While AI tools enhance learning efficiency and effectiveness in the short term, prolonged and frequent use of learning-AI collaboration may lead to psychological dependence, potentially weakening students' ability to complete learning tasks independently [30, 42]. For instance, when students attribute learning outcomes primarily to AI tool functionality rather than their own efforts, they may gradually undervalue their capabilities. This external attribution model can ultimately undermine their learning self-efficacy [43, 44]. Educational technology research indicates that consistent reliance on digital support can undermine self-efficacy through psychological mechanisms such as reduced mastery experiences and dependency habit development. Overreliance on AI tools diminish students' critical thinking and independent reasoning abilities, leading them to doubt their capacity for autonomous task completion [45, 46].

Research in educational contexts has shown that reading anxiety and writing anxiety represent distinct but related psychological constructs that can significantly impact academic performance [47]. Reading anxiety typically manifests as apprehension and worry when students encounter complex texts, particularly in academic settings where comprehension demands are high [48]. Similarly, writing anxiety involves emotional distress and avoidance behaviors related to written expression, often resulting in decreased writing quality and reduced willingness to engage in writing tasks [49]. These domain-specific anxieties become particularly relevant in AI-assisted learning environments where students may develop dependencies on technological support for fundamental academic skills [50].

Research has demonstrated that reading and writing tasks involve distinct cognitive processes and emotional responses [51, 52]. Reading primarily involves receptive cognitive processes such as comprehension, interpretation, and information extraction, while writing requires generative cognitive processes including ideation, organization, and expression [53, 54]. Given these cognitive differences, the impact of AI collaboration on self-efficacy may vary across these domains, warranting separate examination of reading and writing anxiety responses.

Self-efficacy theory provides a useful psychological lens for interpreting this phenomenon. Self-efficacy refers to an individual's belief in their capacity to execute tasks successfully, influencing both emotional responses and behavioral performance when facing challenges. When self-efficacy is low, individuals are more likely to experience doubt, anxiety, and avoidance in response to difficult tasks. In educational contexts, students who frequently rely on learning-AI collaboration may experience elevated stress and anxiety when required to complete tasks without AI support, such as reading comprehension or academic writing, due to diminished self-efficacy [43].

Based on the theoretical analysis and prior empirical findings, this study proposes the following research hypotheses:

H1: Learning-AI collaboration significantly and positively affects unaided reading anxiety.

H2: Learning-AI collaboration significantly and positively affects unaided writing anxiety.

H3: Learning-AI collaboration significantly and positively affects reduced learning self-efficacy.

H4: Reduced learning self-efficacy significantly and positively affects unaided reading anxiety.

H5: Reduced learning self-efficacy significantly and positively affects unaided writing anxiety.

Furthermore, drawing on self-efficacy theory, the study posits that reduced learning self-efficacy serves as a mediating mechanism in the relationship between learning-AI collaboration and learning anxiety. Rather than directly inducing anxiety, learning-AI collaboration may indirectly heighten students' anxiety in unaided contexts by gradually weakening their self-efficacy.

This leads to two additional hypotheses:

H6: Reduced learning self-efficacy significantly mediates the relationship between learning-AI collaboration and unaided reading anxiety.

H7: Reduced learning self-efficacy significantly mediates the relationship between learning-AI collaboration and unaided writing anxiety.

Testing these hypotheses will provide insights into the potential psychological risks associated with long-term use of AI tools in learning and offer guidance for optimizing AI integration in educational settings.

III. Research Methodology

A. Research Population and Data Collection

This study adopted a cross-sectional survey design and collected data from students at two comprehensive universities in central China. Convenience sampling combined with snowball sampling was employed. The research team initially distributed the questionnaire through institutional and class WeChat groups, encouraging participants to forward it to eligible peers for broader reach. To ensure data quality, attention check items were embedded in the questionnaire, and responses completed too quickly were excluded. A total of 212 valid responses were obtained.

B. Measurement Instruments

The questionnaire included four core constructs: learning-AI collaboration, reduced learning self-efficacy, unaided reading anxiety, and unaided writing anxiety. Following established practices for scale adaptation in PLS-SEM research, measurement items for each construct were adapted from validated scales and modified to fit AI-assisted learning contexts [55–59]. To ensure content validity and appropriateness for this study, three experts reviewed the adapted instrument: two education specialists and one structural equation modeling scholar, including one bilingual researcher. Following the recommendations of Brown [60] and Dawes [61], a seven-point Likert scale was used to enhance measurement precision and capture nuanced participant responses. Table 1 presents the final measurement items.

Table 1. Measurement items for constructs

[1] Construct	Item
LAC	AI participates in my learning and development process. AI participates in my knowledge acquisition and accumulation process. AI participates in my mistake reduction process. AI participates in my knowledge-sharing process. AI participates in my communication process.
RLSE	I find it difficult to independently maintain consistent study habits throughout the academic year. I am unable to independently follow my self-designed study plan. I struggle to independently focus on the main points of what I am learning. I find it difficult to independently establish connections, analogies, and distinctions between different subjects. I struggle to independently express clearly what I have learned in written assignments.
URA	I feel anxious when I have to read without AI assistance. I fear reading lengthy texts without AI support. I fear not understanding lengthy texts when reading on my own. I become anxious when I have to answer questions about what I have read without AI help.
UWA	I feel anxious when writing without AI assistance. I worry about making mistakes when writing independently. The thought of composing text without AI help makes me nervous. I doubt my ability to express my ideas clearly without AI support. Writing academic papers without AI assistance causes me discomfort. I feel tense when I cannot use AI to help with my writing process. I worry about my writing quality when working without AI tools.

[1] LAC = Learning-AI collaboration; RLSE = Reduced Learning self-efficacy; URA = Unaided reading anxiety; UWA = Unaided writing anxiety. All items were measured on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree). Items were adapted from validated scales in previous research.

C. Data Analysis Methods

Data were analyzed using Structural Equation Modeling (SEM), specifically the variance-based Partial Least Squares (PLS) technique via SmartPLS 4.0. Partial Least Squares Structural Equation Modeling (PLS-SEM) is well-suited for exploratory theoretical research and accommodates small sample sizes and non-normal data distributions [62]. The analysis proceeded in two stages: measurement model assessment and structural model assessment. The former included reliability and validity testing, while the latter evaluated path coefficients, model explanatory power, predictive relevance, and hypothesis significance using 5,000 bootstrap resamples [63].

D. Research Framework

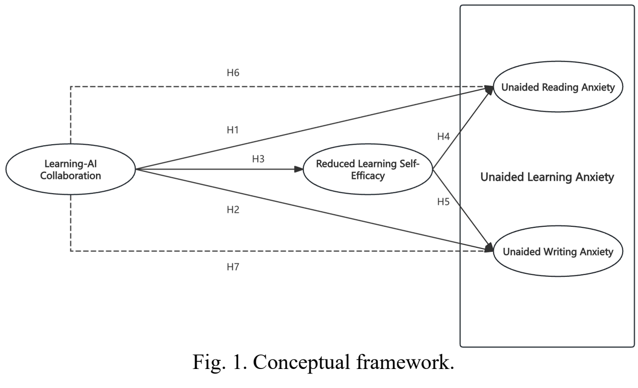

Fig. 1. Conceptual framework.

IV. RESULT

Based on the theoretical foundation and hypotheses outlined earlier, a conceptual model was developed to examine the mechanism through which learning-AI collaboration influences learning anxiety. As illustrated in Fig. 1, the model includes both direct effects on unaided reading anxiety and unaided writing anxiety, as well as the mediating role of reduced learning self-efficacy. This framework provides a basis for testing the seven hypotheses and deeper understanding of the psychological pathways through which AI tools impact learners.

A. Sample Characteristics

As shown in Table 2, a total of 212 valid responses were collected. Among the participants, 49.1% (n = 104) were male and 50.9% (n = 108) were female. Regarding academic level, the sample included freshmen (22.2%), sophomores (26.9%), juniors (25.5%), seniors (17.9%), and graduate students (7.5%).

Participants' academic backgrounds were diverse: 23.1% were from science and engineering majors, 22.2% from humanities and history, 19.8% from the arts, 17.9% from medical-related fields, 16.0% from business and management, and 1.0% from other disciplines.

In terms of time spent using AI learning tools, 40.1% reported using them for 7–14 h per week, 24.5% for 14–21 h, 18.9% for 3–7 h, 10.4% for less than 3 h, and 6.1% for more than 21 h. The most frequently used tools were DeepSeek

(44.8%), followed by ChatGPT (29.2%), Claude (13.7%), Doubao (10.4%), and other tools (1.9%). The prevalence of DeepSeek (44.8%) reflects its popularity among Chinese students, while ChatGPT (29.2%) remains a widely used academic AI tool [64, 65]. This distribution is consistent with current AI tool usage patterns in Chinese higher education contexts.

Table 2. Demographic characteristics of participants

Description	Characteristics	No. of Students	Percentage (%)
Gender	Male	104	49.1
	Female	108	50.9
Education Level	Freshman	47	22.2
	Sophomore	57	26.9
	Junior	54	25.5
	Senior	38	17.9
	Graduate Students	16	7.5
Field of Study	Science & Engineering	49	23.1
	Humanities & History	47	22.2
	Arts	42	19.8
	Medical Sciences	38	17.9
	Business & Management	34	16
	Other	2	1
Weekly Hours Using AI Learning Tools	Less than 3 h	22	10.4
	3–7 h	40	18.9
	7–14 h	85	40.1
	14–21 h	52	24.5
	21+ h	13	6.1
Primary AI Tool Used	ChatGPT	62	29.2
	DeepSeek	95	44.8
	Doubao	22	10.4
	Claude	29	13.7
	Other	4	1.9
	Total	212	100

B. Common Method Bias

When testing the model for multicollinearity, the Variance Inflation Factor (VIF) values for all paths ranged from 1.000 to 1.388, well below the critical threshold of 5.0 [66, 67], suggesting that multicollinearity does not pose a problem in this model.

To assess Common Method Bias (CMB), the Harman one-way test was employed. Results of principal component analysis showed that the unrotated first principal component explained 40.0% of the total variance, below the critical value of 50% [68], indicating that Common Method Bias does not constitute a major threat to the study results.

C. Reliability and Validity of Measurement Model

Table 3. Reliability and validity of measurement model

Construct	Item	Loadings	Cronbach's alpha	CR	AVE
LAC	LAC1	0.879	0.871	0.907	0.66
	LAC2	0.813			
	LAC3	0.81			
	LAC4	0.789			
	LAC5	0.767			
RLSE	RLSE2	0.826	0.809	0.875	0.636
	RLSE3	0.803			
	RLSE4	0.800			
	RLSE5	0.760			
URA	URA1	0.849	0.83	0.886	0.661
	URA2	0.815			
	URA3	0.805			
	URA4	0.782			
UWA	UWA1	0.747	0.894	0.917	0.611
	UWA2	0.805			
	UWA3	0.795			
	UWA4	0.805			
	UWA5	0.787			
	UWA6	0.781			
	UWA7	0.751			

As shown in Table 3, reliability and validity analyses confirmed that all constructs met recommended thresholds. Cronbach's alpha values ranged from 0.809 to 0.894, and Composite Reliability (CR) values ranged from 0.875 to 0.917, both exceeding the 0.70 benchmark [69].

Convergent validity was also supported. All item loadings ranged between 0.747 and 0.879, surpassing the 0.70 threshold [70, 71], and Average Variance Extracted (AVE) values ranged from 0.611 to 0.661, above the 0.50 minimum [72].

D. Discriminant Validity Analysis

Discriminant validity was assessed using the Fornell–Larcker criterion and Heterotrait-Monotrait (HTMT) ratio. As shown in Table 4, the square roots of AVE or each construct (shown on the diagonal) was higher than their correlations with other constructs, supporting discriminant validity [72]. HTMT values ranged from 0.462 to 0.630, below the 0.90 threshold [73], further confirming discriminant validity.

Table 4. Discriminant VALIDITY ANALYSIS

	LAC	RLSE	URA	UWA
[1] Fornell-Larcker criterion	**0.813**			
	0.529	**0.798**		
	0.482	0.511	**0.813**	
	0.52	0.524	0.415	**0.782**
	LAC	**RLSE**	**URA**	**UWA**
HTMT ratio	0.63			
	0.553	0.609		
	0.581	0.607	0.462	

[1] Diagonal values in the Fornell–Larcker table represent the square root of AVE for each construct. Values below the diagonal represent inter-construct correlations.

E. Hypothesis Testing

Prior to hypothesis testing, the measurement and structural models were comprehensively validated. The measurement model demonstrated strong psychometric properties, with all reliability indicators (Cronbach's alpha: 0.809–0.894; composite reliability: 0.875–0.917), convergent validity measures (factor loadings: 0.747–0.879; AVE: 0.611–0.661), and discriminant validity criteria (HTMT: 0.462–0.630) meeting recommended thresholds. Multicollinearity (VIF: 1.000–1.388) and common method bias (first factor: 40.0% variance) were not concerns. These results confirm the adequacy of the model for hypothesis testing.

Results from SmartPLS analysis with 5,000 bootstrap resamples showed that all hypothesized paths were statistically significant ($p < 0.001$). Learning-AI collaboration had significant positive direct effects on both unaided reading anxiety ($\beta = 0.294$) and unaided writing anxiety ($\beta = 0.337$), supporting H1 and H2. It also significantly predicted reduced learning self-efficacy ($\beta = 0.529$), supporting H3. Reduced learning self-efficacy had significant effects on both unaided reading anxiety ($\beta = 0.356$) and unaided writing anxiety ($\beta = 0.345$), supporting H4 and H5.

Mediation analysis further showed that reduced learning self-efficacy significantly mediated the effects of learning-AI collaboration on unaided reading anxiety ($\beta = 0.188$, 95% CI [0.121, 0.273]) and unaided writing anxiety ($\beta = 0.183$, 95% CI [0.115, 0.260]), supporting H6 and H7.

The R^2 values were 0.279 (reduced learning self-efficacy), 0.324 (unaided reading anxiety), and 0.356 (unaided writing anxiety), indicating moderate explanatory power [62].

The statistical details of hypothesis testing are presented in Table 5, while Table 6 provides a concise narrative summary of each hypothesis and its interpretation.

Table 5. Results of hypothesis testing

Hypothesis	β	t	p	95% CI	Result
H1	0.294	4.134	0.000	[0.150, 0.430]	Supported
H2	0.337	5.241	0.000	[0.207, 0.460]	Supported
H3	0.529	11.183	0.000	[0.432, 0.620]	Supported
H4	0.356	5.96	0.000	[0.240, 0.477]	Supported
H5	0.345	5.53	0.000	[0.222, 0.469]	Supported
H6	0.188	4.881	0.000	[0.121, 0.273]	Supported
H7	0.183	4.86	0.000	[0.115, 0.260]	Supported

$p < 0.001$. Bootstrap resampling = 5,000 iterations. CI = Confidence Interval. All path coefficients are standardized estimates.

Table 6. Narrative summary of hypothesis testing

Hypothesis	Statement	Interpretation
H1	LAC → URA	The findings indicate that students collaborating more with AI experience higher anxiety when reading without AI support.
H2	LAC → UWA	The results show that greater AI collaboration leads to stronger anxiety when writing independently.
H3	LAC → RLSE	The analysis demonstrates that frequent AI collaboration is associated with diminished self-efficacy in learning tasks.
H4	RLSE → URA	The results reveal that lower self-efficacy increases reading anxiety in the absence of AI.
H5	RLSE → UWA	The findings show that lower self-efficacy increases writing anxiety without AI support.
H6	LAC → RLSE → URA	The analysis confirms that self-efficacy mediates the relationship between AI collaboration and reading anxiety.
H7	LAC → RLSE → UWA	The results confirm that self-efficacy mediates the relationship between AI collaboration and writing anxiety.

V. Discussion

This study investigates the psychological mechanisms linking learning-AI collaboration to students' learning experiences. The findings reveal that frequent collaboration with AI may weaken students' confidence in their own learning abilities, which in turn intensifies their reading and writing anxiety in unaided contexts. Although learning-AI collaboration enhances learning efficiency, it simultaneously erodes learning self-efficacy and heightens anxiety when students must perform independently. These results support the research hypotheses and offer important insights for understanding the broader psychological implications of integrating AI into educational practice.

The finding that learning-AI collaboration significantly reduces learning self-efficacy contrasts sharply with previous studies emphasizing AI's positive effects on student confidence [74]. While Lee and Moore [75] found that AI tools initially boost learner self-efficacy through immediate feedback and success experiences, the present findings indicate that learning-AI collaboration is negatively correlated with students' confidence in their independent capabilities. When students frequently rely on AI to complete learning tasks, they grow increasingly doubtful of their ability to work independently. Recent scholarship has shifted focus from skill enhancement to cognitive dependency concerns as humans increasingly delegate skills to AI tools [76, 77]. This research provides empirical evidence for this concern by identifying a specific psychological mechanism: AI collaboration reduces students' opportunities to accumulate mastery experiences, which are central to self-efficacy development according to Bandura's theory [33]. When AI completes substantial portions of learning tasks, students may find it difficult to achieve success through their own efforts, thereby weakening their internal attribution of competence [78].

Reduced learning self-efficacy was found to significantly and positively predict both unaided reading anxiety and unaided writing anxiety. This aligns with educational psychology research on self-efficacy and academic anxiety, yet extends this understanding substantially [79]. Previous studies typically examined learning anxiety as a unitary construct [39, 80]. This research reveals that reading and writing anxiety, while responding to self-efficacy changes through comparable pathways, maintain distinct domain-specific characteristics. Without AI support, students with diminished confidence perceive these tasks as stressors, triggering anxiety. For instance, a student who lacks confidence in academic writing may anticipate failure when writing independently, which leads to increased anxiety. Self-efficacy thus operates as a common underlying mechanism across academic domains in AI-mediated learning, a pattern that contrasts with some domain-specific anxiety research [44]. Learning self-efficacy influences both students' willingness to engage with academic challenges and their emotional experiences during engagement [81].

This study confirms learning self-efficacy as a significant mediator between learning-AI collaboration and learning anxiety. Most educational technology research examines direct effects of technology use on learning outcomes [82, 83]. These findings reveal an important yet underexplored indirect pathway. Rather than examining immediate behavioral or performance changes from AI integration, this research demonstrates that psychological impact operates through cognitive self-evaluation processes [29]. Student anxiety in unaided contexts stems not from AI use itself, but from how AI influences self-appraisals of competence. Recent systematic evidence shows AI's multifaceted psychological impacts on students, including both positive outcomes like increased engagement and negative effects like over-reliance and anxiety, yet underlying mechanisms remain underexplored [84]. The present findings reveal a specific mediating pathway through learning self-efficacy, highlighting the crucial role of cognitive self-evaluation processes in technology-enhanced learning. This cognitive pathway clarifies how educational technology affects psychological processes by linking technology use, self-assessment, and emotional response. When AI becomes an integral part of learning, it may unconsciously reduce students perceived ability to complete tasks without assistance.

Despite accounting for learning self-efficacy's mediating role, learning-AI collaboration maintained direct effects on both unaided reading anxiety and unaided writing anxiety. This suggests that other explanatory variables may also be involved. One possibility is that learning-AI collaboration reduces opportunities for students to engage in active practice [85]. Research suggests that reliance on AI assistance may accelerate skill decay and hinder skill acquisition among learners, potentially without users' conscious awareness of these effects [86].

Another potential explanation relates to dependency on AI convenience and customization. Although generative AI tools offer personalized learning opportunities, reliance on AI scaffolding may undermine students' independent thinking and problem-solving abilities [87]. Students accustomed to AI-facilitated task completion may experience heightened anxiety when demonstrating capabilities independently, creating psychological dependency beyond self-efficacy concerns. These additional pathways suggest that the relationship between AI use and learning anxiety is multifaceted and warrants further investigation.

Learning-AI collaboration offers short-term convenience and efficiency, yet long-term dependence may lead to weakened learning capacity and increased emotional vulnerability. Theoretically, this study integrates classical theories of self-efficacy and academic anxiety into AI-assisted learning contexts, extending their relevance to contemporary educational environments. Practically, the findings highlight the importance of striking a balance between technological convenience and the development of independent learning capabilities. Educators and AI tool developers should implement strategies that gradually reduce AI reliance and encourage unaided practice. For example, instructors can design tasks that transition from AI-supported to AI-free phases, helping students strengthen their sense of control and resilience.

A. Theoretical Implications

This study extends classical self-efficacy theory into AI-supported learning contexts, highlighting how external cognitive agents like AI can alter students' internal attribution of competence. AI improves task efficiency while potentially weakening students' confidence in their own abilities, a shift rarely considered in traditional motivation models.

Identifying reduced learning self-efficacy as a mediator between learning-AI collaboration and unaided learning anxiety provides a theoretical link connecting technology use, cognitive evaluation, and emotional outcomes. This offers a refined framework for understanding how digital tools shape learners' psychological processes.

This study makes a unique theoretical contribution by distinguishing unaided reading anxiety from unaided writing anxiety as separate psychological constructs influenced by AI collaboration. Previous research has typically treated learning anxiety as a unitary concept [50, 88, 89]. However, these findings demonstrate that AI collaboration affects reading and writing contexts through similar psychological mechanisms while showing different effect magnitudes. This differentiation advances theoretical understanding of domain-specific anxiety in AI-assisted learning and suggests that self-efficacy theory applications must account for task-specific characteristics in technology-mediated learning experiences.

B. Policy and Practical Implications

The findings provide important insights for optimizing AI integration in education while preserving students' learning self-efficacy. Educators should design instructional models that gradually reduce AI dependency, ensuring students maintain agency over their learning processes and internal attribution of outcomes while using AI tools [80]. Given that this study found differential effects of AI collaboration on reading and writing anxiety, instructional design should develop differentiated AI usage strategies for different learning tasks [90].

Educational institutions should establish monitoring and support mechanisms to identify students experiencing declining learning confidence. When students show excessive AI dependence, training should help them recognize their role in the learning process and avoid attributing outcomes entirely to AI tools [28]. Particular attention should be paid to regularly assessing the confidence levels of high-frequency AI users in completing tasks independently.

Course design should ensure AI tools enhance learning effectiveness without compromising critical thinking and independent learning abilities [91]. Instructional processes should emphasize developing students' reflective awareness and self-regulation regarding AI tool usage, helping students distinguish AI-assisted content from personal contributions and select appropriate AI usage levels across learning contexts [92].

Additionally, considering the differential impacts of various learning tasks on self-efficacy, educational practices should develop specialized capability maintenance strategies for core skills such as reading comprehension and academic writing [93]. For writing tasks, emphasis should target creative generation and critical thinking processes that AI cannot fully replace. For reading tasks, instruction should cultivate text analysis and reasoning abilities.

Educational institutions should emphasize comprehensive AI literacy education, encompassing not only technical skills but also awareness of AI dependency risks and healthy technology usage habits [94]. Teacher training programs should focus on maintaining student learning autonomy in AI-assisted environments, with strategy effectiveness validated through subsequent empirical research [95].

C. Limitation and Recommendation

This study has several limitations. The cross-sectional design limits causal interpretation, revealing only associations between variables. The sample, restricted to Chinese university students in central China, may reflect cultural influences on technology dependency and academic anxiety patterns. The generalizability of findings to other cultural contexts requires further investigation.

Reliance solely on quantitative survey methods may not fully capture nuanced psychological processes and lived experiences during AI collaboration.

Based on these limitations, future research could proceed in several directions. Longitudinal or experimental designs should reveal trajectories of AI collaborative learning's impact on student psychological states. Expanding research scope to include diverse cultural backgrounds and institution types would enhance external validity. A mixed methods approach incorporating semi-structured interviews or focus groups could explore students lived experiences, perceptions of AI's impact on confidence, and emotional states during transitions to unaided tasks. Qualitative methods could provide valuable complementary insights to the quantitative findings and help elucidate the psychological mechanisms identified in this study.

VI. Conclusion

As artificial intelligence becomes increasingly integrated into educational environments, this study addressed a critical question about the psychological consequences of learning-AI collaboration: how does such collaboration affect students' experiences when they must perform without AI assistance? Through empirical investigation, the underlying psychological mechanism through which learning-AI collaboration influences students' anxiety in unaided learning contexts was identified.

The results demonstrate that higher levels of learning-AI collaboration significantly reduce learning self-efficacy ($\beta = 0.529$, $p < 0.001$), which in turn increases both unaided reading anxiety and unaided writing anxiety ($\beta = 0.356$ and $\beta = 0.345$ respectively, both $p < 0.001$). Mediation analysis confirmed that reduced learning self-efficacy plays a central role in this psychological pathway, with significant indirect effects of 0.188 and 0.183 (both $p < 0.001$) on reading and writing anxiety respectively. These findings directly address our core research question about the mediating mechanism linking AI collaboration to domain-specific anxieties.

These findings provide empirical evidence for a previously unrecognized consequence of AI-enhanced learning efficiency: The systematic erosion of students' confidence in their independent capabilities. The study addresses the theoretical gap by extending self-efficacy theory to AI-assisted learning environments and resolves the research question about domain-specific anxiety by demonstrating comparable psychological mechanisms across reading and writing contexts. To address the practical implications of these findings, educational institutions should implement pedagogical strategies that preserve student autonomy while leveraging technological benefits, ensuring that AI integration supports rather than undermines learners' psychological resilience and independent competence.

Appendix

A. Complete Questionnaire

1) Demographic information

1) Gender: ☐ Male ☐ Female ☐ Other
2) Academic Level: ☐ Freshman ☐ Sophomore ☐ Junior ☐ Senior ☐ Graduate Student
3) Field of Study: ☐ Science & Engineering ☐ Humanities & History ☐ Arts ☐ Medical Sciences ☐ Business & Management ☐ Other
4) Weekly hours using AI learning tools: ☐ Less than 3 hours ☐ 3-7 hours ☐ 7-14 hours ☐ 14-21 hours ☐ 21+ hours
5) Primary AI tool used: ☐ ChatGPT ☐ DeepSeek ☐ Doubao ☐ Claude ☐ Other

2) Learning-AI Collaboration (LAC)

1) AI participates in my learning and development process.
2) AI participates in my knowledge acquisition and accumulation process.
3) AI participates in my mistake reduction process.
4) AI participates in my knowledge-sharing process.
5) AI participates in my communication process.

3) Reduced Learning Self-Efficacy (RLSE)

1) I find it difficult to independently maintain consistent study habits throughout the academic year.
2) I am unable to independently follow my self-designed study plan.
3) I struggle to independently focus on the main points of what I am learning.
4) I find it difficult to independently establish connections, analogies, and distinctions between different subjects.
5) I struggle to independently express clearly what I have learned in written assignments.

4) Unaided Reading Anxiety (URA)

1) I feel anxious when I have to read without AI assistance.
2) I fear reading lengthy texts without AI support.
3) I fear not understanding lengthy texts when reading on my own.
4) I become anxious when I have to answer questions about what I have read without AI help.

5) Unaided Writing Anxiety (UWA)

1) I feel anxious when writing without AI assistance.
2) I worry about making mistakes when writing

independently.

3) The thought of composing text without AI help makes me nervous.
4) I doubt my ability to express my ideas clearly without AI support.
5) Writing academic papers without AI assistance causes me discomfort.
6) I feel tense when I cannot use AI to help with my writing process.
7) I worry about my writing quality when working without AI tools.

B. PLS-SEM Analysis Settings

SmartPLS 4.0 Configuration:

1) PLS Algorithm Settings:
   - Weighting Scheme: Path.
   - Type of Results: Standardized.
   - Initial Weight: Default.
2) Bootstrap Settings:
   - Subsamples: 5,000.
   - Confidence Interval Method: Percentile bootstrap.
   - Test Type: Two tailed.
   - Significance Level: 0.05000.
   - Random Number Generator: Fixed seed.

Conflict of Interest

The authors declare no conflicts of interest.

Author Contributions

Feng, J. X. conceived the research idea, designed the study methodology, developed the theoretical framework, conducted data collection, performed statistical analyses using PLS-SEM, interpreted the results, and drafted the initial manuscript. Sudiarta, I.G.P. provided theoretical guidance on self-efficacy theory and educational psychology, supervised the research design and data analysis process, contributed to the interpretation of findings, reviewed and revised the manuscript for theoretical coherence and academic rigor, and provided overall project supervision. Both authors collaboratively refined the research hypotheses, discussed the implications of findings, and approved the final version of the manuscript.

Acknowledgment

We thank the students who participated in this study for their time and valuable responses.

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