OPEN ACCESS

Artificial Intelligence in Language Education
ISSN
https://www.castledown.com/journals/aile/

Artificial Intelligence in Language Education, *1* (1), 103205 (2025)
https://doi.org/10.29140/aile.v1n1.103205

Exploring the relationship between growth mindset, self-efficacy, anxiety, and perceived learning performance in AI-enhanced language learning

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Abstract

Despite the extensive studies of psychological states in computer- or mobile-assisted language learning, studies on learners' growth mindset, self-efficacy, and anxiety in the AI learning setting are limited. The present study sets the goal of unveiling the relationship between growth mindset, self-efficacy, anxiety, and perceived learning performance in AI-enhanced language learning. Data collected from 437 valid questionnaires were analyzed using structural equation modeling (SEM) and bootstrap-mediated moderation analysis to examine the proposed mediating and moderating effects. The main finding suggested there is a mediating role of learning anxiety and growth mindset in influencing learners' perceived performance in AI-enhanced language learning. The findings also showed a positive relationship among self-efficacy, growth mindset, and their perceived learning performance. Based on the findings, the paper puts forward some practical suggestions to improve the use of AI for language education.
Keywords: anxiety, growth mindset, self-efficacy, perceived learning performance, AI-enhanced language learning

Introduction

In recent decades, the field of language education has undergone a profound transformation in teaching paradigms, with its core gradually shifting from the acquisition of grammar and vocabulary to teaching concepts based on tasks and projects, oriented towards communication. In this transformation process, technology has played a vital role, reshaping the language learning process. Specifically, technology empowerment makes learning activities more interactive, capable of providing real-time feedback, personalizing learning materials and tasks, and effectively alleviating negative emotions in the classroom (Crompton et al., 2024). Particularly notable is the emergence of computer-assisted tools such as Massive Open Online Courses (MOOCs) and Wikipedia, as well as the integration of mobile technologies driven by instant messaging software, which have brought revolutionary changes to the ways of teaching and learning. In addition, the wave of innovation in fields such as the metaverse and artificial intelligence has further expanded the possibilities for development (Wu et al., 2023). Thus, more and more English learners have begun utilizing innovative AI tools (e.g., ChatGPT, Kimi, and Claude) to aid in their learning. These AI tools have the potential of catering to the learning needs of language learners, leveraging learning analytics and data mining capabilities (Lai & Tu, 2024). For example, learners can leverage AI tools to customize educational resources and teaching and learning activities to tailor to their individual learning pace (Chen et al., 2020). These tools can also assist in enhancing English proficiency in reading and writing by identifying errors and offering constructive feedback (Guo et al., 2024). In addition, AI-driven chatbots or virtual companions can offer emotional companionship and support, fostering interest and immersion in the language learning journey, while also providing instant voice feedback (Tu, 2024). These previous studies all indicate that the benefit of AI in language education can make language learning more engaging and diverse, providing different learning experiences for various students and ensuring that each student benefits from personalized AI-enhanced language learning and avoids the distress and impact of negative emotions.

However, upon reviewing previous literature, a notable research gap emerges. Although Computer-Assisted Language Learning (CALL) and Mobile-Assisted Language Learning (MALL) have undergone extensive research on affective constructs (Buddha et al., 2024), empirical investigations specifically within AI-enhanced language learning environments remain scarce. Most existing studies focus on cognitive and behavioral outcomes, while the complex interrelationships among key psychological factors, such as growth mindset, self-efficacy, and anxiety, are still underexplored in the context of AI-driven learning tools (Klimova & Pikhart, 2025). Moreover, while limited research exists on the efficacy of generative AI in language education, the application and emotional impact of these technologies are still in their nascent stages, particularly concerning how they shape learners' perceived performance and emotional experiences (Kohnke & Moorhouse, 2025).

Therefore, this empirical study seeks to thoroughly investigate AI-enhanced language learning, offering solid data backing for the field and helping to propel forward the evolution of relevant theories. The research focuses on key psychological factors in learners, such as growth mindset, self-efficacy, and learning anxiety, aiming to uncover their underlying connections and operational mechanisms within AI-driven environments. Gaining a thorough understanding of the interactions between these psychological elements will furnish practical grounds for devising intelligent and effective language teaching strategies, particularly as technology continues to evolve at an astonishing pace.

Literature Review and Hypothesis Development

The integration of artificial intelligence (AI) in educational settings has transformed language learning, providing innovative methods that can influence learners' outcomes. In particular, English as a Foreign Language (EFL) learners may experience various psychological factors that impact their language acquisition, such as self-efficacy, growth mindset, language anxiety, and perceived learning performance (Bandura, 1997; Dweck, 2006; Horwitz, 2001). This literature review explores these constructs and their interrelations within AI-assisted language learning environments, leading to the development of theoretical hypotheses for the research.

Self-Efficacy in Language Learning

Self-efficacy is defined by Bandura (1997) as a person's belief in their own ability to plan and carry out tough tasks to reach certain goals. This idea has many sub-types with common ones being academic, computer, mobile device, and creative self-efficacy (Hong et al., 2014; Liao et al., 2021). It plays an essential part in personal choices, effort in actions, sticking with things, emotional responses, and overall results (Mensah et al., 2023). In academic settings, higher self-efficacy helps learners to build learning confidence, reduce worry, and support the growth of self-control skills (Schunk & Pajares, 2002).

In the field of learning EFL, self-efficacy links positively with school success. It can strongly predict a student's drive level, effort, and staying power in language tasks (Bai & Wang, 2023; Teng, 2024). In settings where AI-assisted in language learning, the AI tools cultivate students' self-efficacy by giving personal feedback and paths that adjust to their needs (Cheng & Chiou, 2010). This in turn raises their wish to use learning tech and how often they work with English materials (Lin & Wang, 2021). Also, self-efficacy is seen as a key predictor of how people view their learning results, especially in judging their own language skills and outcomes (Derakhshan et al., 2022; Mensah et al., 2023; Teng et al., 2023; Zhang et al., 2022). Based on this theory backing, this study puts forward the following first hypothesis:

> **H1:** Self-efficacy positively predicts perceived learning performance in AI-assisted language learning environments.

Growth Mindset and Its Role as a Mediator

Mindset theory comes from Dweck's (2006, 2017) model of success drive in social thinking. This theory splits into two main types: fixed mindset and growth mindset. Growth mindset means a person's core belief that skills can grow over time. This belief can greatly boost drive to learn and build mental strength (Dweck, 2017; Yin et al., 2022). In language learning, growth mindset has been shown to help learners better handle challenges with mental adjustment and more effort (Bai & Wang, 2023).

Studies show that growth mindset acts as a bridge between self-efficacy and school results. Some previous studies show that learners with high self-efficacy and growth mindset traits often show better learning performance (Zander et al., 2018; Zou et al., 2024). In settings where AI assisted in learning, learners who think skills or talent could be changed are more likely to use AI tools on their own. This then improves how they view their own learning results (Hu et al., 2022; Macnamara & Burgoyne, 2023). However, in the specific area of AI-assisted language learning, research regarding how growth mindset links things are still under-investigated. Based on this, the second hypothesis is:

> **H2:** Growth mindset mediates the relationship between self-efficacy and perceived learning performance among EFL learners in AI-assisted environments.

Language Anxiety as a Moderator

Language anxiety is defined as the worry a person feels when using a second language (Horwitz, 2001). It has bad effects on language talking, effort in learning, and academic results (Bellinger et al., 2015; MacIntyre, 1999). This worry might stem from fear of making mistakes, bad judgments from others, or not being ready enough (Zheng & Cheng, 2018).

Anxiety plays a changing role between self-efficacy, mindset, and learning results. Learners with high anxiety often show lower self-efficacy and worse learning results (Wang et al., 2021).

But learners with strong self-efficacy can use plans to ease anxiety well (Zuo et al., 2024). Similarly, language anxiety also links with mindset in ways that affect each other. For instance, anxious people tend to have a fixed mindset and avoid hard tasks, but growth mindset people could view anxiety as something they can handle (Ozdamir & Papi, 2022). In settings where AI assisted in learning, tech tools can lower anxiety by giving safe spaces for practice. Still, high anxiety levels might weaken the positive effects (Hawes & Arya, 2023; Wang & Sun, 2020). Therefore, the third hypothesis is proposed below:

> **H3:** Language anxiety moderates the relationship between self-efficacy and growth mindset in AI-assisted language learning environments, with the relationship being stronger for learners with low anxiety.

Integration of Theoretical Frameworks

This study integrates Bandura's (1986) Social Cognitive Theory (SCT) and Dweck's (2006) Mindset Theory as a theoretical foundation for understanding the outlined relationships. Specifically, the SCT theory framework emphasizes the role of self-efficacy in influencing motivation, learning strategies, and resilience in the face of challenges. By adding the aspect of a growth mindset, Dweck's theoretical lens offers a more comprehensive understanding of learners' abilities to adapt and thrive in their learning environments. Thus, a research model for the current study is hypothesized in Figure 1.

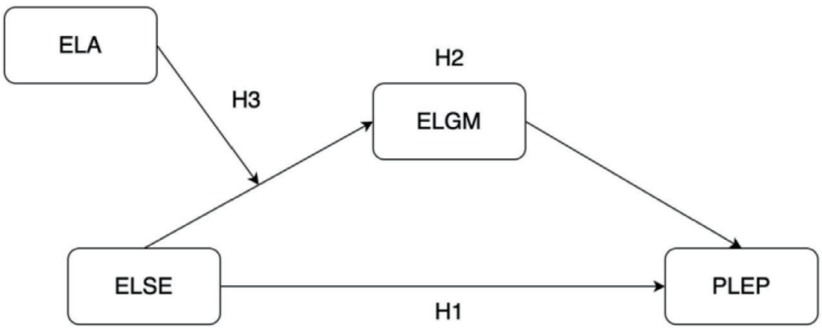

Figure 1. *The hypothesized model for the study*

Note. ELSE = Self-efficacy of AI-assisted English learning, ELGM = Growth-mindset of AI-assisted English learning, ELA = Anxiety of AI-assisted English learning, PELP = Perceived performance of Al-assisted English learning.

Research Design

Questionnaire Measurement

The present study adapted 4 established scales (self-efficacy, growth mindset, perceived learning performance, and learning anxiety) to the context of AI-enhanced English learning. These scales were contextually modified to align with the specific scenario under investigation. A 7-point Likert scale was employed for measurement, with scores ranging from low to high, indicating increasing levels of agreement.

English Learning Self-Efficacy (ELSE) was assessed using a scale derived from Wang and Chuang (2024), originally designed to evaluate self-efficacy in AI technology usage. The instrument consists of 22 items across four dimensions: Assistance, Anthropomorphic Interaction, Comfort with AI, and Technological Skills. Each item was adapted to the context of

English learning to align with the objectives in this study. The scale demonstrated high internal consistency (Cronbach's alpha = 0.972).

English Learning Growth Mindset (ELGM) was measured with 10 items adapted from Zander et al. (2018), capturing beliefs about the malleability of ability in educational settings. Items were semantically tailored to AI-enhanced learning environment. In present study, the tool demonstrated good internal consistency (Cronbach's alpha = 0.959).

English Learning Anxiety (ELA) was evaluated using a 4-item scale originally developed by Hong et al. (2014) for smartphone-assisted English learning. To meet the needs of this study, smartphones were uniformly referred to as AI application devices. The scale showed excellent reliability (Cronbach's alpha = 0.928).

Perceived English Learning Performance (PELP) was measured using items adapted from Zou and Jin (2022), who designed the scale for smartphone-assisted language learning. Similar to the adaption of the anxiety scale, references to smartphones were adapted to AI. The instrument also exhibited high reliability (Cronbach's alpha = 0.955).

To ensure conceptual clarity and linguistic appropriateness, all scales were translated into Chinese through a process of translation and back-translation by qualified translators and reviewed by the research team. A pilot study involving 59 participants was conducted to examine the psychometric properties of the adapted instruments. Based on item analysis and factor loadings, four poorly performing items were removed prior to the formal survey. The specific items of the questionnaire employed in the formal survey and their cited sources are detailed in the Appendix.

Questionnaire Data Collection

Data were collected from 592 students ranging from freshmen to seniors in various universities in Chinese mainland. Among these participants, there were 143 male students (33%) and 294 female students (67%). Regarding academic years, there were 183 freshmen (42%), 92 sophomores (21%), 83 juniors (19%), and 74 seniors (17%). To ensure the quality of the collected data, those who had no prior experience with AI-enhanced English learning and those whose answer time was too short were excluded from this study. In other words, only students who have previously used AI tools in their English learning process are considered the target group for this survey. For example, Figure 2 shows a screenshot of a student using ChatGPT to prepare for the IELTS exam. Finally, after rigorous screening, 155 invalid questionnaires were removed, leaving 437 valid questionnaires for formal data analysis.

Data Analysis Process

In this study, SPSS 24.0 was used to calculate the internal consistency of the measurement indicators, sample descriptive statistics, correlations between variables, and moderating effect analysis. Additionally, the structural equation model (SEM) of AMOS 27.0 was used to test the research model. Before testing, confirmatory factor analysis (CFA) was employed to verify the reliability of the constructs (Anderson & Gerbing, 1988). To address the issue of mediating effects, this study utilized the SPSS macro-PROCESS 4.1 (Model-4) developed by Hayes (2013). Bootstrap sampling was performed, extracting 5000 samples repeatedly to calculate a 95% confidence interval (CI). The researchers then examined whether the confidence interval for each path included zero to determine the significance of the mediating effect. Similarly, the PROCESS macro was used to test the moderating effect of ELA (Model-7). Participants were divided into high and low English learning anxiety perception groups to estimate the influence of the mediating effect of ELGM on different anxiety perception groups, thereby addressing research hypothesis 3 (H3).

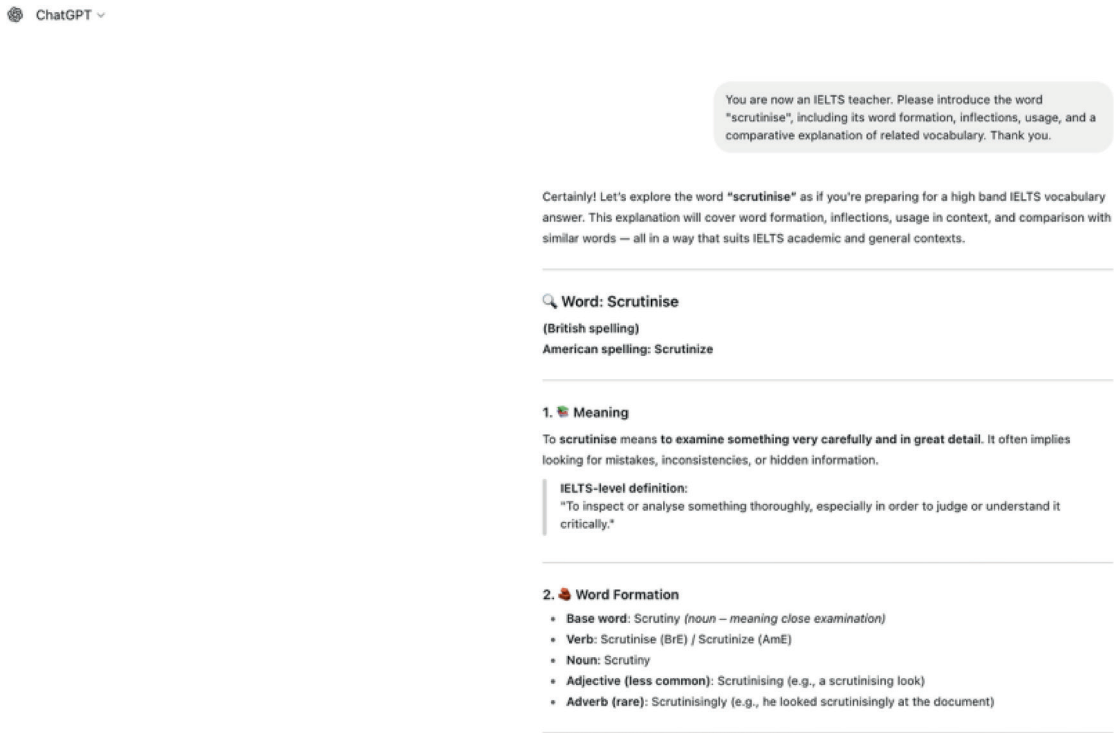

Figure 2. *Screenshot of AI-assisted language learning from one student (Taking ChatGPT as an example)*

Research Results

Descriptive Statistical Analysis

This study used SPSS 24.0 software to analyze the mean and standard deviation of each research variable. All measurement items in this study were normally distributed, as the values of skewness and kurtosis coefficients were less than ± 2.58 (see Table 1).

Table 1. Descriptive statistics and correlations among all variables (N = 437).

Variable label	*M*	*SD*	Skewness	Kurtosis
1. ELSE	5.21	1.22	–.06	–.34
2. ELGM	4.01	1.60	–.32	.24
3. ELA	5.18	1.14	–.30	–.64
4. PELP	5.21	1.22	–.40	1.05

Note. *p-value <.05; **p-value <.01; ***p-value <.001. ELSE = Self efficacy of AI-assisted English learning, ELGM = Growth-mindset of AI-assisted English learning, ELA = Anxiety of AI-assisted English learning, PELP = Perceived performance of Al-assisted English learning.

Measurement Model Analysis

Before evaluating the structural model, the reliability and validity of the measurement scales should be tested. This study assesses them using three indicators: Cronbach's alpha, composite reliability (CR), and convergent validity, with convergent validity measured by average variance extracted (AVE). Cronbach's alpha and composite reliability are strong indicators of a scale's reliability, while AVE checks the internal consistency of a construct and how much variation it captures compared to measurement error. For studies based on established theories, the usual thresholds are that composite reliability and Cronbach's α should be above 0.70, and AVE should exceed 0.50 (Fornell & Larcker, 1981; Hair et al., 2012). Meeting these standards shows that the measurement items for each latent variable have good composite reliability and convergent validity.

The results summarized in Table 2 show that all constructs surpass the recommended thresholds: Cronbach's alpha ranges from 0.928 to 0.972, composite reliability values range from 0.915 to 0.960, and all AVE values are well above 0.50, ranging from 0.729 to 0.856. These findings strongly confirm that the measurement items in present study have high reliability and excellent internal consistency.

Table 2. Reliability and convergent validity analysis (convergent validity and reliability) (N = 437).

Construct / questionnaire items	**Factor loading**	***t*-value**	**CR**	**AVE**	**Cronbach's alpha**
ELSE			.915	.729	
ASS	.833	/			
ANT	.778	19.244***			.972
COM	.942	25.453***			
TECH	.856	22.190***			
ELGM					
GM-1	.899	/			
GM-2	.940	33.515***	.960	.856	.959
GM-3	.923	31.393***			
GM-4	.938	32.849***			
ELA					
LA-1	.861	/			
LA-2	.937	27.232***	.929	.766	.928
LA-3	.881	24.488***			
LA-4	.817	21.935***			
PELP					
LP-1	.896	/			
LP-2	.928	31.656***	.955	.843	.955
LP-3	.917	30.587***			
LP-4	.931	31.616***			

Note. ****p*-value <. 001. "/" indicates a fixed item. ELSE = Self efficacy of AI-assisted English learning, ELGM = Growth-mindset of AI-assisted English learning, ELA = Anxiety of AI-assisted English learning, PELP = Perceived performance of Al-assisted English learning.

In addition, the validation of a measurement model typically encompasses an evaluation of convergent, content, and discriminant validity. In this research, convergent validity was firmly established using the AVE metric, as reported above. Content validity was secured during the initial questionnaire development phase. The item scales were adapted from previously validated instruments, ensuring a strong foundational validity. Furthermore, the Delphi method and consultations with domain experts were conducted to refine the wording and context of the items to fit the specific setting of AI-enhanced language learning, thereby further enhancing the content validity.

This study places additional emphasis on discriminant validity, which assesses the extent to which a construct is distinct from others in the model. It is evaluated by comparing the square root of the AVE for each construct with the correlation coefficients between that construct and all others. Following the criterion established by Fornell and Larcker (1981), discriminant validity is confirmed if the square root of the AVE (displayed diagonally in Table 3) is greater than any of the inter-construct correlations in its corresponding row and column. The results in Table 3 show that the diagonal values (ranging from 0.85 to 0.93) are indeed consistently greater than all the off-diagonal correlation coefficients in their respective rows and columns. Therefore, it can be concluded that the measurement model demonstrates adequate discriminant validity.

Table 3. Discriminant validity testing (N = 437).

Construct	PELP	ELA	ELGM	ELSE
PELP	***.92***			
ELA	– .11	***.85***		
ELGM	.77	– .19	***.93***	
ELSE	.60	– .24	.70	***.85***

Note. All correlations (off-diagonal elements) are significant at $p < .05$. Diagonal elements (in italics and bold) are square roots of AVE. ELSE = Self efficacy of AI-assisted English learning, ELGM = Growth-mindset of AI-assisted English learning, ELA = Anxiety of AI-assisted English learning, PELP = Perceived performance of Al- assisted English learning.

Structural Model Analysis

After analyzing the structural model using maximum likelihood estimation, we obtained results on model fit, hypothesis testing significance, and explained variance (R^2). Nine widely accepted fit indicators from SSCI international journals were adopted in this part, following Jackson et al. (2009) and Kuo and Hwang (2015). To enhance model reliability and parsimony, this study followed Little et al.'s (2002) "unit weighted factor score" recommendation, which could reduce the risk of residual correlations. This involved aggregating items related to self-efficacy in AI-enhanced English learning with their mean values. The results, presented in Table 4, show that the model fit meets statistical standards, indicating good overall fit.

Regarding the statistical testing of RQ 1, this study utilized IBM SPSS AMOS 27.0 software to validate the first three research hypotheses using SEM techniques. Combining the results from Table 5 and Figure 3, it was evident that ELSE ($\beta = .70$, $p < .001$) significantly and positively predicted ELGM. Additionally, both ELSE ($\beta = .13$, $p < .05$) and ELGM ($\beta = .68$, $p < .001$) had significant and positive predictive effects on self-perception of PELP. These findings supported the research hypotheses of the model. In terms of explanatory power, the use of ELSE explained

Table 4. Goodness-of-fit of the measurement and structural model (N = 437).

Model fit indices	χ2/df.	GFI	NFI	RFI	PGFI	PCFI	PNFI	RMR	RMSEA
Goodness-of-fit criteria	1–5	≥.9	≥.9	≥.9	≥.5	≥.5	≥.5	≥.08	.05-.08
Measurement model	3.14	.91	.96	.95	.66	.79	.78	.06	.07
Structural model	2.91	.95	.97	.97	.62	.76	.75	.05	.07
Supported	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. χ2/df.= Chi-squared Divided by Degrees of Freedom; GFI = Goodness-of-fit Index; CFI = Comparative Fit Index; NFI = Normed Fit Index; IFI = Incremental Fit Index; RFI = Relative Fit Index; PGFI = Parsimony Goodness-of-fit Index; PCFI = Parsimonious Comparative Fit Index; PNFI = Parsimonious Normed Fit Index; RMR = Root Mean Square Residual; RMSEA= Root Mean Square Error of Approximation.

Table 5. Testing results of hypotheses (N = 437).

Hypothesis	From --> to	Standardised path (β)	*Z*-value	Supported
H1	ELSE --> PELP	.13*	2.56	Yes
H2	ELSE --> ELGM	.70***	15.6	Yes
H3	ELGM --> PELP	.68***	12.64	Yes

Note. **p*-value < .05; ***p*-value < .01; ****p*-value < .001

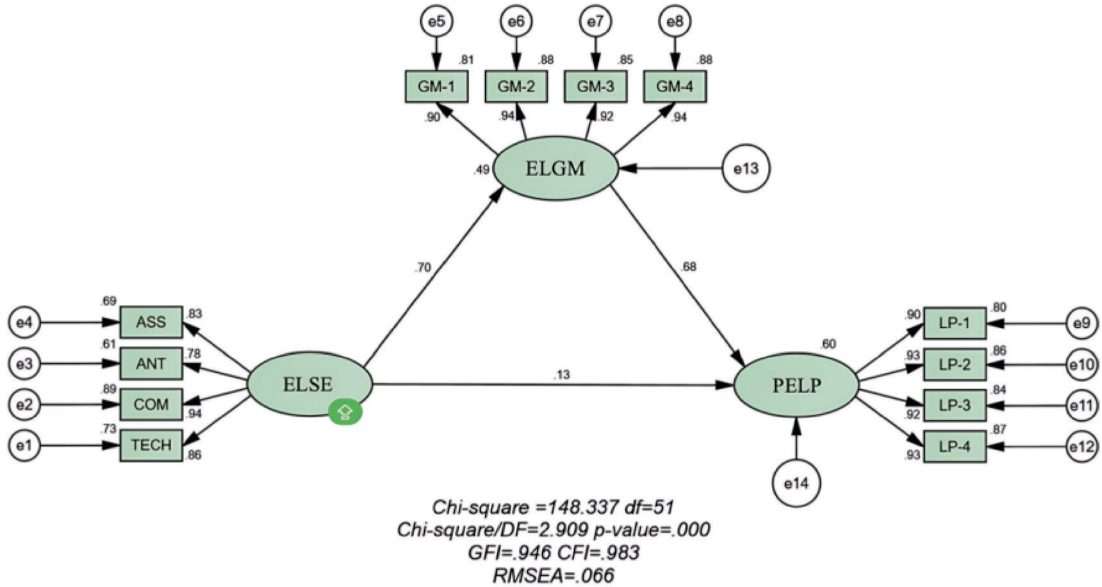

Figure 3. *Standardised path coefficients of the research model*
Note. ELSE = Self efficacy of AI-assisted English learning, ELGM = Growth-mindset of AI-assisted English learning, ELA = Anxiety of AI-assisted English learning, PELP = Perceived performance of Al-assisted English learning.

49% of the variance in ELGM. Furthermore, ELSE (β = .13, $p < .05$) and ELGM (β = .68, $p < .001$) together explained 60% of PELP.

Mediation Analysis

Analysis from the mediation model's indirect effect table revealed that the indirect effect between ELGM and ELP through ELSE is 0.540, with a Bias Corrected Percentile 95% Confidence Interval of [0.429, 0.668], excluding 0 (refer to Table 6). This indicated a significant mediating effect of ELGM between ELSE and PELP, thereby confirming H2.

Table 6. Mediation effect of ELGM (N = 437).

Path	Estimate	S.E.	Bootstrapping = 5000			
			Percentile 95 CI		Bias-corrected percentile 95 CI	
			Lower	Upper	Lower	Upper
Total effect	.685***	.059	.568	.798	.569	.799
Direct effect	.146*	.057	.006	.315	.001	.310
Indirect effect	.540***	.061	.411	.653	.429	.668

Note. *p-value < .05; **p-value < .01; ***p-value < .001; LLCI, bootstrap 95% lower limit confidence interval; ULCI, bootstrap 95% upper limit confidence interval.

Analysis of Moderation Effects

Considering the mediating effect of ELGM between ELSE and ELP, this study employed Model-7 (Hayes, 2013) from IBM SPSS 24.0 macro-Process 4.1. Results, as depicted in Table 7, revealed that the moderating effect of ELSE * ELA on ELGM is −0.077 (t = -2.884, p = .004 <.01), indicating the presence of an effective moderating effect.

Table 7. Moderation effect of english learning anxiety (ELA) (N = 437).

DV	IV	Estimate	S.E.	t-value	LLCI	ULCI
	ELSE	.751	.447	114.186***	.663	.839
ELGM	ELA	−.001	.031	−.041	−.061	.059
	ELSE * ELA	−.077	.027	−2.884**	−.129	−.024
R^2			.423			
F			105.826			

Note. *p-value < .05; **p-value < .01; ***p-value < .001; LLCI, bootstrap 95% lower limit confidence interval; ULCI, bootstrap 95% upper limit confidence interval.

In addition, to further elucidate the significance of the moderating effect of ELA, this study conducted a simple slope analysis. Results indicated that when the score of ELA was low (M-1SD), ELSE positively predicted ELGM (β = 0.874, $p < .001$). Conversely, when individual scores for ELA were high (M + 1SD), the positive predictive effect of ELSE on ELGM was significantly weakened (β = 0.628, $p < .001$), as depicted in Table 8 and Figure 4 below. In sum, the current study found that ELGM acted as a mediator between self-efficacy in ELSE and ELP. Furthermore, the mediating effect of growth-oriented thinking in ELGM was negatively moderated by ELA. Specifically, as individuals' anxiety levels in AI-enhanced English learning decreased, the positive predictive effect of self-efficacy in ELSE on ELGM strengthened, thereby reinforcing the mediating effect on ELP.

Table 8. The effect of ELSE on ELGM in different level of ELA (N = 437).

ELA	β	BootSE	T	*p*	BootLLCI	BootULCI
−1 SD	.874	.061	14.267	***	.754	.994
M	.751	.045	16.805	***	.663	.839
+1 SD	.628	.062	10.096	***	.506	.751

Note. *p-value < .05; **p-value < .01; ***p-value < .001; LLCI, bootstrap 95% lower limit confidence interval; ULCI, bootstrap 95% upper limit confidence interval.

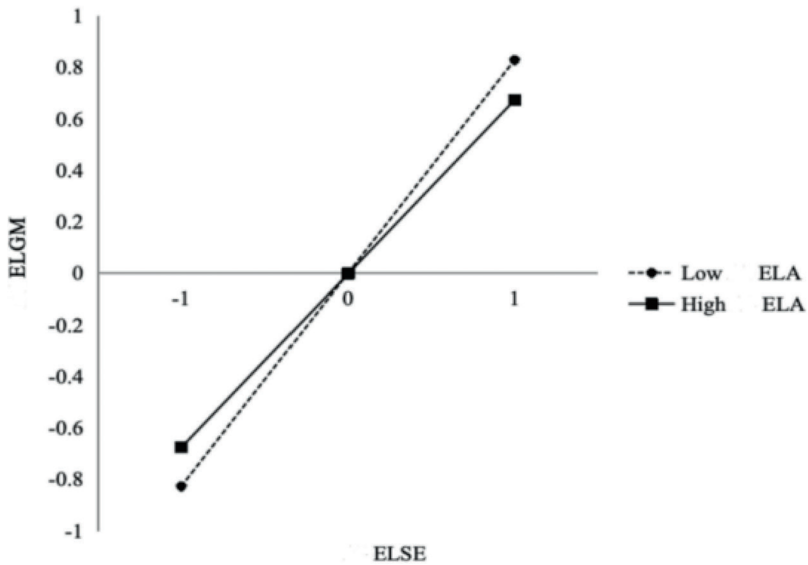

Figure 4. *The moderator role of ELA in the relationship between ELSE and ELGM*

Discussion and Conclusion

In terms of theoretical contributions, the results of this study substantiate and extend the existing literature within the theoretical frameworks of Bandura's Social Cognitive Theory (SCT) and Dweck's Mindset Theory. Our findings strongly align with SCT, which emphasizes the reciprocal interactions among personal factors, behavior, and environmental influences (Bandura, 1997). The significant positive effect of self-efficacy on perceived learning performance reinforces the core tenet of SCT that individuals' beliefs in their capabilities profoundly shape their motivation and behavioral outcomes. This relationship underscores the need for educational frameworks that prioritize the development of self-efficacy as a precursor to improving learning results. Furthermore, this study establishes that self-efficacy indirectly predicts perceived learning performance through growth mindset. This mediating mechanism integrates Bandura's SCT with Dweck's (2006) Mindset Theory, suggesting that learners' self-efficacy not only directly enhances performance but also fosters a growth mindset, which in turn promotes resilience and adaptive learning behaviors. This finding is consistent with recent research in technology-enhanced language learning (TELL) that highlights the dynamic interplays among psychological factors in technology-mediated environments (e.g., Teng, 2024; Zuo et al., 2024). It advances Dweck's theory by revealing that self-efficacy acts as an antecedent to growth mindset in AI-assisted contexts, thereby illustrating how a supportive technological environment can facilitate positive psychological cycles. The moderating role of learning anxiety in the relationship between self-efficacy and growth mindset further enriches both SCT and Mindset Theory within digital learning settings. According to SCT, emotional states such as anxiety can significantly influence cognitive and motivational processes. Our results confirm that high anxiety disrupts the positive effect of self-efficacy on growth mindset, illustrating how emotional barriers can attenuate the beneficial pathways proposed by both Bandura (1997) and Dweck (2006). This aligns with emerging TELL research indicating that affective factors are critical in mediating technology acceptance and learning outcomes (Lai & Tu, 2024). It reinforces the need to consider emotional regulation as an integral component of AI-supported educational designs.

In terms of practical contributions, these findings offer actionable insights for educators and instructional designers in AI-assisted EFL settings. To enhance self-efficacy, pedagogical strategies should incorporate structured mastery experiences, constructive feedback, and peer modeling, which are practices strongly rooted in SCT (Bai & Wang, 2023). Similarly, cultivating a growth mindset can be achieved through explicit instruction on neuroplasticity, effort-based praise, and reflective activities that normalize struggle and learning from errors (Wei, 2023). Moreover, given the moderating effect of anxiety, educators should implement evidence-based anxiety-reduction strategies such as mindfulness exercises, adaptive learning scaffolds, and emotionally supportive feedback mechanisms (Hwang et al., 2017). Teacher training programs should also emphasize the recognition and management of language anxiety to foster more inclusive and effective AI-enhanced learning environments.

To summarize, both self-efficacy (ELSE) and growth mindset (ELGM) directly predict perceived English learning performance (PELP), supporting H1. This confirms prior studies in traditional and technology-enhanced contexts (Derakhshan et al., 2022; Zhang et al., 2022), while specifically validating these relationships in AI-enhanced language learning. Furthermore, self-efficacy indirectly predicts PELP through growth mindset, supporting H2 and emphasizing the importance of mediating mechanisms as outlined in Dweck's theory and recent TELL empirical work (Macnamara & Burgoyne, 2023; Yin et al., 2022). Lastly, learning anxiety (ELA) moderates the relationship between self-efficacy and growth mindset, indicating that the benefits of self-efficacy are attenuated under high anxiety. This finding echoes contemporary studies on the complex role of anxiety in technology-mediated learning (e.g., Ozdemir & Papi, 2022; Tu, 2024).

Limitation and Prospects

This study has several limitations that should be acknowledged. First, the sample only includes students from three provinces in China, which may limit how well the findings apply to other cultural or educational settings. Second, learning performance was measured solely through self-reported data. Future studies could use objective measures, like test scores or system-recorded data, to improve validity. Also, key variables like gender, major, and grade level were not considered. Exploring these factors later could clarify how the model proposed by the present study works across different learner groups. Finally, since anxiety and mindset are influenced by cultural background (Zegrean, 2025), the relationships observed among variables in the present study may differ in other cultural contexts.

References

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, *103*(3), 411–423. https://doi.org/10.1037/0033-2909.103.3.411

Bandura, A. (1997). *Self-efficacy: The exercise of control*. Macmillan.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice-Hall, Inc.

Bai, B., & Wang, J. (2023). The role of growth mindset, self-efficacy and intrinsic value in self-regulated learning and English language learning achievements. *Language Teaching Research*, *27*(1), 207–228. https://doi.org/10.1177/1362168820933190

Bellinger, D. B., DeCaro, M. S., & Ralston, P. A. (2015). Mindfulness, anxiety, and high-stakes mathematics performance in the laboratory and classroom. *Consciousness and Vognition*, *37*, 123–132. https://doi.org/10.1016/j.concog.2015.09.001

Buddha, H., Shuib, L., Idris, N., & Eke, C. I. (2024). Technology-assisted language learning systems: A systematic literature review. *IEEE access, 12*, 33449–33472. https://doi.org/10.1109/ACCESS.2024.3366663

Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access*, *8*, 75264–75278. https://doi.org/10.1109/ACCESS.2020.2988510

Crompton, H., Edmett, A., Ichaporia, N., & Burke, D. (2024). AI and English language teaching: Affordances and challenges. *British Journal of Educational Technology*, *55*, 2503–2529. https://doi.org/10.1111/bjet.13460

Derakhshan, A., Fathi, J., Pawlak, M., & Kruk, M. (2022). Classroom social climate, growth language mindset, and student engagement: The mediating role of boredom in learning English as a foreign language. *Journal of Multilingual and Multicultural Development*, 1–19. https://doi.org/10.1080/01434632.2022.2099407

Dweck, C. S. (2006). *Mindset: The new psychology of success*. Random House.

Dweck, C. S. (2017). The journey to children's mindsets—and beyond. *Child Development Perspectives*, *11*(2), 139–144. https://doi.org/10.1111/cdep.12225

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.2307/3151312

Guo, K., Pan, M., Li, Y., & Lai, C. (2024). Effects of an AI-supported approach to peer feedback on university EFL students' feedback quality and writing ability. *The Internet and Higher Education*, *63,* Article 100962. https://doi.org/10.1016/j.iheduc.2024.100962

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science*, *40*(3), 414–433. https://doi.org/10.1007/s11747-011-0261-6

Hawes, D., & Arya, A. (2023). Technology solutions to reduce anxiety and increase cognitive availability in students. *IEEE Transactions on Learning Technologies*, *16*(2), 278–291. 10.1109/TLT.2023.3239985

Hayes, A. F. (2013). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. The Guilford Press. https://doi.org/10.1111/jedm.12050

Hong, J. C., Hwang, M. Y., Tai, K. H., & Chen, Y. L. (2014). Using calibration to enhance students' self-confidence in English vocabulary learning relevant to their judgment of over-confidence and predicted by smartphone self-efficacy and English learning anxiety. *Computers & Education*, *72*, 313–322. https://doi.org/10.1016/j.compedu.2013.11.011

Horwitz, E. (2001). Language anxiety and achievement. *Annual Review of Applied Linguistics*, *21*, 112–126. https://doi.org/10.1017/S0267190501000071

Hu, X., Sidhu, G. K., & Lu, X. (2022). Relationship between growth mindset and English language performance among Chinese EFL university students: The mediating roles of grit and foreign language enjoyment. *Frontiers in Psychology*, *13*, Article 935506. https://doi.org/10.3389/fpsyg.2022.935506

Hwang, G. J., Hsu, T. C., Lai, C. L., & Hsueh, C. J. (2017). Interaction of problem-based gaming and learning anxiety in language students' English listening performance and progressive behavioral patterns. *Computers & Education*, *106*, 26–42. https://doi.org/10.1016/j.compedu.2016.11.010

Jackson, D. L., Gillaspy, J. A., Jr., & Purc-Stephenson, R. (2009). Reporting practices in confirmatory factor analysis: An overview and some recommendations. *Psychological Methods*, *14*(1), 6–23. https://doi.org/10.1037/a0014694

Klimova, B., & Pikhart, M. (2025). Exploring the effects of artificial intelligence on student and academic well-being in higher education: A mini-review. *Frontiers in Psychology*, *16*, Article 1498132. https://doi.org/10.3389/fpsyg.2025.1498132

Kohnke, L., & Moorhouse, B. L. (2025). Enhancing the emotional aspects of language education through generative artificial intelligence (GenAI): A qualitative investigation. *Computers in Human Behavior*, *167*, Article 108600. https://doi.org/10.1016/j.chb.2025.108600

Kuo, F. R., & Hwang, G. J. (2015). A structural equation model to analyse the antecedents to students'web-based problem-solving performance. *Australasian Journal of Educational Technology*, *31*(4), 400–420. https://doi.org/10.14742/ajet.284

Lai, C. L., & Tu, Y. F. (2024). Roles, strategies, and research issues of generative AI in the mobile learning era. *International Journal of Mobile Learning and Organisation*, *18*(4), 516–537. https://doi.org/10.1504/ijmlo.2024.141836

Liao, J., Chen, J., & Mou, J. (2021). Examining the antecedents of idea contribution in online innovation communities: a perspective of creative self-efficacy. *Technology in Society*, *66*, Article 101644. https://doi.org/10.1016/j.techsoc.2021.101644

Lin, Y. J., & Wang, H. C. (2021). Using virtual reality to facilitate learners' creative self-efficacy and intrinsic motivation in an EFL classroom. *Education and Information Technologies*, *26*(4), 4487–4505. https://doi.org/10.1007/s10639-021-10472-9

Little, T. D., Cunningham, W. A., Shahar, G., & Widaman, K. F. (2002). To parcel or not to parcel: Exploring the question, weighing the merits. *Structural Equation Modeling*, *9*(2), 151–173. https://doi.org/10.1207/S15328007SEM0902_1

MacIntyre, P. D. (1999). Language anxiety: A review of the research for language teachers. In D. J. Yong (Ed.), *Affect in foreign language and second language learning: A practical guide to creating a low-anxiety classroom atmosphere* (pp. 24–45). McGraw-Hill.

Macnamara, B. N., & Burgoyne, A. P. (2023). Do growth mindset interventions impact students' academic achievement? A systematic review and meta-analysis with recommendations for best practices. *Psychological Bulletin*, *149*(3–4), Article 133. https://doi.org/10.1037/bul0000352

Mensah, C., Azila-Gbettor, E. M., Nunyonameh, C. R., Appietu, M. E., & Amedome, S. N. (2023). Research methods anxiety, attitude, self-efficacy and academic effort: A social cognitive theory perspective. *Cogent Psychology*, *10*(1), Article 2167503. https://doi.org/10.1080/23311908.2023.2167503

Ozdemir, E., & Papi, M. (2022). Mindsets as sources of L2 speaking anxiety and self-confidence: The case of international teaching assistants in the US. *Innovation in Language Learning and Teaching*, *16*(3), 234–248. https://doi.org/10.1080/17501229.2021.1907750

Schunk, D. H., & Pajares, F. (2002). The development of academic self-efficacy. In A. Wigfield & J. S. Eccles (Eds.,), *Development of achievement motivation* (pp. 15–31). Academic Press. https://doi.org/10.1016/B978-012750053-9/50003-6

Teng, L. S. (2024). Individual differences in self-regulated learning: Exploring the nexus of motivational beliefs, self-efficacy, and SRL strategies in EFL writing. *Language Teaching Research*, *28*(2), 366–388. https://doi.org/10.1177/13621688211006881

Teng, M. F., Wang, C., & Wu, J. G. (2023). Metacognitive strategies, language learning motivation, self-efficacy belief, and English achievement during remote learning: A structural equation modelling approach. *RELC Journal*, *54*(3), 648–666. https://doi.org/10.1177/00336882211040268

Tu, Y. F. (2024). Roles and functionalities of ChatGPT for students with different growth mindsets. *Educational Technology & Society*, *27*(1), 198–214. https://doi.org/10.30191/ets.202401_27(1).tp01

Wang, Y. Y., & Chuang, Y. W. (2024). Artificial intelligence self-efficacy: Scale development and validation. *Education and Information Technologies*, *29*(4), 4785–4808. https://doi.org/10.1007/s10639-023-12015-w

Wang, Y., Shen, B., & Yu, X. (2021). A latent profile analysis of EFL learners' self-efficacy: Associations with academic emotions and language proficiency. *System*, *103*, Article 102633. https://doi.org/10.1016/j.system.2021.102633

Wang, C., & Sun, T. (2020). Relationship between self-efficacy and language proficiency: A meta-analysis. *System*, *95*, Article 102366. https://doi.org/10.1016/j.system.2020.102366

Wei, L. (2023). Artificial intelligence in language instruction: Impact on English learning achievement, L2 motivation, and self-regulated learning. *Frontiers in Psychology*, *14*, Article 1261955. https://doi.org/10.3389/fpsyg.2023.1261955

Wu, J. G., Zhang, D., & Lee, S. M. (2023). Into the brave new metaverse: Envisaging future language teaching and learning. *IEEE Transactions on Learning Technologies*, *17*, 44–53. https://doi.org/10.1109/TLT.2023.3259470

Yin, X., Sidhu, G. K., Shamida, A., & Shuoteng, H. (2022). Relationship among self-determination, growth mindset and EFL students' language proficiency. *Environment-Behaviour Proceedings Journal*, *7*(21), 73–78. https://doi.org/10.21834/ebpj.v7i21.3723

Zander, L., Brouwer, J., Jansen, E., Crayen, C., & Hannover, B. (2018). Academic self-efficacy, growth mindsets, and university students' integration in academic and social support networks. *Learning and Individual Differences*, *62*, 98–107. https://doi.org/10.1016/j.lindif.2018.01.012

Zegrean, T. (2025). Social anxiety in culturally diverse young people: An insight into lived experiences. *Counselling and Psychotherapy Research*, *25*(2), Article e12836. https://doi.org/10.1002/capr.12836

Zhang, L. J., Saeedian, A., & Fathi, J. (2022). Testing a model of growth mindset, ideal L2 self, boredom, and WTC in an EFL context. *Journal of Multilingual and Multicultural Development*, *45*(8), 1–16. https://doi.org/10.1080/01434632.2022.2100893

Zheng, Y., & Cheng, L. (2018). How does anxiety influence language performance? From the perspectives of foreign language classroom anxiety and cognitive test anxiety. *Language Testing in Asia*, *8*(1), 1–19. https://doi.org/10.1186/s40468-018-0065-4

Zuo, S., Huang, Q., & Qi, C. (2024). The relationship between cognitive activation and mathematics achievement: mediating roles of self-efficacy and mathematics anxiety. *Current Psychology*, *43*(39), 1–12. https://doi.org/10.1007/s12144-024-06700-3

Appendix

Question items and references

Constructs	Sub-dimension	Coding	Items (English version)	References
ELSE	ASS	ASS-1	I believe that using AI can make my English learning more efficient.	Wang & Chuang (2024)
		ASS-2	I feel that AI is very helpful in improving my English proficiency.	
		ASS-3	I think AI-assisted English learning is a good way to enhance my English ability.	
		ASS-4	Using AI to learn English makes the entire learning process more interesting.	
		ASS-5	With necessary technical guidance, I am confident that I can learn English well with the help of AI.	
		ASS-6	I believe AI can help me save time in learning English.	
		ASS-7	I can easily use AI to assist me in completing my English learning tasks.	
	ANT	ANT-1	I feel that using AI to learn English is as vivid as communicating with a real person.	
		ANT-2	I think the interactive way AI assists in English learning is unique.	
		ANT-3	When using AI to learn English, I feel that its communication style is no different from that of a real person.	
		ANT-4	I feel that the tone of communication when using AI to learn English is as natural as talking to a real person.	
		ANT-5	I believe that AI's expressions in English interactive texts are very similar to real human interactions.	

(*Continued*)

Constructs	Sub-dimension	Coding	Items (English version)	References
	COM	COM-1	I don't feel restless when using AI to learn English.	
		COM-2	Using AI makes me feel that learning English has become very simple.	
		COM-3	I feel comfortable inside when using AI to learn English.	
		COM-4	I feel very calm when using AI to learn English.	
		COM-5	I feel very relaxed when using AI to learn English.	
		COM-6	I can happily use AI to learn English.	
	TECH	TEACH-1	I am confident in my software operation when using AI software to assist in English learning.	
		TEACH-2	I am not worried about pressing the wrong button and breaking the software when using AI software to assist in English learning.	
		TEACH-3	I understand the functions of AI software and know how to use it to improve my English learning.	
		TEACH-4	AI terminology does not hinder my English learning.	
ELGM		GM-1	With the help of AI software, I believe that any student can improve their English proficiency through their own efforts.	Zander et al. (2018)
		GM-2	As long as they put in the effort, I think any student can achieve good results in English learning with AI assistance.	
		GM-3	With AI assistance, I think any student can find their strengths in English learning.	

(*Continued*)

Constructs	Sub-dimension	Coding	Items (English version)	References
		GM-4	I believe that students can significantly improve their basic English level through AI-assisted English learning.	
ELA		LA-1	I tend to feel anxious when learning English.	Hong et al. (2014)
		LA-2	I always worry that my current English level affects my English learning.	
		LA-3	Using AI software to assist in English learning makes me feel nervous.	
		LA-4	I always worry about making mistakes when communicating in English (e.g., forgetting words, grammatical errors, etc.).	
PELP		LP-1	Using AI to assist in English learning has a positive impact on my overall English learning performance.	Zou & Jin (2022)
		LP-2	Using AI to assist in English learning plays an important role in improving my English learning process.	
		LP-3	Using AI to assist in English learning has given me a better understanding of some language points.	
		LP-4	Adopting AI-assisted forms in the process of English learning helps to improve my learning performance.	
Basic information	Gender; Grade; The single-session duration of using AI-based applications to assist in English learning; The device status for using AI-based applications to assist in English learning.			