

Research on the Reconstruction Pathways of English Majors' Self-Efficacy in the Era of Artificial Intelligence

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Abstract: This study, based on Davis's (1989) technology acceptance model (TAM), Bandura's (1982) self-efficacy theory (SET), and the concepts of AI literacy and human-AI collaboration (AILHAIC), constructs a structural equation model to examine the reconstruction pathways of English majors' self-efficacy (SE) in the AI era. A total of 240 questionnaires were collected from English majors at a university in Dongguan City, Guangdong Province, and 214 valid questionnaires were retained after data screening. The results show that AI Usage Perception (AIUP) has a significant positive effect on SE. AIUP also has significant positive effects on self-efficacy sources (SES) and AILHAIC. Both SES and AILHAIC have significant positive effects on SE. Simultaneously, Bootstrap analysis (5,000 resamples) indicates that AILHAIC (indirect effect=0.120) and SES (indirect effect=0.062) both significantly mediate the relationship between AIUP and SE, with AILHAIC playing a stronger mediating role. These findings reveal that AIUP influences SE both directly and indirectly through SES and AILHAIC, highlighting the key role of AILHAIC in reconstructing English majors' SE. This study provides theoretical and practical implications for English teaching reform and SE enhancement in the AI era.

Keywords: AI usage perception (AIUP); Self-efficacy (SE); Self-efficacy sources (SES); AI literacy and human-AI collaboration (AILHAIC); English majors

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1. Introduction

With the popularity of artificial intelligence (AI) tools such as ChatGPT, Claude, Gemini, DeepSeek, Doubao, ERNIE Bot, etc., English majors' English learning methods are undergoing profound changes. AI tools can provide support such as translation, polishing, grammar correction, writing assistance, and oral practice, but they also, to some extent, affect students' confidence in their own English abilities. Self-efficacy

(SE) is an individual's belief in their ability to complete specific tasks and is an important factor affecting learning motivation and effectiveness ^[1]. In the context of AI-assisted English learning, learners' self-efficacy sources (SES), AI usage perception (AIUP), and human-machine collaboration abilities may all affect the reconstruction of their SE.

However, existing research has mostly focused on the impact of AI tools on English learning performance or behavior, with little exploration from the perspective of SE reconstruction on AIUP, SES, and the underlying mechanisms between AI literacy and human-AI collaboration (AILHAIC) ^[2-3]. Based on this, this study takes English majors as the research object, integrates Davis's (1989) technology acceptance model (TAM), Bandura's (1982) self-efficacy theory (SET), and the concepts of AILHAIC, constructs a structural equation model, and explores the impact paths of AIUP, SES, and AILHAIC on SE, in order to provide a reference for the improvement of SE among English majors in the AI era and English teaching reform.

2. Literature review

2.1. AI usage perception (AIUP) and English learning

With the continuous penetration of AI technology in the field of education, AI usage perception (AIUP) has gradually become an important factor affecting students' English learning behavior and psychological state. The use of perception in AI originates from Davis's TAM, which mainly includes two core dimensions: perceived usefulness and perceived ease of use ^[4]. In recent years, scholars both domestically and internationally have conducted extensive research on the application of AI tools in English learning. Ouchene and Belmekki (2025) pointed out that the more actively college students perceive the usefulness and ease of use of AI tools, the stronger their English learning engagement and autonomous learning ability ^[5]. Mansoor et al. (2026) found that perceived ease of use significantly affects the willingness of English major students to use AI translation and writing aids ^[6]. Qiu Guanghua (2025) further claimed that the use of AI perception not only affects learning behavior, but may also affect students' psychological states by influencing their learning experience ^[7]. In a word, AIUP has been proven to be an important antecedent variable affecting the English learning process, but its mechanism of action on SE still needs to be further explored.

2.2. Self-efficacy (SE)

Self-efficacy (SE), proposed by Bandura, refers to an individual's belief in their ability to complete specific tasks ^[8]. In the era of AI, the connotation and formation mechanism of SE are undergoing changes. Wang Yingchun (2023) argued that SE in AI-assisted learning contexts includes not only confidence in traditional English abilities, but also critical judgment skills in AI-generated content and the ability to maintain autonomy in human-machine collaboration ^[9]. Ismail and Alharkan (2024) put forward that while AI tools can improve students' English learning efficiency, they may also trigger dependency psychology, thereby weakening their confidence in independently completing tasks ^[10]. Thus, how to reconstruct the SE of English majors in an AI-assisted environment has become an important research topic. Wang Linyan and Wang Long (2025) further emphasized that SE in the AI era is a key psychological resource for students to achieve deep learning and self-directed learning ^[11].

2.3. Self-efficacy sources (SES)

Bandura declared that SE mainly comes from experiences of success and failure, substitute experiences,

verbal persuasion, as well as emotional and physiological states^[12]. In the era of AI, these four sources are embedded into human-computer interaction, forming a new self-efficacy source (SES). Hongxia and Razali (2026) found that students can significantly enhance their SE by successfully completing challenging English tasks through human-machine collaboration^[13]. Wu et al. (2026) stated that observing peers using AI tools to improve their English proficiency can generate alternative experiences, thereby enhancing their own confidence^[14]. El et al. (2026) explored that teacher encouragement and support still play an important role in verbal persuasion in AI-assisted English learning^[15]. In addition, Yan et al. (2025) reported that reducing anxiety when using AI tools helps students form positive emotional experiences, thereby enhancing their SE^[16]. In this way, it can be seen that SES plays a crucial mediating role in the formation of SE in the AI age.

2.4. AI Literacy and human-AI collaboration (AILHAIC)

AI literacy and human-AI collaboration (AILHAIC) is an emerging concept in AI education research in recent years. Long and Magerko (2020) first proposed the AI literacy framework, centering on the idea that individuals should have the ability to critically evaluate AI, effectively communicate and collaborate with AI, and understand the ethical and social impacts of AI^[17]. Ng et al. (2021) further categorized AI literacy into four dimensions: knowledge and understanding, use and application, evaluation and creation, and ethics and safety^[18]. In terms of human-machine collaboration, Wilson and Daugherty (2018) came up with the concept of “collaborative intelligence,” emphasizing that humans and AI should leverage their respective strengths and complement each other^[19]. Molenaar (2022) introduced human-AI collaboration into the field of education and proposed a framework for human-AI collaborative learning, arguing that AI should serve as a learning partner rather than a substitute^[20]. Presently, Chinese scholars have also increasingly focused on the impact of AI literacy and human-machine collaboration on English learning. For example, Zhang et al. (2025) found that students with higher AI literacy are better at critically using AI tools and maintaining higher levels of autonomy and confidence in English learning^[21]. Zhang et al. (2025) announced that human-machine collaboration ability significantly positively predicts SE and learning satisfaction of English majors^[22].

2.5. Research gaps

Existing research has to some degree explored the AIUP, SE, SES, and AILHAIC, providing a theoretical basis for this study. However, there are still some shortcomings. Firstly, most studies focus on the impact of AI tools on English learning performance or behavior, and there is relatively little exploration of their underlying mechanisms from the perspective of SE reconstruction. Secondly, there is a lack of empirical testing on the comprehensive effects of AIUP, SES, and AILHAIC on SE. Thirdly, targeted research on English majors is still insufficient. Based on this, this study combines the TAM, SET, and AILHAIC to construct a structural equation model to investigate the impact pathways of AIUP, SES, and AILHAIC on SE, so as to fill the gaps in current research.

3. Theoretical model and research hypothesis

3.1. Theoretical model

This study constructs a theoretical model to explain the reconstruction path of SE among English majors in the AI era. This model integrates Davis’s (1989) TAM, Bandura’s (1982) SET, and the concepts of AILHAIC. It takes AIUP as the main antecedent variable, SE as the outcome variable, and SES and AILHAIC as

mediating variables.

First, the TAM suggests that an individual's perception of the usefulness and ease of use of technology will affect their usage behavior and confidence ^[23]. In AI-assisted English learning, if students find AI tools useful and easy to use, they are more likely to integrate them into their learning and enhance their confidence in English proficiency. Hence, AIUP is set as an antecedent variable that affects SE.

Then, Bandura proclaimed that SE mainly comes from experiences of success or failure, substitute experiences, verbal persuasion, and emotional states ^[24]. In the era of AI, these sources are embedded in human-computer interaction: successful human-machine collaboration constitutes success or failure experience, observing classmates using AI to improve English constitutes substitute experience, teacher encouragement constitutes verbal persuasion, and using AI reduces anxiety and reflects positive emotional states. Therefore, SES is introduced as a mediator variable.

What is more, AILHAIC has become an important ability for English majors. Students who can critically evaluate AI content, understand the advantages and limitations of AI, and manage AI usage behavior reasonably are more likely to effectively utilize AI and maintain confidence in English learning. For this reason, AILHAIC is considered another mediating variable.

Based on the above theories and analyses, this study proposes a conceptual model: AIUP affects SE through two pathways, SES and AILHAIC, and may have a direct effect on SE (**Figure 1**).

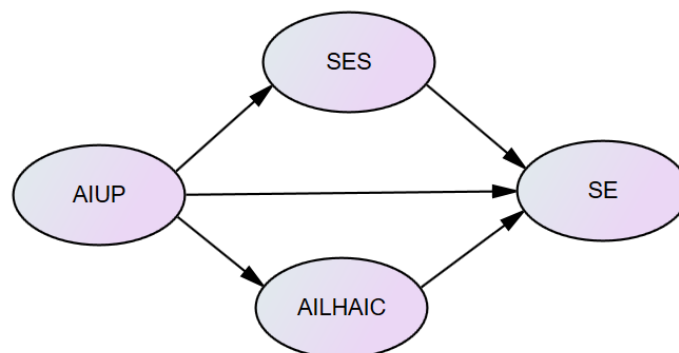


Figure 1. Theoretical model of the study

3.2. Research hypothesis

In accordance with the theoretical model, the following hypotheses are raised:

- H1: AIUP has a significant positive impact on SE.
- H2: AIUP has a significant positive effect on SES.
- H3: AIUP has a significant positive effect on AILHAIC.
- H4: SES has a significant positive impact on SE.
- H5: AILHAIC has a significant positive effect on SE.
- H6: AILHAIC mediates between AIUP and SE.
- H7: SES mediates between AIUP and SE.

4. Methodology

4.1. Research design

This study adopted a quantitative research approach, employing a cross-sectional questionnaire survey design to explore the reconstruction pathways of SE among English majors in the AI era. Using Structural Equation Modeling (SEM) as the core analytical method, the study examined the impact mechanisms of AIUP, SES, and AILHAIC on SE in the AI Era. By setting AIUP, SES, and AILHAIC as independent variables and SE as the dependent variable, the study also investigated potential direct, indirect, and mediating effects among these variables. The rationale for adopting a cross-sectional questionnaire design was that this research focused on the psychological perceptions and SE levels of English majors in AI-assisted English learning contexts at a specific point in time, while testing the structural relationships between variables through sample data.

4.2. Participants

This study concentrated on English majors in a Chinese university in Dongguan City, Guangdong Province as the research subjects, distributing questionnaires via an online survey platform in September 2026. Then, a total of 240 questionnaires were collected. To ensure data quality, strict screening of the collected responses was conducted, excluding 26 questionnaires with excessively short (less than 1.5 minutes) or excessively long (4 minutes or more) completion times. The exclusion criteria were based on the following considerations: excessively short completion time may indicate respondents did not carefully read the questions or answered randomly; excessively long completion time may suggest respondents were interrupted or distracted during the survey, both of which could affect the authenticity and reliability of the data. Ultimately, 214 valid questionnaires were obtained, with an effective recovery rate of 89.17%.

Table 1 presents the demographic characteristics of the valid sample (N=214). In terms of grade distribution, freshmen, sophomores, and juniors accounted for 28.0%, 28.5%, and 29.0%, respectively, while seniors made up 14.5%. Regarding gender distribution, females constituted 65.9%, while males accounted for 34.1%. As for AI tool usage frequency, the majority of students used them 3–5 times per week (32.7%), followed by 1–2 times per week (30.4%), nearly daily (14.0%), rarely (18.7%), and never (4.2%). In the most frequently used AI tools for tasks, the most selected combination was “translation and polishing, writing assistance and idea generation, reading material interpretation, English oral practice” (38.8%), followed by “translation and polishing, grammar correction, reading material interpretation” (23.4%) and “translation and polishing, grammar correction, English oral practice” (17.3%).

Table 1. Demographic characteristics of participants (N=214)

Variable	Category	Frequency (n)	Percent (%)
Grade	Freshman	60	28.0
	Sophomore	61	28.5
	Junior	62	29.0
	Senior	31	14.5
Gender	Male	73	34.1
	Female	141	65.9

AI Tool Usage Frequency	Almost Every Day	30	14.0
	3–5 Times a Week	70	32.7
	1–2 Times a Week	65	30.4
	Rarely Use	40	18.7
	Never Use	9	4.2
Most Common Tasks Completed with AI Tools	Translation and Polishing	2	0.9
	Translation and Polishing; Grammar Correction; Explanation of Reading Materials	50	23.4
	Translation and Polishing; Grammar Correction; English Conversation Practice	37	17.3
	Translation and Polishing; English Conversation	2	0.9
	Translation and Polishing; English Conversation Practice; Other Foreign Trade Knowledge	1	0.5
	Translation and Polishing; Writing Assistance and Idea Inspiration; Explanation of Reading Materials	1	0.5
	Translation and Polishing; Writing Assistance and Idea Inspiration; Explanation of Reading Materials; English Conversation Practice	83	38.8
	Translation and Polishing; Writing Assistance and Idea Inspiration; Grammar Correction	1	0.5
	Translation and Polishing; Writing Assistance and Idea Inspiration; Grammar Correction; Explanation of Reading	3	1.4
	Translation and Polishing; Writing Assistance and Idea Inspiration; Grammar Correction; Explanation of Reading Materials; English Conversation Practice	3	1.4
	Translation and Polishing; Writing Assistance and Idea Inspiration; Grammar Correction; Other Daily Life Problems	1	0.5
	Writing Assistance and Idea Inspiration	1	0.5
	Writing Assistance and Idea Inspiration; Explanation of Reading Materials; English Conversation Practice	9	4.2
	Writing Assistance and Idea Inspiration; Grammar Correction; English Conversation Practice	20	9.3
	Total	214	100

4.3. Data collection

This study used anonymous online questionnaires for data collection. The questionnaire was categorized into five parts. The first part was basic information, including grade, gender, frequency of AI tool usage, and the types of tasks most commonly completed using AI tools. The second part was AIUP, developed based on the TAM dimension, mainly measuring perceived usefulness and perceived ease of use (4 items). The third part was SE in the AI era, which was the dependent variable of this study and was used to measure the confidence level of English majors in their own English abilities in AI-assisted English learning contexts (5 items). The fourth part was the SES, compiled based on Bandura's SET, which included four sources of efficacy: success or failure experience, substitution experience, verbal persuasion, and emotional and physiological states (4 items). The fifth part was AILHAIC, which was used to measure students' critical thinking of AI-generated content, recognition of AI strengths and limitations, awareness of human-machine collaboration,

and self-management ability in AI use (7 items). Except for basic information and multiple-choice questions, all questionnaire items were scored using the Likert five-point scoring system, ranging from 1 (strongly disagree) to 5 (strongly agree). Before the formal distribution of the questionnaire, the clarity of expression and content validity of the questionnaire items were checked and revised to ensure that the participants could accurately understand the meaning of the items.

4.4. Data analysis

Data analysis was mainly completed using SPSS 25.0 and AMOS 24.0, which were divided into the following steps: (1) data screening and cleaning: Excluding invalid questionnaires according to the response time standard, and conducting missing value checks and outlier handling on the remaining data; (2) descriptive statistical analysis: Performing frequency and percentage statistics on the demographic characteristics of the sample, and calculate the mean, standard deviation, skewness, and kurtosis of each variable to test whether the data satisfies the assumption of normal distribution; (3) reliability and validity testing: Using Cronbach's alpha coefficient and Composite Reliability (CR) to test the internal consistency of each scale; Confirmatory Factor Analysis (CFA) was used to test the convergence validity and discriminant validity of the model, and in the meantime the Average Variance Extracted (AVE) was calculated; (4) correlation analysis: Utilizing Pearson correlation analysis to investigate the correlation between AIUP, SES, AILHAIC, and SE, and providing a foundation for subsequent SEM analysis; (5) SEM analysis: Constructing a structural equation model to examine the direct, indirect, and total effects of AIUP, SES, and AILHAIC on SE. The model fit was evaluated by means of multiple indicators, including Chi-square statistics, Non-Normed Fit Index (NFI), Relative Fit Index (RFI), Incremental Fit Index (IFI), Tucker-Loo-Improved Fit Index (TLI), Comparative Fit Index (CFI), and Root Mean Square Error of Approximation (RMSEA). Meanwhile, the bootstrap method (repeated sampling 5000 times) to test the significance of indirect effects was also implemented. The significance level was set to $P < 0.05$.

4.5. Ethical considerations

This study followed ethical standards for research involving human subjects. All participants were informed of the research purpose, anonymity principle, voluntary participation principle, and data confidentiality principle before filling out the questionnaire. The questionnaire did not collect any personally identifiable information, and all data were used only for academic research and properly stored. Participants were also informed that they could withdraw at any time without any negative consequences. Informed consent was obtained implicitly through the completion and submission of the online questionnaire.

5. Results

5.1. Reliability test results

Table 2 presents the reliability test results of each scale ($N=214$). Analysis shows that AIUP consists of four items, with a Cronbach's alpha coefficient of 0.911. SE contains 5 items, with an alpha coefficient of 0.845. SES covers four items, with an alpha coefficient of 0.885. AILHAIC is composed of 7 items, with an alpha coefficient of 0.853. The total scale includes 20 items, with an overall alpha coefficient of 0.911. The Cronbach's alpha coefficients for all dimensions are higher than 0.8, indicating that the scale used in this study has high internal consistency reliability and stable, reliable measurement results.

Table 2. Reliability test results (N=214)

Variable	Number of Items	Cronbach's α Coefficient
AIUP	4	0.911
SE	5	0.845
SES	4	0.885
AILHAIC	7	0.853
Total Scale	20	0.911

5.2. Validity test results

Figure 2 and **Table 3** demonstrate the fit indices of the CFA model for the scale used in this study (N=214). The results show that the value of Chi-Square Minimum/Degrees of Freedom (CMIN/DF) is 1.213, falling within the ideal range of 1–3. The RMSEA is 0.032, which is less than 0.05. The NFI, RFI, IFI, TLI, and CFI are 0.919, 0.906, 0.985, 0.982, and 0.985, respectively, all exceeding 0.9. All these indices meet the excellent standard, indicating that the measurement model in this study fits the data well. The scale exhibits good construct validity.

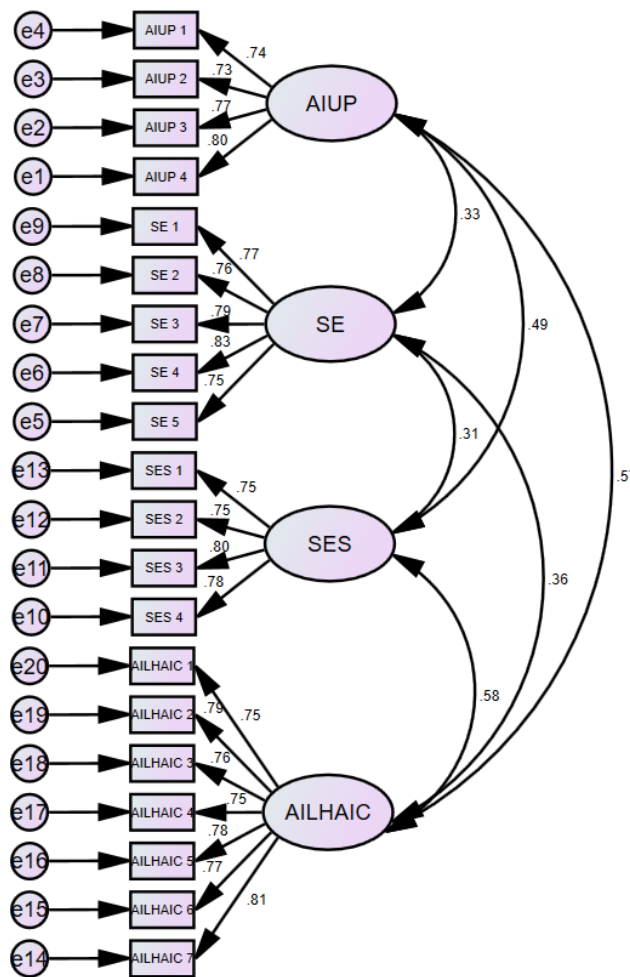


Figure 2. Scale CFA model diagram (N=214)

Table 3. CFA model fit indices for the scale (N=214)

Index	Reference Standard	Actual Results
CMIN/DF	1-3 Excellent, 3-5 Good	1.213
RMSEA	<0.05 Excellent, <0.08 Good	0.032
NFI	>0.9 Excellent, >0.8 Good	0.919
RFI	>0.9 Excellent, >0.8 Good	0.906
IFI	>0.9 Excellent, >0.8 Good	0.985
TLI	>0.9 Excellent, >0.8 Good	0.982
CFI	>0.9 Excellent, >0.8 Good	0.985

At the same time, **Table 4** shows the results of the convergent validity and CR tests for each scale (N=214). The results display that the standardized factor loadings for each item of AIUP, SE, SES, and AILHAIC are greater than 0.7 (ranging from 0.734 to 0.827). The AVE value for each dimension is greater than 0.5 (ranging from 0.5805 to 0.6088), and the CR value for each is greater than 0.7 (ranging from 0.8469 to 0.9125). This implies that each scale has good convergent validity and CR.

Table 4. The results of convergent validity and CR (N=214)

	Path Relationship		Estimate	AVE	CR
AIUP4	<---	AIUP	0.797	0.5805	0.8469
AIUP3	<---	AIUP	0.775		
AIUP2	<---	AIUP	0.734		
AIUP1	<---	AIUP	0.740		
SE5	<---	SE	0.755	0.6088	0.8860
SE4	<---	SE	0.827		
SE3	<---	SE	0.788		
SE2	<---	SE	0.760		
SE1	<---	SE	0.769	0.5922	0.8530
SES4	<---	SES	0.778		
SES3	<---	SES	0.799		
SES2	<---	SES	0.751		
SES1	<---	SES	0.749	0.5986	0.9125
AILHAIC7	<---	AILHAIC	0.810		
AILHAIC6	<---	AILHAIC	0.769		
AILHAIC5	<---	AILHAIC	0.781		
AILHAIC4	<---	AILHAIC	0.754		
AILHAIC3	<---	AILHAIC	0.762		
AILHAIC2	<---	AILHAIC	0.789		
AILHAIC1	<---	AILHAIC	0.749		

What is more, **Table 5** mirrors the results of the discriminant validity test for each variable (N=214). The values on the diagonal of the table represent the square roots of the AVE for each variable, which are AIUP=0.762, SE=0.708, SES=0.77, and AILHAIC=0.774, respectively. These values are all greater than the

correlation coefficients between this variable and other variables (the non-diagonal values range from 0.307 to 0.584), meaning that there is both a certain correlation among the variables and good discriminant validity. Among them, the correlations between AILHAIC and SES (0.584) and between AILHAIC and AIUP (0.574) are relatively high, but still lower than the corresponding square roots of AVE, suggesting that the dimensions can be effectively distinguished and the measurement model has good discriminant validity.

Table 5. Discrimination validity test results (N=214)

Variable	AIUP	SE	SES	AILHAIC
AIUP	0.762			
SE	0.329	0.708		
SES	0.489	0.307	0.77	
AILHAIC	0.574	0.355	0.584	0.774

5.3. Normality test results

Table 6 presents the results of the normality test for each variable (N=214). The results show that the mean of AIUP is 3.597, with a standard deviation of 0.962, a skewness of -0.893, and a kurtosis of -0.456. The mean of SE is 3.569, with a standard deviation of 0.996, a skewness of -0.964, and a kurtosis of -0.389. The mean of SES is 3.661, with a standard deviation of 0.968, a skewness of -0.968, and a kurtosis of -0.268. The mean of AILHAIC is 3.682, with a standard deviation of 0.928, a skewness of -1.081, and a kurtosis of -0.274. The absolute values of skewness for each variable are all less than 2, and the absolute values of kurtosis are all less than 7, demonstrating that the data generally conform to the normal distribution assumption and are suitable for SEM analysis using the Maximum Likelihood method.

Table 6. Normality test results (N=214)

Variable	Mean	Std. Deviation	Skewness	Kurtosis
AIUP	3.597	0.962	-0.893	-0.456
SE	3.569	0.996	-0.964	-0.389
SES	3.661	0.968	-0.968	-0.268
AILHAIC	3.682	0.928	-1.081	-0.274

5.4. Results of correlation analysis

Table 7 reveals the results of the correlation analysis among the four main variables (N=214). The results reflect that AIUP is significantly and positively correlated with SE ($r=0.291$, $P<0.01$), SES ($r=0.413$, $P<0.01$), and AILHAIC ($r=0.509$, $P<0.01$). SE is significantly and positively correlated with SES ($r=0.270$, $P<0.01$) and AILHAIC ($r=0.321$, $P<0.01$). SES is also significantly and positively correlated with AILHAIC ($r=0.514$, $P<0.01$). All correlation coefficients are statistically significant at the 0.01 level (two-tailed), indicating that the four variables are positively associated with one another and providing preliminary support for the hypothesized relationships in the structural model.

Table 7. Results of correlation analysis (N=214)

Variable	AIUP	SE	SES	AILHAIC
AIUP	1			
SE	0.291**	1		
SES	0.413**	0.270**	1	
AILHAIC	0.509**	0.321**	0.514**	1

Note: ** Correlation is significant at the 0.01 level (2-tailed).

5.5. SEM results

5.5.1. Model fit indices

Table 8 presents the model fit test results of the structural equation model (N=214). The results show that the CMIN/DF value is 1.367, which matches the excellent range of 1-3. The RMSEA is 0.041, which is below the excellent threshold of 0.05. Then, NFI is 0.908, RFI is 0.894, IFI is 0.974, TLI is 0.969, and CFI is 0.973. Among these, NFI, IFI, TLI, and CFI all exceed 0.9, indicating excellent fit, while RFI is 0.894, which is slightly below 0.9 but still above the acceptable threshold of 0.8 and very close to the excellent level. On the whole, all fit indices meet the recommended standards, displaying that the hypothesized structural model fits the data well and is appropriate for further path analysis and hypothesis testing.

Table 8. Model fit test results (N=214)

Index	Reference Standard	Actual Results
CMIN/DF	1-3 Excellent, 3-5 Good	1.367
RMSEA	<0.05 Excellent, <0.08 Good	0.041
NFI	>0.9 Excellent, >0.8 Good	0.908
RFI	>0.9 Excellent, >0.8 Good	0.894
IFI	>0.9 Excellent, >0.8 Good	0.974
TLI	>0.9 Excellent, >0.8 Good	0.969
CFI	>0.9 Excellent, >0.8 Good	0.973

5.5.2. Results of path relationship and hypothesis test

Table 9 and **Figure 3** exhibit the results of the path relationship and hypothesis testing of the structural equation model (N=214). The results indicate that AIUP has a significant positive effect on SE ($\beta=0.161$, $P<0.05$), SES ($\beta=0.530$, $P<0.001$), and AILHAIC ($\beta=0.607$, $P<0.001$), supporting H1, H2, and H3, respectively. In addition, SES has a significant positive effect on SE ($\beta=0.116$, $P<0.05$), supporting H4, and AILHAIC also has a significant positive effect on SE ($\beta=0.197$, $P<0.05$), supporting H5. All five hypothesized paths are statistically significant, indicating that AIUP, SES, and AILHAIC are all significant predictors of SE.

Table 9. Results of path relationship and hypothesis test (N=214)

Path Relationship			Standardized Estimate	S.E.	C.R.	P	Hypothesis Test
SE	<---	AIUP	0.161	0.115	1.389	0.015	H1 (Valid)
SES	<---	AIUP	0.530	0.082	6.323	***	H2 (Valid)
AILHAIC	<---	AIUP	0.607	0.081	7.676	***	H3 (Valid)

SE	<---	SES	0.116	0.094	1.251	0.011	H4 (Valid)
SE	<---	AILHAIC	0.197	0.095	2.028	0.043	H5 (Valid)

Note: *** $P < 0.001$.

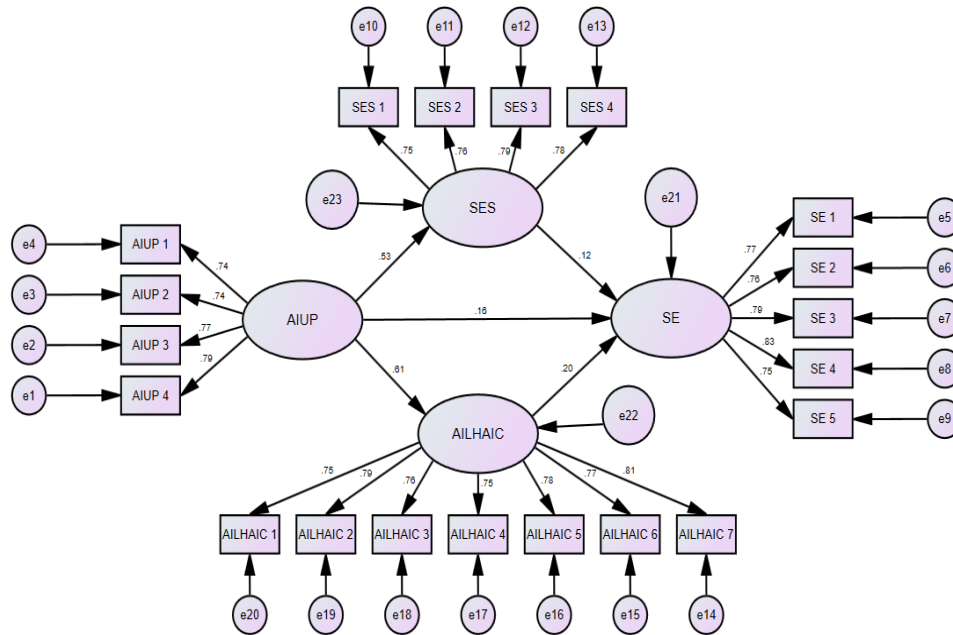


Figure 3. The SEM path diagram of the measurement model (N=214)

As for research hypotheses H6 and H7, **Table 10** reveals the results of the Bootstrap analysis (5,000 resamples) used to test the indirect effects. The mediating path AIUP→AILHAIC→SE (H6) has an indirect effect of 0.120, with a standard error of 0.046 and a 95% confidence interval of [0.034, 0.215], which does not include zero ($p < 0.01$), indicating that AILHAIC significantly mediates the relationship between AIUP and SE. The mediating path AIUP→SES→SE (H7) has an indirect effect of 0.062, with a standard error of 0.038 and a 95% confidence interval of [0.010, 0.140], which also does not include zero ($P < 0.01$), indicating that SES also significantly mediates the relationship between AIUP and SE. Both mediation effects are statistically significant, though the indirect effect of H6 (0.120) is larger than that of H7 (0.062), suggesting that AILHAIC plays a stronger mediating role than SES in the relationship between AIUP and SE.

Table 10. Mediation effect bootstrap test results (N=214)

Mediating Path	Indirect Effect	SE	95% Confidence Interval	<i>P</i>
AIUP→AILHAIC→SE (H6)	0.120	0.046	[0.034, 0.215]	0.007
AIUP→SES→SE (H7)	0.062	0.038	[0.010, 0.140]	0.008

6. Discussion

6.1. The direct effect of AIUP on SE in the AI era

This study found that AIUP has a significant positive impact on SE in the AI era ($\beta = 0.161$, $P = 0.015$), supporting H1. This result aligns with the fundamental viewpoint of the TAM, which suggests that

individuals' perceptions of technology's usefulness and ease of use influence their usage behavior and psychological state. In the context of AI-assisted English learning, students who perceive AI tools as helpful in enhancing English learning efficiency and easy to operate and master are more likely to integrate them into their daily learning and gain confidence in their English abilities during use. This finding is consistent with the research conclusions of Ouchene and Belmekki (2025), indicating that the more positive the perception of AI usage, the stronger students' engagement and autonomous learning abilities. Furthermore, this study confirms that AIUP not only affects learning behavior but also directly impacts students' SE, providing empirical support for Qiu's (2025) viewpoint on the impact of AIUP on students' psychological state.

6.2. The mediating role of SES and AILHAIC

This study revealed that AIUP indirectly influences SE through two paths: SES and AILHAIC, with both H6 and H7 being supported. Specifically, the indirect effect of $\text{AIUP} \rightarrow \text{AILHAIC} \rightarrow \text{SE}$ is 0.120 (95% CI [0.034, 0.215]), and the indirect effect of $\text{AIUP} \rightarrow \text{SES} \rightarrow \text{SE}$ is 0.062 (95% CI [0.010, 0.140]), both of which are significant. This indicates that AIUP can influence students' SE both by enhancing their SES and by improving their AILHAIC skills.

Specifically, AIUP has a significant positive impact on SES ($\beta=0.530$, $P<0.001$), supporting H2. This proves that students who have a positive perception of AI tools are more likely to gain experience of success and failure, vicarious learning, verbal persuasion, and positive emotional experiences during human-computer collaboration, thereby strengthening their SES. This result is the same as the findings of Hongxia and Razali (2026), Wu et al. (2026), and Yan et al. (2025), which suggest that successful human-computer collaboration, observing peers using AI, teacher encouragement, and reduced anxiety can all enhance students' SE.

Meanwhile, AIUP has a significant positive impact on AILHAIC ($\beta=0.607$, $P<0.001$), supporting H3. This verifies that students with a more positive perception of AI use are more likely to develop higher AILHAIC skills. This result aligns with the findings of Zhang et al. (2025), who found that students with higher AI literacy are better at critically using AI tools and maintain a higher level of autonomy and self-confidence in English learning.

Furthermore, SES has a significant positive impact on SE ($\beta=0.116$, $P<0.05$), supporting H4; AILHAIC has a significant positive impact on SE ($\beta=0.197$, $P<0.05$), supporting H5. This indicates that SES, along with AILHAIC ability, are important predictors of SE in the AI era. This result further validates the applicability of Bandura's (1982) SET in the AI era and expands its scope of application in emerging technology contexts.

6.3. Comparison of two mediating paths

By comparing the indirect effects of H6 and H7, it can be seen that the mediating effect of AILHAIC (0.120) is greater than that of SES (0.062), implying that AILHAIC plays a stronger mediating role in the process of AIUP affecting SE. This result has important theoretical and practical significance. Theoretically, this result indicates that in AI-assisted English learning, merely acquiring SES (such as successful experiences, teacher encouragement, etc.) is insufficient to fully enhance students' SE. More importantly, students need to possess high AILHAIC skills in order to transform their perception of AI use into stable SE. This matches the human-machine collaborative learning framework proposed by Molenaar (2022), which suggests that AI should serve as a learning partner rather than a substitute, and students need to maintain critical thinking and autonomy in human-machine collaboration. Practically, this result suggests that English teaching reform should place

greater emphasis on cultivating students' AILHAIC skills. Teachers should not only encourage students to use AI tools, but also guide them to critically evaluate AI-generated content, understand the strengths and limitations of AI, and manage AI usage behavior reasonably, thereby enhancing their confidence in English learning through human-machine collaboration.

7. Conclusion

7.1. Summary of key findings

This study takes 214 English majors as the research subjects, integrates Davis's TAM, Bandura's SET, and the concepts of AILHAIC, constructs a structural equation model, and explores the influence paths of AIUP, SES, and AILHAIC on SE in the AI Era. The main research findings are as follows. First, AIUP has a significant positive impact on SE in the AI era. This indicates that the more positive English majors perceive the usefulness and ease of use of AI tools, the higher their SE. Second, AIUP has a significant positive impact on SES and AILHAIC, showing that students' positive perception of AI tools aids them in gaining experience of success and failure, vicarious experience, verbal persuasion, and positive emotional experiences during human-machine collaboration. Simultaneously, it also contributes to enhancing their AILHAIC skills. Third, SES and AILHAIC have a significant positive impact on SE. This implies that SES and AILHAIC are vital predictive variables for SE in the AI era. Fourth, both SES and AILHAIC play a significant mediating role between AIUP and SE. Specifically, the mediating effect of AILHAIC (0.120) is stronger than that of SES (0.062), indicating that AILHAIC exerts a stronger mediating effect in the process where AIUP influences SE.

7.2. Research limitations and future directions

Although this study makes great contributions to integrating the TAM, SET, and AILHAIC concepts to construct and validate a structural equation model containing two mediating paths, there are still some limitations. First, the study adopts a cross-sectional questionnaire design, which cannot strictly infer the causal relationship between variables. Future research can adopt a longitudinal tracking design or experimental research to verify this. Second, the sample is only from English majors in one university, with limited representativeness. Future research can expand the sample scope to include English majors from different regions and types of universities. Third, this study mainly uses self-report questionnaires, which may have common method bias. Future research can combine qualitative interviews, classroom observations, and other methods for triangulation. Fourth, this study does not include other variables that may affect SE, such as AI usage experience, English proficiency, learning motivation, etc. Future research can further expand the research model.

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Disclosure statement

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