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AI Competency, Attitudes, and Experience as Predictors of Overall Learning Interaction via AI Integration and Creative Tasks in GenAI-Supported EFL Classrooms

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Abstract:

Although generative AI is increasingly integrated into higher education, its impact on students' learning experience remains unclear. This study examined factors predicting learning interactions in EFL (English as a Foreign Language) contexts, focusing on students' AI competency, attitudes, and experience. Grounded in constructivist theory and the WEST model (Will, Experience, Skill, and Tools), a questionnaire was administered to 884 students at a Chinese higher vocational college. Structural equation modeling shows that AI integration and involvement in creative tasks directly predict learning interaction, while competency, attitudes, and experience exert indirect effects via these variables. Theoretically, this study provides quantitative evidence that students' AI-related characteristics may contribute to learning interaction through AI-supported learning practices and creative task involvement. In practice, students can be more active in classroom interactions by adopting AI tools and participating in appropriate creative tasks designed by their teachers. Consequently, teachers play an important role in determining how AI tools are integrated and what types of tasks are assigned to students in the English classroom to support a better interactive learning environment.

Keywords: learning interaction; AI integration; creative tasks; EFL learning; improving classroom teaching.

1. Introduction

Generative AI, exemplified by ChatGPT, is increasingly impacting our work, lives, and studies; these large language models can predict, understand, and generate text with high accuracy and human-like quality[1]. It has attracted widespread attention across all sectors of society for its powerful language capabilities and astonishing speed of iteration. The academic community is combining generative AI with the characteristics of their respective disciplines to explore its potential applications and methods[2]. The revolution led by these AI tools has brought significant changes in education and pedagogy, especially in English as a foreign language (EFL) learning, as English learners can make full use of them to produce better language and understand information originally accessible only to competent users of English. They may be able to convey their ideas more accurately and fluently by using AI tools efficiently. In college English classrooms, integrating this AI-based technology has become a trend. However, how to apply this new technology to improve the learning interaction, which is a basic part of language learning, still needs to be explored.

Theoretically, research on learning interaction primarily stems from the cognitive and sociocultural schools of thought. Long-established, the interaction hypothesis is a cornerstone of cognitive interaction theory. Its core argument is that learners need to resolve communication breakdowns stemming from comprehension barriers through interaction, thereby engaging in meaning negotiation. Meanwhile, there is a process known as form negotiation, in which native speakers or those with stronger language skills may help learners adjust discourse structure to make it easier for

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them to understand[3] The sociocultural school, grounded in concepts like internalization, zone of proximal development, and scaffolding, views interaction as a social adjustment process learners undergo during learning to obtain assistance from experts or more capable individuals, thereby achieving internalization. During interaction, learners receive scaffolding-like support from their interaction partners.

To understand what learning interaction is and how it works, many scholars have proposed their ideas. Learning interaction refers to the continuous interaction between learners and learning elements, through which learners adjust their behavior and cognition, and is regarded as an effective motivator in foreign language learning[4]. Interaction stems from the communicative function of language and is an important condition and core element of second language learning[5]. Learning is not merely an interaction between students and individual learning elements, but also a result of interactions between learners and their entire ecological environment. Interaction creates contextualized opportunities for learners to use their second language and allows them to verify their language hypotheses based on feedback received[4]absorbing knowledge and skills from the interactive environment, thereby improving their second language proficiency.

To apply AI integration in EFL learning, several ideas have been proposed by various scholars and practitioners. For teachers, GenAI can serve as an instructional co-designer by helping create learning materials, including presentation slides, worksheets, and lesson plans. For students, GenAI may serve as a tutor providing personalized guidance on writing, project building, and self-regulated learning[6]. It also functions as a feedback supplier, cognitive enhancer, interaction facilitator, and conversational partner[7]. A multimodal large language model can be used as an effective way to enhance interaction[8]. Teachers are encouraged to use the ICE model (Idea, Connection, Expansion), grounded in Bloom's Taxonomy, to assess and build on ChatGPT-generated work. First, students fact-check key ideas. Second, they refine the content to adapt to the language expression. Third, they extend the content by connecting it to personal experience or demonstrating learning through authentic tasks or alternative formats[9]. The Cognitive Theory of Multimedia Learning (CTML) framework proposes that learners follow the processes of selecting relevant information, organizing learning materials, integrating materials, and discussing in context[10].

Despite the growing attention to AI integration in EFL learning, significant gaps remain in the literature. First, prior studies offer suggestions and recommended procedures for integrating generative AI into English classrooms, but these approaches to enhancing classroom interaction still require empirical support. Second, English learning urgently needs to improve students' interactive abilities and adapt to the technological advancements of the AI era to enhance learning efficiency. However, the factors associated with interactive English learning require empirical evidence; how these predictive factors can inform the development of new models of English learning warrants further exploration. Based on the above background, the following research question is proposed:

What factors predict student English learning interaction in the context of generative AI?

2. Literature review

2.1 The West model

This study adopts a constructivist perspective, which holds that learners construct new ideas and concepts during learning activities based on their prior and existing knowledge[11]. Educator John Dewey argued that learning should be closely integrated with real life, and that knowledge and skills should be acquired through practical activities. This perspective emphasizes active student participation and exploration[12]. Moreover, it is also the theoretical basis for the "learning by doing" approach in

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vocational colleges. This corresponds to the “AI integration” and "involvement in creative tasks" variables, both of which are closely related to practical action in this study.

This study is based on the Will, Experience, Skill, and Tools (WEST) theoretical model, which reveals the different factors influencing the integration of generative AI into the learning process. It originated from the Will, Skill, Tool model by Knezek[13], and later, the technology experience factor was added in technology integration[14]. The WEST model encompasses numerous factors affecting technology integration, including attitudes and beliefs towards technology (will), learning experience (experience), technological skills (skill), and access to technological tools (tool)[14]. This study omitted the "tool" dimension, which refers to the availability of technological infrastructure that enables the use of technology, because, in the context of generative AI, this dimension has been substantially transformed. Generative AI tools are widely accessible in China through free web-based platforms and mobile applications, significantly reducing traditional barriers related to access, cost, and institutional availability. In the present study, all participants were provided with equal access to generative AI tools within an instructional environment supported by the institution's internet infrastructure. Therefore, variability in “tool” is minimized; it does not function as a meaningful explanatory construct for individual differences in AI integration behavior, and it is viewed as a constant environment. Additionally, to explore the mechanism of learning interaction, the research hypotheses need to be validated: that AI integration and involvement in creative tasks are directly associated with learning interaction.

2.2 **Learning interaction**

Interaction is a reciprocal process requiring at least two entities and two actions; interaction occurs when these entities and actions influence each other[15]. Interaction enables learners to connect existing knowledge with new information and construct new meaning through analysis or integration. Learning interaction is considered one of the decisive factors that can influence academic performance[16]. In the AI era, learning interaction can be divided into three dimensions: learner-instruction interaction, learner-learner interaction, and learner-AI interaction[17].

Interaction exhibits diverse characteristics, encompassing traditional learner-instructor and peer interactions in the classroom, as well as learner-AI interactions with tools such as ChatGPT[17]. Learner-instructor interaction refers to the mutual exchange between learners and course instructors, encompassing the feedback given to each other during the interaction[18]. Learner-learner interaction refers to the communication and collaboration among learners[19]. Learner-AI interaction mainly refers to the process by which learners use AI tools for learning and thinking, which plays a positive role in promoting the development of language complexity among English learners[17].

Effectively combining appropriate teaching methods with technology can enhance the interaction process between students and teachers or learning content[20]. Integrating artificial intelligence tools in higher education can improve personalized learning, engagement, and learning motivation, while also fostering collaborative learning environments. [21].

2.3 AI integration

Technology integration refers to an individual’s adoption of technology[22]. AI integration refers to the extent to which generative AI is integrated into English learning and is evaluated from a behavioral perspective. According to the WEST model, the integration of new technologies is associated with learners' experience, attitudes, and abilities[23]. Previous empirical research in language education has demonstrated that the effective integration of GenAI systems in classroom settings can facilitate

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language acquisition, including speaking and writing performance, by providing immediate feedback and personalized instruction[7]. AI integration in higher education has been proven to enhance cognitive achievement and student learning behavior. It is assumed to have the capacity to improve the learning experience by increasing engagement, personalization, efficiency, and creativity[24]. Engagement, immediate feedback, cognitive achievement, learning behavior, and creativity are all closely related to interaction in English learning. AI integration simulates real-time interaction and transforms learning from an individual activity to a socially mediated one[25].

A pedagogically guided AI integration can promote interaction, autonomy, competency, and responsible learning[26]. AI-generated feedback greatly increased the motivation, academic emotion, and trait EI of EFL students while also improving their writing abilities[27]. Thematic analysis showed that AI tools enabled educators to create dynamic, student-centered learning environments and greatly enhanced students' speaking and listening abilities[28]. AI-ready pedagogies greatly enhance EFL learning results, particularly in areas like writing accuracy, speaking fluency, and student motivation, leading to a decrease in anxiety and a rise in students' enjoyment[29]. Problems with AI integration exist, such as academic dishonesty, unreliable information sources, academic integrity, and over-reliance[7]. The use of generative AI may also lead to ethical and psychological tensions, including uncertainty about creativity, effort, over-reliance, and the boundary between student work and AI assistance[30]. Positive attitudes and AI experience might not always result in positive interactions unless they are accompanied by task designs that maintain student agency and critical thinking, reflective pedagogy, and AI literacy[30].

2.4 Competency, attitudes, and experience with generative AI

Competency in generative AI refers to the fundamental skills and knowledge of generative AI technologies, and how to apply them to achieve personal and educational goals[31]. Technological competency is crucial for the successful integration of technology. Technological expertise helps individuals progress in innovation and creative development. In the business scope, Generative AI expertise can predict managers' ability to integrate and manage generative AI technologies[23].

Attitude refers to the extent to which an individual perceives and values a particular technological application[32]. Attitude towards generative AI refers to the degree of interest and positive evaluation that students have in using it in English learning activities. Teachers' attitudes significantly predict the integration of technology in the classroom. Attitudes and beliefs play a crucial role in planning and implementing technology. Attitudes towards generative AI are positively correlated with its integration and involvement in creative tasks[23].

Generative AI experience refers to the quantity and quality of firsthand experience with AI integration in the learning process[33], and it is evaluated from the cognitive aspect. Experience is a significant motivating factor in integrating technology into the learning process[23]. Experience with technology predicts technology integration[14]. Managers' experience using AI is significantly linked to a company's integration of AI technologies[23].

2.5 Involvement in creative tasks

Engagement in creative tasks refers to the extent to which individuals participate in creative work tasks[34]. Numerous studies have confirmed that engagement in creative tasks has a positive effect on or mediates a range of dependent variables, promoting learning and improvement in various contexts[23]. In a collaborative learning environment, creative tasks can improve students' academic performance in reading and writing and enhance group creativity and collaboration[35]. Collaborative learning and collaboration levels are manifestations of learning interaction. Recreational creative activities for youth

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are reported to foster communication, reinforce social ties, and facilitate greater collaboration[36]. In language education, creative oral tasks triggered more negotiation of meaning and interaction among participants than controlled tasks, as students needed to make more requests for clarification and confirmation during group work[37].

3. Research methods and materials

3.1 Research framework

Studying earlier research frameworks led to the development of the conceptual framework. It is mainly adapted from the WEST model, which originated from preservice teacher training[13] and was applied in the business scope[23]. Figure 1 presents the study's research framework.

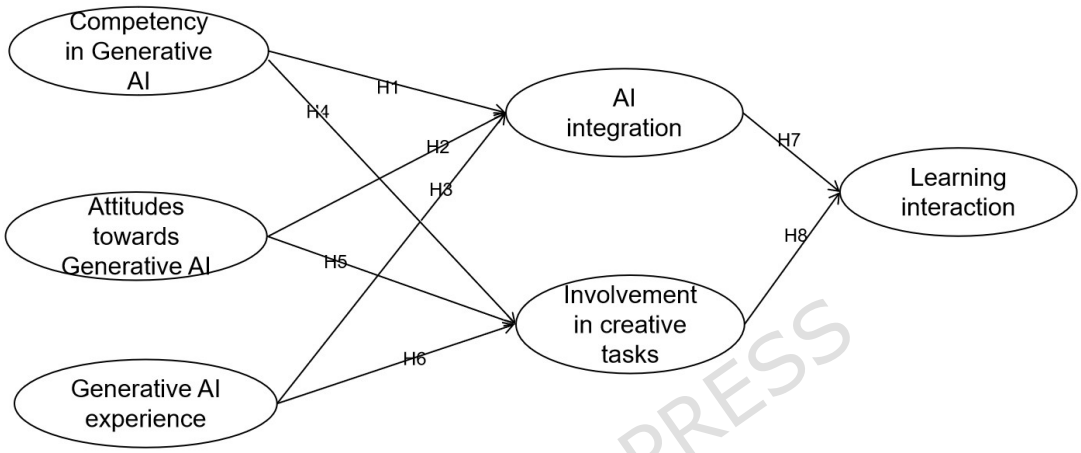

Fig. 1 Conceptual framework and hypothesized research model. This model proposes the relationships among students' competency in generative AI (CG), attitudes towards generative AI (AG), generative AI experience (AE), AI integration (AI), involvement in creative tasks (ICT), and learning interaction (INTERACTION) in EFL learning contexts. The arrows represent the hypothesized relationships among the constructs. Specifically, AI integration and involvement in creative tasks are hypothesized as mediators linking students' generative AI competency, attitudes, and experiences to learning interaction. The model assumes that AI-related competency, attitudes, and experience may enhance learning interaction through increased AI integration and involvement in creative tasks.

To explore how learning interaction occurs in English as a Foreign Language (EFL), this research intends to analyze the key predictors of learning interaction in EFL and evaluate their predictive power. These factors include competency in generative AI, attitudes towards generative AI, generative AI experience, AI integration, and involvement in creative tasks. Additionally, it examines the mediating roles of AI integration and involvement in creative tasks in student learning interaction. Therefore, the following hypotheses are to be tested.

H1: Competency in generative AI has a significant association with AI integration.
H2: Attitudes towards generative AI have a significant association with AI integration.
H3: Generative AI experience has a significant association with AI integration.
H4: Competency in generative AI is significantly associated with Involvement in creative tasks.
H5: Attitudes towards generative AI have a significant association with Involvement in creative tasks.
H6: Generative AI experience has a significant association with Involvement in creative tasks.
H7: AI integration is significantly associated with learning interaction.
H8: Involvement in creative tasks has a significant association with learning interaction.

3.2 Methodology

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The target population of this study was higher vocational college students. The sample was drawn from one higher vocational college located in Chengdu, China, using a non-probability convenience sampling method. Given the sampling method and the fact that data were collected from a single institution, the sample is not representative of all Chinese EFL learners or all higher education students in China. Therefore, the findings should be interpreted as context-specific, and generalizations to broader populations should be made with caution. The primary purpose of this study is to examine the proposed relationships among variables within this specific sample, rather than to make broad population claims.

The questionnaire was sent to the target group online via the popular survey website SurveyStar. The data were gathered and examined for key factors assumed to affect student learning interactions significantly. There are three sections of the survey. First, the screening questions are used to obtain respondents' consent to participate in the survey. The second type of questions concerns demographic information, such as gender, grade, and years of English study. Third, six suggested variables were measured on a 5-point Likert scale ranging from strong disagreement (1) to strong agreement (5) to examine all eight hypotheses.

The scales were adapted from previously validated instruments. Measures of competency in generative AI, attitudes toward generative AI, generative AI experience, generative AI integration, and involvement in creative tasks were adapted from Korayim et al.[23]. Although some constructs are conceptually related, as they all concern students' AI use in learning, they represent different aspects of AI-supported learning. For example, the AI experience scale asks respondents about their prior exposure to and familiarity with AI tools. In contrast, the AI competency scale measures their self-perceived ability to use AI effectively. The learner-AI interaction scale focuses on the frequency and quality of exchanges with AI during learning. In contrast, the AI integration scale captures the extent to which AI is embedded in learning activities.

In contrast, the learning interaction scale was adapted from Kuo et al.[20] for the GenAI-supported EFL context. To enhance contextual relevance and reduce participant burden, selected items were retained from the original scale, and the learner-content interaction dimension was modified to reflect learner-AI interaction. Although Kuo et al.[20] conceptualized learner-learner, learner-instructor, and learner-content interactions as distinct dimensions, the present study incorporated these dimensions to capture different forms of interaction in a GenAI-supported EFL environment. It aggregated them into an overall learning interaction construct that reflected students' holistic interactive experience and served as the focal variable in the analysis. As a result, the three dimensions of learning interaction were viewed as a whole and not tested separately. All the measurement items are listed in the appendix.

To ensure participants fully understood the questionnaire items, all measures were translated into Chinese and then back-translated to verify equivalence with the original English version. The translation and back-translation were completed by two researchers with master's degrees in applied linguistics and translation studies, respectively. To confirm the validity of the measurement scales, expert ratings of the index of item-objective congruence (IOC) were obtained. To ensure the reliability of the scales, a pilot test with 60 respondents was conducted, and Cronbach's alpha was assessed. The IOC evaluation of the scales' items, with three experts, was all above 0.6[38] and the Cronbach's Alpha scores of all constructs were above 0.7, indicating acceptable content validity and reliability[39].

Due to the cross-sectional and single-source nature of the data, common method bias (CMB) is a potential concern. Although we cannot statistically rule out CMB, the following procedural remedies were implemented during the survey design: (1) ensuring respondent anonymity to reduce social

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desirability bias, (2) using established and validated scales, and (3) separating conceptually unrelated constructs in the questionnaire [40]. Nevertheless, because all variables were collected from the same respondents using a single questionnaire at one point in time, common method bias cannot be completely ruled out. Therefore, the findings should be interpreted with appropriate caution.

After these tests, the questionnaire was distributed to the target respondents, yielding 884 valid responses. The researcher used Jamovi and SPSS AMOS 26.0 to analyze the data. The convergence accuracy and validity were tested using Confirmatory Factor Analysis (CFA). To verify the model's validity and reliability, the model fit measurement was computed using the entire test with the provided data. Finally, to investigate the structural paths, the researcher used the Structural Equation Model (SEM).

3.3 Population and sample size

The population consists of college students who take college English as a required course. The study's participants are Chinese college students learning English as a foreign language at higher vocational institutions. Students at vocational colleges usually have poor English proficiency and, as a result, have limited interaction with the English teacher, peers, or learning tools. The Structural Equation Model Sample Size Calculator recommends a minimum sample size of 236 when the statistical power is set at 0.95.

3.4 Sampling technique

The study's sample was chosen from the population using convenience sampling, a non-probabilistic sampling technique. Questionnaires were distributed by English instructors to readily accessible students enrolled in AI-supported English courses during the data collection period. 884 college English students from a Chengdu higher vocational college were selected for this study. They were first- or second-grade engineering and liberal arts students who volunteered to participate, reflecting the main academic and demographic characteristics of college EFL students.

The Questionnaire Star website was used to collect data in November 2025. The survey was administered directly to students by their English teachers, who told them to complete it in about 10 minutes, either during class or in their free time.

All methods were carried out in accordance with appropriate regulations and guidelines, and the Institutional Review Board of Chengdu Polytechnic officially approved the study. To ensure that participants took part voluntarily, the study obtained informed consent before data collection. In particular, the 900 students who took part in the survey were informed that participation was entirely voluntary and that their names would stay anonymous. Students verbally confirmed that they could choose to participate, as stated in the survey's introduction. The survey included a screening question that gave students the option to participate in data collection, and they could withdraw at any time before submission, so consent was implied by submitting the questionnaire. As a result, 884 interested students worked with the researchers, and those who chose not to participate in the study did not respond to the questionnaires.

4. Results

4.1 Demographic information

Table 1 Demographic Profile

Variables	Category	Frequency	Percentage
Gender	Male	331	37.4%
	Female	553	62.6%
	Total	884	100%

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Grade	Grade 1	800	90.5 %
	Grade 2	79	8.9 %
	Grade 3	5	0.6%
	Total	884	100%
Discipline area	Engineering	422	47.7%
	Liberal arts	462	52.3%
	Total	884	100%
Years of English study (choose the nearest number of years)	Four years	114	12.9%
	Seven years	315	35.6%
	Ten years	341	38.6%
	13 years	114	12.9%
	Total	884	100%

884 students completed the survey, and their answers were retained for data analysis. The demographic profiles of the 884 participants are listed in Table 1. There were 37.4% male respondents and 62.6% female respondents in the group. Of those in attendance, 90.5% were in grade 1 and 8.9% were in grade 2. This showed that the respondents mainly came from grades 1 and 2, because college students do not have the required English classes in grade 3. In the discipline area, 47.7% of students majored in engineering, and 52.3% majored in liberal arts. 12.9% of students said they had studied English for about four years, 35.6% for about seven years, 38.6% for about ten years, and 12.9% for about thirteen years. Most students reported having 7 or 10 years of English learning experience, meaning they started learning English in the 3rd grade of primary school or the 1st grade of secondary school.

The model was estimated using maximum likelihood (ML) estimation. Descriptive statistics were first examined at the item level. The results indicated that the mean values of all the items ranged from 3.650 to 4.060, suggesting generally positive perceptions across all constructs. Standard deviations ranged from 0.581 to 0.794, indicating acceptable variability. Before CFA, the normality assumptions were examined using skewness and kurtosis. For all measurement items, the skewness values ranged from −0.636 to 0.087, while the kurtosis values ranged from −0.682 to 1.581. All values were within the recommended thresholds for normality (|skewness| < 2 and |kurtosis| < 2), indicating that the data were approximately normally distributed and therefore acceptable for subsequent analyses[41].

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) was employed in the statistical analysis of this study. Confirmatory factor analysis, or CFA, was used to evaluate the fit of the measurement model and the item correlations in the latent variables. The measurement model's convergent and discriminant validity can be confirmed by CFA[42]. Construct validity confirms the relationships or interactions among the constructs in the conceptual framework[43]. The two popular statistical methods for construct validity are convergent and discriminant validity[39]. CFA can be utilized for testing, and the validity test is essential for the research project to guarantee the validity of the constructs[44].

Convergent validity was assessed using factor loadings, average variance extracted, composite reliability, and Cronbach's alpha. Table 2 provides an overview of the findings. Each of the more than three items that make up each variable in Table 3 independently exhibits a factor loading in the discriminant validity test. The factor loadings in the study were appropriate for CFA analysis if the p-value was less than 0.05 and the factor loading was greater than 0.50. CR values of 0.7 or greater and AVE values of 0.5 or greater, respectively, were considered suitable[45]. The AVE values and CR scores

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in this study were mostly higher than the threshold points. The AVE for INTERACTION was 0.452, which is slightly below the commonly recommended threshold of 0.50[45]. However, Fornell and Larcker[45] themselves argued that convergent validity can be considered adequate when composite reliability exceeds 0.60, even if AVE is below 0.50. Given that the CR for INTERACTION is 0.915 (well above 0.60) and all factor loadings are statistically significant and exceed 0.60, the construct was retained with caution. Nevertheless, the relatively low AVE indicates that the convergent validity of this construct should be interpreted cautiously and represents a measurement limitation of the present study.

According to Table 3, the square root of AVE for each diagonal structure was higher than the inter-scale correlations, indicating discriminant validity: 0.764, 0.773, 0.733, 0.737, 0.742, and 0.672. Discriminant validity was therefore guaranteed.

The acceptable fit index value in Table 4 was used to estimate the model fit. Each index's statistical results were compared to the permissible bounds. The seven indices—CMIN/DF = 3.513, GFI = 0.874, AGFI = 0.856, NFI = 0.888, CFI = 0.917, TLI = 0.910, and RMSEA = 0.054- all achieved a satisfactory model fit without any model adjustment.

Table 2 Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of Questionnaire	No. of Items	Cronbach's Alpha	Factors Loading	CR	AVE
Competency in generative AI (CG)	[23]	5	0.874	0.695-0.811	0.874	0.582
Attitudes toward generative AI(AG)	[23]	6	0.874	0.708-0.756	0.875	0.538
Generative AI experience (AE)	[23]	4	0.853	0.730-0.805	0.855	0.597
Generative AI integration (AI)	[23]	5	0.856	0.681-0.785	0.856	0.543
Involvement in creative tasks (ICT)	[23]	4	0.824	0.679-0.780	0.830	0.550
Learning interaction(INTERACTION)	[20]	13	0.913	0.646-0.709	0.915	0.452

Note: CR = Composite Reliability, AVE = Average Variance Extracted

Table 3 Discriminant Validity

	CG	AE	AG	AI	ICT	INTERACTION
CG	**0.764**					
AE	0.619	**0.773**				
AG	0.697	0.724	**0.733**			
AI	0.672	0.730	0.721	**0.737**		
ICT	0.591	0.626	0.620	0.680	**0.742**	
INTERACTION	0.596	0.625	0.637	0.665	0.656	**0.672**

Note: The diagonally listed value is the AVE square roots of the variables.

Table 4 Goodness of Fit for Confirmatory Factor Analysis (CFA)

Index	Acceptable Values	Statistical Values
CMIN/DF	< 5.00[46,47]	3.513
GFI	≥ 0.85[48]	0.874
AGFI	≥ 0.80[48]	0.856
NFI	≥ 0.80[49]	0.888
CFI	≥ 0.80[50]	0.917
TLI	≥ 0.80[51]	0.910
RMSEA	< 0.08[52]	0.054
Model summary		**Acceptable Model Fit**

Remark: CMIN/DF = the ratio of the chi-square value to the degree of freedom, GFI = goodness-of-fit

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index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, IFI = Incremental Fit Indices, CFI = comparative fit index, TLI = Tucker Lewis index, and RMSEA = root mean square error of approximation

4.3. Structural Equation Model (SEM)

To verify model fit, the predictive path between variables, and the factors predicting learning interaction in college EFL, the structural model was assessed using structural equation modeling. The structural model is shown in Figure 2 after being modified to ensure model fit. The path or relationship between the latent variables—which may be direct or indirect—is shown by the structural model. [53].

The model fit was assessed by comparing the acceptable goodness-of-fit values with the statistical values from the indices in Table 5. The indices' statistical values were CMIN/DF = 4.821, GFI = 0.853, AGFI = 0.830, NFI = 0.849, CFI = 0.876, TLI = 0.864, and RMSEA = 0.066. Based on the data, the CMIN/DF, GFI, AGFI, NFI, CFI, TLI, and RMSEA indices were judged acceptable, indicating an adequate but not strong model fit by stricter SEM standards.

To improve model fit, modification indices (MI) were examined following the initial model estimation[54]. Adjustments were made only when MI values exceeded 10 and when the modifications were theoretically justifiable. All modifications were limited to the measurement model; no structural paths were added or deleted among latent variables. Specifically, covariances were added between error terms of indicators within the same latent construct (e.g., between e1 and e2 for CG; between e31 and e32 for INTERACTION). These modifications are justified because items measuring the same construct often share common method variance or content overlap. Additionally, a covariance was added between the residual terms of the two mediators, AI and ICT (e40↔e39), acknowledging that these two related constructs may share unmodeled common causes (e.g., students' overall technological engagement). Covariances were also added between the residual terms of CG and AG (e3↔e7/e8), likely reflecting overlap between behavioral experience and attitudinal evaluation of generative AI. These adjustments do not alter any hypothesized structural paths and are consistent with standard SEM practices[55]All modifications are reported in the Appendix.

Table 5 Goodness of Fit for Structural Model after Adjustment (SEM)

Index	Acceptable Values	Statistical Values After Adjustment
CMIN/DF	< 5.00[46,47]	4.821
GFI	≥ 0.85[48]	0.853
AGFI	≥ 0.80[48]	0.830
NFI	≥ 0.80[49]	0.849
CFI	≥ 0.80[50]	0.876
TLI	≥ 0.80[51]	0.864
RMSEA	< 0.08[52]	0.066
Model summary		Acceptable Model Fit

4.4. Research Hypothesis Testing Result

Standardized path coefficients quantify the degree of correlation between the independent and dependent variables. All eight hypotheses were supported, as shown in Table 6.

Learning interaction in EFL learning was predicted by AI integration and involvement in creative tasks, with path coefficients of 0.484 (CI [0.356, 0.612]) and 0.303 (CI [0.185, 0.421]), respectively. AI integration was predicted by competency in generative AI (β=0.413, CI[0.337, 0.489]), attitudes towards generative AI (β=0.451, CI[0.373, 0.529]), and generative AI experience (β=0.591, CI[0.504, 0.678]).

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Involvement in creative tasks was predicted by competency in generative AI (β=0.368, CI[0.291, 0.445]), attitudes towards generative AI (β=0.334, CI[0.259, 0.409]), and generative AI experience(β=0.436, CI[0.359, 0.513]).AI integration and involvement in creative tasks mediated the relationships between the independent variables of competency in generative AI, attitudes towards generative AI, and generative AI experience, and the dependent variable of learning interaction.

The link between these factors is graphically depicted in Figure 2. An asterisk placed on solid lines denotes a significant relationship. The numbers on the arrow lines show the standardized path coefficients and t-values of the two variables.

Table 6 Hypotheses Testing Results of the Structural Model

Hypothesis	Paths	Standardized path coefficient (β)	S.E.	t-value	P	95% Confidence intervals	Testing result
H1	AI<---CG	0.413	0.028	10.604	p< .001	[0.337, 0.489]	Supported
H2.	AI<---AG	0.451	0.033	11.151	p< .001	[0.373, 0.529]	Supported
H3	AI<---AE	0.591	0.032	13.229	p< .001	[0.504, 0.678]	Supported
H4	ICT<---CG	0.368	0.035	9.468	p< .001	[0.291, 0.445]	Supported
H5	ICT<---AG	0.334	0.039	8.738	p< .001	[0.259, 0.409]	Supported
H6	ICT<---AE	0.436	0.035	10.970	p< .001	[0.359, 0.513]	Supported
H7	INTERACTION<---AI	0.484	0.066	7.447	p< .001	[0.356, 0.612]	Supported
H8	INTERACTION<---ICT	0.303	0.050	5.044	p< .001	[0.185, 0.421]	Supported

Note: Abbreviations: CG = competency in generative AI; AG= attitudes towards generative AI; AE=generative AI experience; AI =AI integration; ICT= involvement in creative tasks., INTERACTION=learning interaction.

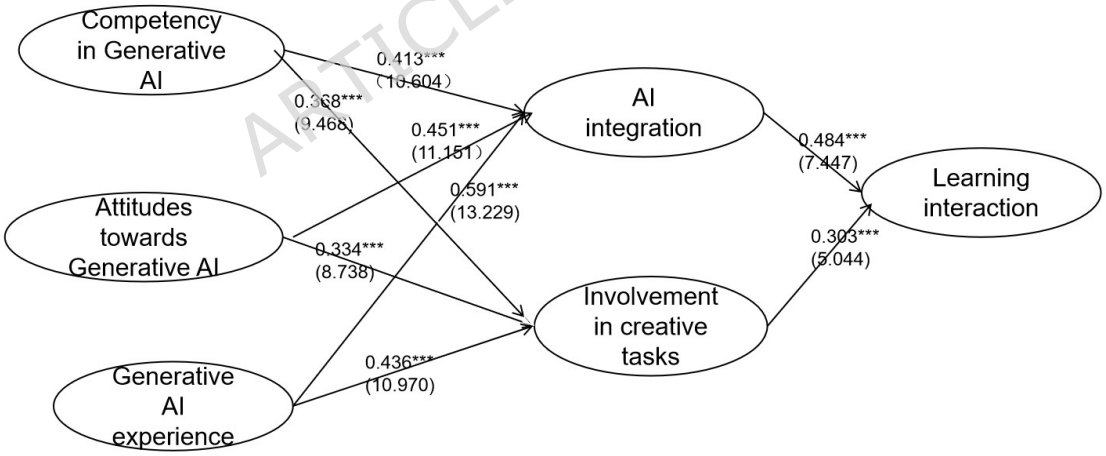

Fig. 2. Structural equation model results showing standardized path coefficients and t-values. The structural equation model presents the hypothesized relationships among competency in generative AI (CG), attitudes towards generative AI (AG), generative AI experience (AE), AI integration (AI), involvement in creative tasks (ICT), and learning interaction (INTERACTION). The arrows represent hypothesized SEM paths. The values displayed on the paths are standardized path coefficients, with t-values reported in parentheses. Asterisks indicate statistical significance (***p < .001). The results show that AI integration and involvement in creative tasks significantly and directly predict learning interaction, with AI integration demonstrating a stronger direct association. Moreover, generative AI experience shows the strongest predictive effects on both AI integration and involvement in creative

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tasks among the antecedent variables, indicating that AI-related experience contributes to learning interaction indirectly through these mediating mechanisms.

4.5 Direct, Indirect, and Total Effects of the Relationship

AMOS software assists in calculating and determining the potential direct and indirect effects on the relationship between the variables. A direct effect (DE) relationship occurs when two variables are connected without the mediation of a mediator variable. An indirect effect (IE) relationship occurs when the association between variables is facilitated by at least one mediating variable. The total effect (TE) of a relational pathway is the sum of its direct and indirect effects[56]. The R-squared (R^2) value signifies the proportion of variance in the dependent variable[45]. The R-squared value quantifies the variance in one variable that another variable may explain[57]. The acceptable R^2 threshold is a minimum of 0.1[58]. The findings indicate R^2 values of 0.723, 0.438, and 0.534, all exceeding this minimal criterion. Table 7 illustrates the direct, indirect, and total effects of the connection in line with the given hypotheses.

Table 7 indicates that 53.4% of the variance in learning interaction is accounted for by the two independent variables: AI integration and involvement in creative tasks. 72.3% of the variance in AI integration is explained by its three direct independent variables: AI competency, AI experience, and AI attitudes. 43.8% of the differences in Involvement in creative tasks are explained by the three direct independent variables: AI competency, AI experience, and AI attitudes.

The indirect effects of learning interaction were predicted by three independent variables: AI competency (0.311), AI experience (0.418), and AI attitudes (0.319). The direct effects of learning interaction were predicted by the two independent variables: AI integration (0.484) and involvement in creative tasks (0.303). The total effects of learning interaction were predicted by five variables, namely AI competency (0.311), AI experience (0.418), AI attitudes (0.319), AI integration (0.484), and involvement in creative tasks (0.303). All data were presented in Table 7.

Table 7 Direct, Indirect, and Total Effects of Relationships

Independent Variables	Dependent Variables											
	AI Integration (AI)				Involvement in creative tasks (ICT)				Learning interaction (INTERACTION)			
	Direct Effect	Indirect Effect	Total Effect	R^2	Direct Effect	Indirect Effect	Total Effect	R^2	Direct Effect	Indirect Effect	Total Effect	R^2
AI competency (CG)	0.413	-	0.413		0.368	-	0.368		-	0.311	0.311	
AI attitude (AG)	0.451	-	0.451		0.334	-	0.334		-	0.319	0.319	
AI experience (AE)	0.591	-	0.591	0.723	0.436	-	0.436	0.438	-	0.418	0.418	0.534
AI Integration (AI)	-	-	-		-	-	-		0.484	-	0.484	
Involvement in creative tasks (ICT)	-	-	-		-	-	-		0.303	-	0.303	

To further clarify the underlying mediation mechanisms, the specific indirect effects through the two mediators—AI integration and involvement in creative tasks — were subsequently examined using bias-corrected bootstrapping, as reported in Table 8. Indirect effects were tested using bias-corrected bootstrapping with 5,000 resamples to generate 95% confidence intervals (Preacher & Hayes, 2008). All six indirect paths were statistically significant, as none of the confidence intervals contained zero. Specifically, CG had significant indirect effects on INTERACTION through AI (β=0.200, 95% BC CI [0.086, 0.223]) and through ICT (β=0.111, 95% BC CI [0.034, 0.147]). AG had significant indirect

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effects through AI (β=0.218, 95% BC CI [0.109,0.279]) and through ICT (β=0.101, 95% BC CI [0.029,0.157]). AE had significant indirect effects through AI (β=0.286, 95% BC CI [0.127,0.301]) and through ICT (β=0.132, 95% BC CI [0.042,0.179]). These results support the mediating roles of AI and ICT in the relationships between each antecedent (CG, AG, AE) and INTERACTION.

Table 8 Indirect Effects (Bootstrapped 5000 samples, BC 95% CI)

Indirect Path	Indirect Effect (β)	95% BC Bootstrap CI	Result
CG → AI → INTERACTION	0.200	[0.086, 0.223]	Supported
CG → ICT → INTERACTION	0.111	[0.034, 0.147]	Supported
AG → AI → INTERACTION	0.218	[0.109, 0.279]	Supported
AG → ICT → INTERACTION	0.101	[0.029, 0.157]	Supported
AE → AI → INTERACTION	0.286	[0.127, 0.301]	Supported
AE → ICT → INTERACTION	0.132	[0.042, 0.179]	Supported

5. Discussion

The WEST technology integration model originated from preservice teacher training[14] and later extended to the business domain[23]. This study adapted it to the field of English as a foreign language and made students the research subjects for AI integration. It also analyzed whether the WEST models were effective at predicting learning interaction and other factors that might predict interaction in the language classroom for college students. As shown in the structural model, all component factors were significantly associated with the learning interaction in the EFL classroom, providing support for previous research with the WEST model[23]. Also, this research is an extension of previous studies because, instead of focusing on learning effectiveness, it focuses on interaction, which is considered especially important for language learning. These findings thus offer theoretical support for the cross-domain validity of the WEST model and provide empirical evidence regarding the predictive relationships between AI integration and learning interaction in EFL classrooms. However, these positive findings should be interpreted with caution. As noted in the literature, AI integration may also lead to over-reliance and superficial interaction if students accept AI-generated responses without critical thinking[7]. Therefore, a high level of predicted learning interaction does not necessarily guarantee deep cognitive engagement.

AI integration and involvement in creative tasks together explained 53.4% of the variance in learning interaction. The path coefficient of AI integration to learning interaction was 0.484, and the path coefficient of involvement in creative tasks was 0.303. This is in line with previous research, which stated that these factors significantly associate with the learning effectiveness of company managers in integrating AI in their work[23]. The result also supports prior findings that effective technology integration predicts learning interactions in education[20]. Furthermore, it provides empirical support for previous qualitative research that integrating AI in higher education is associated with learning engagement and an interactive learning environment[21]. By comparison, involvement in creative tasks had less power to predict learning interaction, with a path coefficient of 0.303, indicating a low correlation. The difficulty of the tasks may partly explain this pattern. In this research, students in vocational colleges have less competency in using English, so teachers may consider appropriate task difficulty in task design, such as creating manageable situations to support students' participation in learning interactions during the extension stage[9]. Generally, the observed associations suggest that pedagogically guided AI integration embedded in authentic tasks may be relevant to higher levels of

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learning interactiona[26].

It is found that the three factors of competency, attitudes, and experience with generative AI are significantly associated with AI integration, with path coefficients of 0.413, 0.451, and 0.591, indicating moderate correlations. The three factors explained 72.3% of the variance in AI integration. This is consistent with the earlier research on the construction of technology integration models. The three constructs of attitudes (will), experience, and competency (skills) have been confirmed as important components of the WEST model and have shown significant associations with technology integration. A study of preservice teacher training showed the structural relationships among attitudes, experience, competency, and tools in technology integration[14]. A study with the company manager's AI integration also supported that the three factors of attitudes, experience, and competency with AI predict AI integration at work[23].

It is revealed that the three dimensions of competency, attitudes, and experience with generative AI significantly predicted involvement in creative tasks, as evidenced by path coefficients of 0.368, 0.334, and 0.436, indicating low-to-moderate correlations. The three factors explained 43.8% of the differences in involvement in creative tasks. This aligns with prior research showing that confidence and attitudes were significantly associated with creative task involvement among company managers[23]. But it contradicts the previous research in that experience did not significantly predict creative task engagement in company conditions[23]. Differences in contexts may explain this discrepancy. In a company setting, AI experience can be used for both traditional and creative tasks. However, managers mostly follow a set pattern in their work, so AI experience does not necessarily align with creative tasks as often. On the contrary, in educational settings, college students frequently encounter new knowledge and complete new tasks, so AI experience correlates more strongly with creative tasks.

6. Conclusions

6.1. Conclusion

Returning to the research topic "What factors predict student English learning interaction in the context of generative AI?" This study used quantitative methods to show that competency, attitudes, experience with generative AI, AI integration, and involvement in creative tasks was associate with the dependent variable- learning interaction. The statistical analysis of the gathered data verified the research framework grounded in the technology integration WEST model, in that competency, attitudes, and experience are linked to AI integration in English learning, and AI integration was associated with interactive learning in language classrooms. Consequently, the explanatory power of the WEST model is empirically supported and further expanded to EFL learning facilitated by generative AI tools.

This study further extended the WEST model with statistical evidence and found that integrating AI with creative tasks predicted better learning interactions. Meanwhile, students' willingness, experience, and skill with generative AI are indirectly associated with learning interaction, mediated by AI integration activity and involvement in creative tasks. Students' AI-related characteristics are related to interactive learning experiences when supported by appropriate AI use and task design. This mediating effect indicates that students' competency, attitudes, and experience with generative AI are indirectly associated with learning interaction via AI integration and involvement in creative tasks. This reaffirms the constructionist perspective that knowledge and skills should be acquired through practical activities, which emphasizes that student participation and exploration need to be intensified in EFL learning[12].

Interaction is also a kind of learning, a practical activity in which students interact with instructors, peers, or generative AI. Creating a lively, interactive environment allows students to have contextual

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opportunities to use their second language, and also allows them to validate their language hypotheses based on the feedback they receive [4]. This kind of communication of ideas and language is considered one of the decisive factors influencing academic performance[16], reflecting the basic function of language.

Theoretically, by combining constructivist learning theory with the WEST model, this study provides an empirical framework for examining factors associated with interactive learning in AI-supported EFL settings. Through quantitative empirical methods, it demonstrates how AI-related characteristics may be indirectly linked to learning interaction through AI integration and creative task involvement. This cross-theoretical integration not only broadens the research horizons of generative AI in education but also provides theoretical support for cultivating teacher-student-AI interaction capabilities in foreign language education.

Practically, this study also explores new paths to predict learning interactions. AI integration can be combined with creative task design to predict interaction. These research findings can provide innovative pedagogical solutions for English learning, helping students better adapt to the technological development of the AI era and improve their English learning efficiency and career competitiveness.

Unlike studies focused solely on technology acceptance (e.g., TAM), AI literacy, or learner engagement, this study makes three distinctive contributions. First, it develops an integrated framework explaining how AI-related characteristics, AI integration, and creative task involvement are associated with learning interaction. Second, rather than treating AI as just an engagement tool, it positions AI as a learning resource that may support interaction. Third, unlike descriptive work on learner-AI interaction, this study offers a predictive framework that links AI integration to creative task design. Thus, it moves beyond examining whether learners accept or use AI toward understanding how AI-supported learning environments can be designed to foster interaction.

6.2. Recommendation

For pedagogical implications, the concept of the “learning by doing” principle needs to be reinforced. According to the constructivist perspective and this conceptual model, interactive learning is associated with students' active involvement with real tasks and AI tools. Regarding the difficulty of creative tasks, they should be carefully designed by instructors to align with students' English levels. If students were less competent, they might be encouraged to do easier tasks related to their own experience. If students were more proficient, they could be given more challenging work connecting to society and culture. Such task design considerations may support the development of a better interactive learning environment. Consequently, there should be teacher training and discussion guiding them in the use of AI tools and task designs, because the teacher has an important role to take on, such as which AI tools to choose and what tasks to assign to students in the English classroom to support a better interactive learning environment in EFL learning.

While this study identified positive associations of AI integration on learning interactions, we acknowledge that the use of generative AI may also introduce uncertainty, overreliance, concerns about originality, and ethical tensions[7]. Therefore, we recommend that AI integration should not occur in isolation. Instead, it must be supported by key elements such as AI literacy, reflective pedagogy, and well-designed learning tasks. Such considerations may help educators maximize the interactive benefits identified in this study.

The research has limitations. First, the sampling method employed was convenience sampling, conducted exclusively at a higher vocational college in China, hence limiting the representativeness of the research findings. Furthermore, it is recognized that the cross-sectional design limits causal

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inference, and the exclusive use of a single self-report measure raises concerns about common method bias. Lastly, the research treated learning interaction as a single construct, but it can be subdivided into learner-instructor, learner-learner, and learner-to-AI interactions. Further research can examine how different dimensions of interaction are associated with learning outcomes and engagement in AI-supported EFL contexts.

Data Availability Statement: The anonymized data are available from the corresponding author upon reasonable request.

Conflicts of Interest: The author declares that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table A1 Modification report

Type	Construct	Added covariance	justification
within	Interaction	e25–e26, e26–e27, e29-e30,e34-e35,e36-e37,e26-e30	item similarity

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within	AI	e16–e17,e18-e19	item similarity
within	AG	e6–e7	item similarity
between	AI-ICT	e39-e40	conceptual overlap
between	CG-AG	e3-e7,e3-e8	conceptual overlap

Table A2 Measurement items

Variable	Items	Statement
Competency in Generative AI (CG）	CG1	I can learn to use Generative AI quickly.
	CG2	I keep up with Generative AI.
	CG3	I frequently play around with Generative AI.
	CG4	I have good technical skills in using Generative AI.
	CG5	I have had sufficient opportunities to learn different topics with Generative AI.
Attitudes towards Generative AI (AG）	AG1	Generative AI provides an opportunity to improve the learning process.
	AG2	The efficiency of the learning process is increased using Generative AI.
	AG3	Generative AI increases the level of creativity of my classmates and me.
	AG4	Generative AI is used as an assignment tool, and it increases students' motivation.
	AG5	Students with learning difficulties can enormously benefit from the use of Generative AI.
	AG6	The use of Generative AI should be integrated into the training and development programs.
Generative AI experience （AE）	AE1	I saw many examples of Generative AI use in a learning setting.
	AE2	I saw good examples of Generative AI that inspired me to use generative AI for study purposes.
	AE3	I received sufficient help in doing my study-related activities through Generative AI.
	AE4	was encouraged to gain experience in using Generative AI in learning settings.
AI Integration（AI）	AI1	I know about Generative AI, which is most useful for study-related activities.
	AI2	I know how to use generative AI differently for learning-related activities.
	AI3	I can select Generative AI that enhances my understanding of my study.
	AI4	I can choose Generative AI that enhances learning.
	AI5	I think critically about how to use Generative AI in my study.
Involvement in creative tasks(ICT)	ICT1	I demonstrate originality in my assignments/presentations.
	ICT2	I try out new ideas in my study.
	ICT3	I identify opportunities for new learning approaches.
	ICT4	I generate novel but operable study-related ideas.
Learning interaction (LLI=learner-learner interaction, LII=learner-instructor interaction, LAI=learner-AI interaction) Note: these groupings are shown only to clarify the content of the items. The SEM analysis tested overall learning interaction as one construct, not the three interaction types separately.	LLI1	Overall, I had numerous interactions with fellow students related to the course content.
	LLI2	I communicated with my classmates about the course content through various electronic means, such as email/learning management system/instant messaging tools.
	LLI3	I shared my thoughts and ideas about the lectures and their application with other students during this class.
	LLI4	Group activities during class gave me chances to interact with my classmates.
	LII1	I had numerous interactions with the instructor during the class.
	LII2	I asked the instructor my questions through various electronic channels, such as email, the learning management system, and instant messaging tools.
	LII3	The instructor regularly posted some questions for students to discuss in class.
	LII4	I received enough feedback from my instructor when I needed it.
	LAI1	AI tools helped me to understand the class content better.
	LAI2	AI tools stimulated my interest in this course.
	LAI3	AI tools helped me relate my personal experience to new concepts or new knowledge.
	LAI4	It was easy for me to access AI tools.
	LAI5	I browse English or English-related content with AI tools.

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