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Article

From Perception to Choice: Exploring Chinese High School Students' Attitudes Toward AI-Assisted English Learning and Their Academic Intentions

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Abstract

This study examines whether high-school students' attitudes toward AI-assisted English learning (AI-AEL) shape intentions to choose language-related majors. Grounded in Self-Determination Theory and Social Cognitive Theory, we propose a dual-pathway account whereby positive AI-AEL experiences enhance autonomy and self-efficacy, promoting academic intentions, while negative experiences exert weaker effects. Using purposive sampling, Grade-12 students at a key public high school in Hebei, China completed a content-validated attitude scale, autonomy and self-efficacy measures, and a major-intention item. Reliability and factorability were established; exploratory factor analysis supported a two-factor attitude structure. Regression models with demographic and usage controls showed that positive attitude significantly predicted intention to pursue language-related majors, whereas negative attitude was non-significant. Pedagogically, findings support gradual AI integration, choice-based tasks, micro-feedback cycles, collaborative critique of AI outputs, and activities that convert concerns about dependency, accuracy, verbosity, and authenticity into explicit learning goals. While the study provides novel empirical evidence linking AI-assisted learning attitudes to academic intentions through motivational pathways, limitations include the single-school sample (limiting regional generalizability), cross-sectional design (precluding causal inference), and reliance on self-reported attitudes. Future multi-site, longitudinal studies with behavioral measures are needed to validate the proposed framework and assess long-term impacts of AI-assisted learning on actual major enrollment. Overall, thoughtfully embedded AI can strengthen motivation and self-efficacy, inform students' academic choices and support ongoing AI and Humanities integration in language education.

Keywords

AI-Assisted English Learning, Student Attitudes, Academic Major Intention, Self-Determination Theory, Social Cognitive Theory, AI And Humanities Integration.

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Introduction

In this study, AI-assisted English learning refers to the integration of AI tools into EFL instruction to deliver adaptive feedback, personalized pathways, and interactive practice, thereby enhancing learners' autonomy, competence, and engagement rather than foregrounding technical sophistication. Empirical studies confirm AI's positive effects on language expression, motivation, and confidence (Wei, 2023), while systematic reviews show its increasing integration into global education at all levels (Zhu & Wang, 2024).

Despite its centrality in the College Entrance Examination (Chinese *Gaokao*) and school curricula, English education in China faces long-term structural challenges that extend beyond classroom instruction. In recent years, language- and humanities-related programs have experienced a sustained decline in social appeal. National and institutional reports indicate that many foreign-language departments struggle to recruit students, as the post-pandemic generation increasingly gravitates toward STEM- and technology-oriented fields (Wang, 2023). This tendency reflects not only shifting labor market expectations but also the rapid expansion of artificial intelligence across education and society. As AI systems now demonstrate proficiency in translation, summarization, and even creative writing (Kasneci et al., 2023; Solak, 2024), public perceptions of linguistic expertise and humanistic training are being reshaped. Many students and parents perceive AI as capable of automating communicative and textual tasks, thereby questioning the economic and professional value of language-based majors (Hu, 2023; Ratten & Jones, 2023).

In response, universities have begun to reform humanities curricula by integrating artificial intelligence, data science, and digital literacy into traditional language programs, forming what scholars describe as the emerging paradigm of "AI + Humanities" (Lei, Min, & Li, 2025; Yu & Song, 2025). This interdisciplinary transformation aims to reposition language education at the forefront of innovation—bridging humanistic knowledge with computational and analytical skills—and to revitalize students' interest by aligning academic content with future-oriented competencies. Within this reform landscape, understanding how secondary students experience AI-assisted English learning becomes particularly significant. Their attitudes may not only shape classroom motivation but also influence their long-term intentions to pursue language-related majors or newly reconfigured interdisciplinary programs. Accordingly, this study examines whether positive or negative experiences with AI-assisted English learning at the high school level affect students' academic intentions amid the broader redefinition of humanities education in the age of artificial intelligence.

This study addresses two central questions:

1. What are Chinese senior high school students' attitudes toward AI-assisted English learning, and what are the distributional characteristics of these attitudes?
2. Do positive and negative attitudes significantly predict students' intentions regarding academic major selection?

Through empirical testing, this research seeks to uncover mechanisms connecting AI-assisted learning experiences to students' educational choices, providing both theoretical insight and practical guidance for integrating AI into high school English instruction.

Conceptual Framework and Hypotheses

Students' attitudes toward AI-assisted English learning can shape both their engagement in learning and their long-term academic orientations. Grounded in Self-Determination Theory (SDT) and Social Cognitive Theory (SCT), this study conceptualizes a dual motivational pathway linking learning experiences to academic decisions. According to SDT, when learning satisfies the psychological needs for autonomy, competence, and relatedness, intrinsic motivation and sustained behaviors are enhanced (Deci & Ryan, 2000). In AI-assisted environments, personalized feedback and adaptive learning mechanisms can strengthen learner's perceived control and competence, fostering greater interest in language-related disciplines. In parallel, SCT emphasizes the role of self-efficacy—the belief in one's capability to achieve desired outcomes—as a key determinant of learning persistence and goal choice (Bandura, 2001). Positive feedback from AI tools such as ChatGPT or Grammarly has been found to enhance confidence, thereby encouraging exploration of language-related fields (Mohammed & Khalid, 2025). Conversely, delayed feedback, lack of teacher guidance, or overreliance on automation may generate fatigue and anxiety that undermine motivation (Yu & Song, 2025).

Building on these theoretical premises, we propose a dual-pathway conceptual framework (Figure 1) in which positive AI learning experiences strengthen autonomy and self-efficacy, thereby increasing adolescents' intentions to pursue language-related majors, whereas negative experiences (e.g., dependency or authenticity concerns) may elevate anxiety and dampen such intentions, albeit with weaker effects under high-stakes schooling contexts.

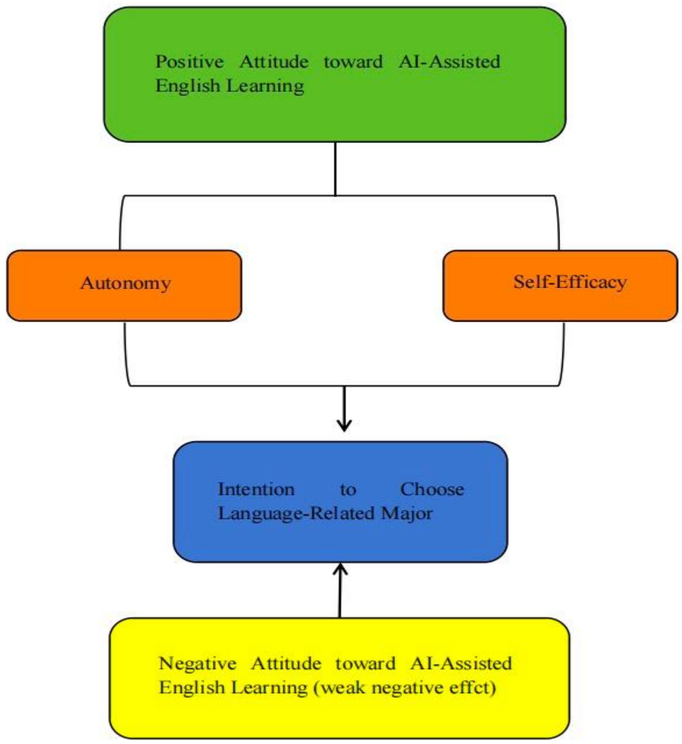

Figure 1: *Conceptual Model of AI-Assisted English Learning Attitudes and Major Decision-Making.*

Figure 1 presents a dual-pathway model linking attitudes toward AI-assisted English learning to academic major intentions. Positive attitudes (efficiency, motivation, personalized feedback) and negative attitudes (dependency, accuracy concerns) function as independent variables. According to Self-Determination Theory (SDT), positive AI experiences foster autonomy and competence, strengthening intrinsic motivation; according to Social Cognitive Theory (SCT), they also enhance self-efficacy through mastery and observational learning. These motivational and cognitive mechanisms mediate the relationship between attitudes and students' intentions to choose language-related majors, suggesting that AI-assisted learning can shape long-term academic orientation by fulfilling psychological needs and building confidence.

Accordingly, this study advances the following hypotheses:

H1: *Positive attitude toward AI-assisted English learning positively predicts intention to choose a language-related major.*

H2: *Negative attitude toward AI-assisted English learning negatively predicts intention to choose a language-related major.*

H3: *The absolute effect size of positive attitude exceeds that of negative attitude.*

Literature Review

AI Integration in Language Education: From Tool Adoption to Pedagogical Transformation

While the integration of artificial intelligence into English as a Foreign Language (EFL) instruction has expanded rapidly, the focus of early studies was primarily technological—exploring how AI tools improve efficiency, feedback, and accuracy. For instance, intelligent writing assistants, grammar checkers, and chatbots have been found to enhance learning outcomes and motivation (Kasneci et al., 2023; Xu, Chen, & Zhang, 2024; Zawacki-Richter et al., 2019). In China, these technologies support real-time correction and adaptive practice aligned with competence-oriented teaching goals (Lei et al., 2025; Yu & Song, 2025). However, as generative AI such as ChatGPT and large language models become embedded in learning processes, recent research has shifted attention from technical functionality to educational psychology—examining how students perceive, trust, and emotionally respond to AI-assisted learning (Zhu & Wang, 2024). This pedagogical turn highlights that the impact of AI on learning outcomes depends not merely on access to technology but on students' attitudes, motivation, and self-efficacy in interacting with AI systems. While these studies demonstrate the technological feasibility of AI in EFL contexts, they provide limited insight into how students emotionally and cognitively appraise these tools—a gap the next section addresses.

Students' Attitudes toward AI-Assisted Learning: Cognitive, Emotional, and Behavioral Dimensions

Empirical findings generally show that learners hold positive attitudes toward AI-assisted language learning (AILL), particularly valuing its efficiency, personalization, and motivational benefits (Yıldız, 2023). Using the MALL:AI scale, Yıldız confirmed improvements in learners' communicative competence and perceived usefulness, while Cai, Lin and Yu (2024) emphasized system quality and hedonic motivation as key predictors of satisfaction. Yet attitudinal divergence persists: motivated learners tend to respond positively, whereas others express resistance or anxiety due to unfamiliarity and overreliance (Chiu, 2024; Viberg, Grönlund, & Andersson, 2023). Moreover, concerns about authenticity, critical thinking, and academic integrity continue to shape student perceptions (Mei, 2024). Collectively, these studies indicate that students' emotional and cognitive responses to AI tools are heterogeneous, suggesting that attitudes play a mediating role between technology adoption and educational outcomes. Although attitudes toward AI are increasingly well-documented, few studies examine how these attitudes translate into long-term academic decisions, particularly in adolescent populations facing critical educational transitions—a theoretical gap we address next.

Linking Attitudes to Academic Decisions: A Motivational Perspective

Despite growing research on AI-assisted learning, few studies have examined how such attitudes influence long-term academic choices. Most existing work relies on the Technology Acceptance Model (TAM) or Unified Theory of Acceptance and Use of Technology (UTAUT), focusing on perceived usefulness and ease of use (Liu & Ma, 2024). While these frameworks explain immediate adoption behaviors, they overlook deeper motivational mechanisms identified in Self-Determination Theory (SDT) and Social Cognitive Theory (SCT). According to SDT, fulfillment of autonomy, competence, and relatedness fosters intrinsic motivation and sustained engagement (Deci & Ryan, 2000). SCT, in turn, emphasizes self-efficacy and feedback as drivers of persistence and goal setting (Bandura, 2001). In the context of AI-assisted learning, positive feedback may enhance students' confidence and curiosity toward language disciplines (Mohammed & Khalid, 2025), whereas negative experiences or dependency may weaken their intrinsic interest (Yu & Song, 2025). Yet, no study has systematically tested whether these attitudinal and motivational dynamics extend to adolescents' academic major intentions—a gap this research aims to fill. Collectively, these theoretical perspectives suggest that attitudes toward AI may shape academic intentions through motivational pathways, yet no study has empirically tested this mechanism among Chinese high school students within the *Gaokao* system—the research gap this study aims to fill.

Research Gap

Although the literature provides ample evidence of AI's pedagogical benefits, three gaps remain. First, the majority of studies focus on university or adult learners (Hu, 2023; Ratten & Jones, 2023; Wang, 2023), leaving high school students—whose academic intentions are still being formed—largely unexplored. Second, few investigations have addressed how attitudes toward AI-assisted learning influence long-term educational pathways, such as university major choice within the *Gaokao* system. Third, existing models have rarely integrated SDT and SCT into a unified "attitude–motivation–behavior" framework capable of explaining both immediate learning engagement and downstream academic orientation.

To address these gaps, the present study empirically examines whether Chinese high school students' positive and negative attitudes toward AI-assisted English learning predict their intentions to pursue language-related majors. By linking AI-assisted learning experiences with motivational theories and academic decision-making, this study contributes new evidence to both AI-in-education research and the emerging interdisciplinary field of "AI + Humanities".

Research Method

Participants and Research Context

This study involved 101 senior high school students (37 male and 64 female) from Handan No. 3 High School, located in Hebei Province, China. All participants were in Grade 12 and had similar academic backgrounds, which ensured consistency in English proficiency and learning exposure.

A purposive sampling approach was adopted to select students who had prior experience with AI-assisted English learning tools. Handan No. 3 High School was chosen for two reasons. First, it ensured curricular consistency and controlled learning conditions, enabling the study to isolate attitudinal effects without confounding regional or curricular differences. Second, the school represents a typical public, academic-oriented institution in northern China, where English learning remains a high-stakes component of the *Gaokao* examination system. The case is therefore contextually representative of how AI is being integrated into secondary English education. While the use of one school limits generalizability, it provides a controlled and realistic setting for investigating the relationship between AI learning experiences and academic intentions. Future research may extend the sampling to multiple regions and school types for broader validation.

Instruments and Data Collection

With the growing influence of generative AI in education, quantitative studies have increasingly examined learners' attitudes toward AI-assisted English learning, often drawing on the Technology Acceptance Model (TAM). However, existing attitude measures vary considerably in scope and contextual suitability. For instance, Liu and Ma (2024) adapted Davis's (1989) Technology Acceptance Scale by replacing "computer" with "ChatGPT," yet its four-item design was too narrow to capture emotional and motivational dimensions. Schepman and Rodway's (2020) instrument provided a more comprehensive view but emphasized general public concerns such as ethics and privacy, limiting its applicability to language learning contexts. To address these shortcomings, Wu, Liu and Zeng (2024) developed the AI-Assisted L2 Learning Attitude Scale for Chinese College Students, a 12-item instrument validated through exploratory and confirmatory factor analyses, which demonstrated strong reliability and cross-group invariance. Nevertheless, because it was derived from the broader Student Attitudes toward AI scale (Suh & Ahn, 2022), it still overlooked the unique features of generative AI in EFL contexts.

Building on Wu et al.'s framework, the present study developed a new AI-assisted English Learning Attitude Scale tailored to high school students. A review of previous literature initially produced 20 items related to motivation, anxiety, dependency, communication, and language expression. Semi-structured interviews with 15 students were then conducted to refine item wording and identify missing dimensions, leading to the addition of eight new items. Three experts in English language teaching subsequently assessed content validity using the Delphi method, which resulted in revisions and the removal of three items. The finalized questionnaire comprised 25 items total, including a 13-item attitude scale rated on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree), which systematically captured students' perceptions of generative AI's role in English learning, including its motivational benefits, emotional influences, and potential limitations. The questionnaire also included demographic questions, one item assessing intention to pursue language-related majors, and open-ended questions about perceived advantages and challenges of AI-assisted learning.

All data were collected via an online self-administered survey under teacher supervision to ensure comprehension and independent completion. The design thus integrated both quantitative and qualitative dimensions, allowing for a comprehensive understanding of students' experiences with AI in English learning.

Variables

This study measured three variables. Positive attitude was calculated from nine items (items 7, 8, 9, 10, 15, 16, 20, 21, 22), reflecting students' positive experiences with AI-assisted English learning, such as increased interest, confidence, reduced anxiety, and enhanced motivation. Example items include: "AI tools have increased my interest in learning English," "After using AI tools, I feel more confident in learning English," and "AI tools have reduced my anxiety about learning English." These items collectively capture how AI fosters engagement, motivation, and positive perceptions of language learning.

Negative attitude was derived from four items (items 11, 12, 13, 14), capturing students' concerns about dependency, reduced accuracy, and weakened communication skills. Example items include: "Using AI tools makes me less willing to think about English problems independently," "I worry that AI tools will weaken my actual ability to communicate in English," and "AI tools often provide expressions that are inaccurate or inappropriate in real communication." These items reflect students' reservations about authenticity, over-reliance, and the potential limitations of AI in supporting long-term English learning.

Choice inclination was assessed with one survey item (item 18): "Due to the widespread use of AI, I am more willing to choose a language-related major," indicating students' academic choice intention.

Data Testing and Collection

Data were collected through in-person questionnaire administration and analyzed using a multi-stage validation approach. The 13 attitude items underwent systematic psychometric validation, while demographic and qualitative items provided contextual information and control variables for subsequent analyses.

Psychometric validation proceeded through four sequential steps. First, sampling adequacy was assessed using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity to confirm appropriateness for factor analysis. Second, exploratory factor analysis (EFA) was conducted to identify the underlying structure of student attitudes. Third, confirmatory factor analysis (CFA) validated the factor structure and assessed convergent validity using standardized factor loadings, Average Variance Extracted (AVE), and Composite Reliability (CR). Fourth, internal consistency reliability was evaluated through Cronbach's α coefficients. After establishing measurement reliability and validity, linear regression analysis tested whether positive and negative attitudes significantly predicted students' intentions to choose language-related majors, with demographic characteristics and AI usage patterns as control variables. All analyses were conducted using SPSS 26.0, with statistical significance set at $p < .05$.

Data Analysis

Data were analyzed using SPSS 26.0 through an integrated approach combining descriptive and inferential statistics. Descriptive analyses were conducted to profile participants' demographics, frequency of AI use, and overall attitudes toward AI-assisted English learning. To test the hypothesized relationships, regression analysis was employed to determine the predictive effects of positive and negative attitudes on students' intentions to pursue language-related majors, with statistical significance set at $p < 0.05$. Furthermore, qualitative thematic analysis of the open-ended responses was undertaken to enrich the quantitative findings, offering deeper insights into students' perceived benefits, limitations, and learning experiences with AI-assisted tools.

Results

Sampling Adequacy and Sphericity Tests (KMO and Bartlett)

The Kaiser–Meyer–Olkin (KMO) test is a measure of sampling adequacy that evaluates the proportion of variance among variables that may be common variance, i.e., variance attributable to underlying latent factors. Values range from 0 to 1, with thresholds commonly interpreted as: values above 0.60 indicate acceptable adequacy, values above 0.70 indicate good adequacy, and values above 0.80 indicate very good adequacy for factor analysis (Field, 2018; Kaiser, 1974). In this study, the overall KMO value of 0.856 suggests that the dataset is highly suitable for factor extraction.

Bartlett's Test of Sphericity examines whether the observed correlation matrix significantly differs from an identity matrix, in which variables are assumed to be uncorrelated. A significant chi-square statistic ($p < 0.05$) indicates that correlations among variables are sufficient for factor analysis (Bartlett, 1954). In this study, Bartlett's test yielded $\chi^2(78) = 748.26$, $p < 0.001$, thereby rejecting the null hypothesis of sphericity and confirming the appropriateness of factor analysis. Taken together, the KMO and Bartlett's test results (see Table 1) confirm that the data meet the necessary statistical assumptions for conducting exploratory factor analysis.

Table 1: *KMO and Bartlett's Test Results for Sampling Adequacy.*

Indicator	Result	Interpretation
KMO Overall	0.856	Above 0.8, indicating strong inter-item correlations, suitable for factor analysis
KMO Item Range	0.70-0.926	All items meet the acceptable standard
Bartlett's Test χ^2	748.26	Large and significant, showing sufficient correlation among variables
Bartlett's Test p-value	<0.001	Below .05, significant, supporting EFA

Exploratory Factor Analysis (EFA)

The structural and reliability tests examined whether Positive Attitude and Negative Attitude could serve as valid predictors of major choice. To examine the underlying factor structure, an exploratory factor analysis (EFA) was conducted. EFA is designed to uncover clusters of items that share common variance, thereby testing whether the observed data can be explained by a smaller number of underlying constructs (Fabrigar & Wegener, 2012; Tabachnick & Fidell, 2019). The analysis revealed two factors with eigenvalues greater than 1 (approximately 5.1 and 2.5), satisfying Kaiser's criterion (Kaiser, 1960). The scree plot (see Figure 2) further confirmed this two-factor solution by displaying a clear "elbow" after the second factor (Cattell, 1966). Taken together, these results support the hypothesized two-dimensional structure—positive attitude and negative attitude—consistent with the theoretical framework.

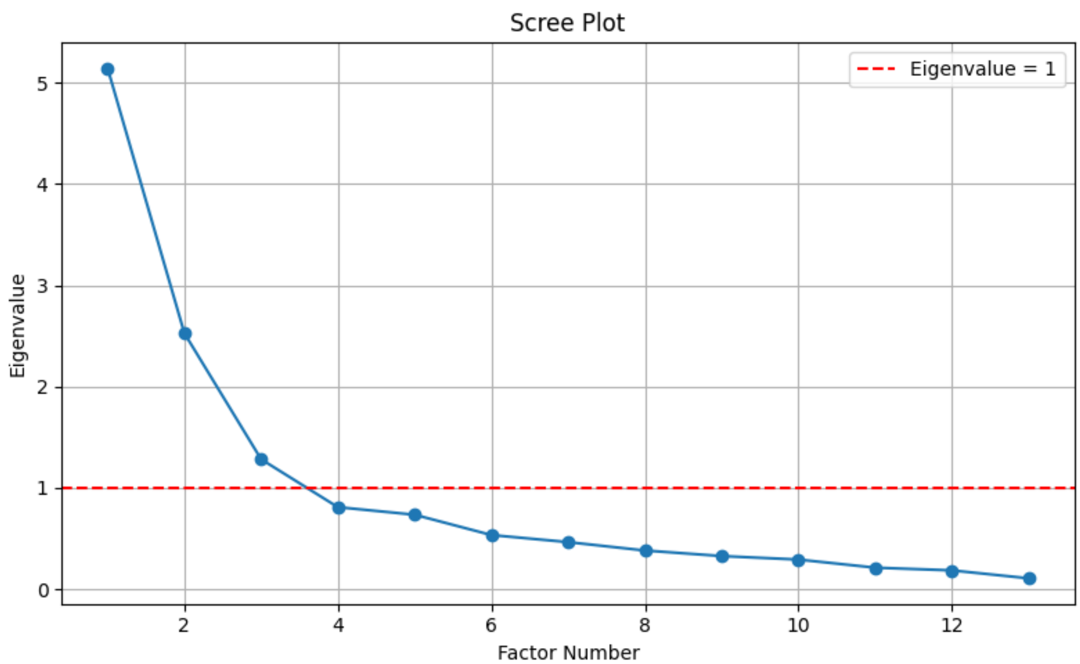

Figure 2: *Eigenvalues and Factor Retention from Scree Plot.*

Confirmatory Factor Analysis (CFA)

To further evaluate the construct validity of the measurement model, Confirmatory Factor Analysis (CFA) was performed on the two latent factors—positive attitude and negative attitude. CFA is a hypothesis-driven technique that tests whether the observed variables load significantly on the pre-specified latent constructs, thereby providing a direct assessment of model fit and convergent validity (Brown, 2015; Kline, 2016).

Model evaluation considered both item loadings and aggregate validity indices. As shown in Figure 3, all standardized factor loadings exceeded the recommended threshold of 0.50 and were statistically significant ($p<0.001$), demonstrating that individual items adequately represented their respective latent constructs. In addition, Average Variance Extracted (AVE) and Composite Reliability (CR) were calculated to assess convergent validity and internal consistency reliability (Fornell & Larcker, 1981). For positive attitude, AVE =

0.561 and CR = 0.916, both surpassing the conventional cutoffs (AVE ≥ 0.50; CR ≥ 0.70), indicating strong convergent validity and reliability. For negative attitude, AVE = 0.612 and CR = 0.863, also above the recommended thresholds, demonstrating satisfactory convergent validity and internal consistency.

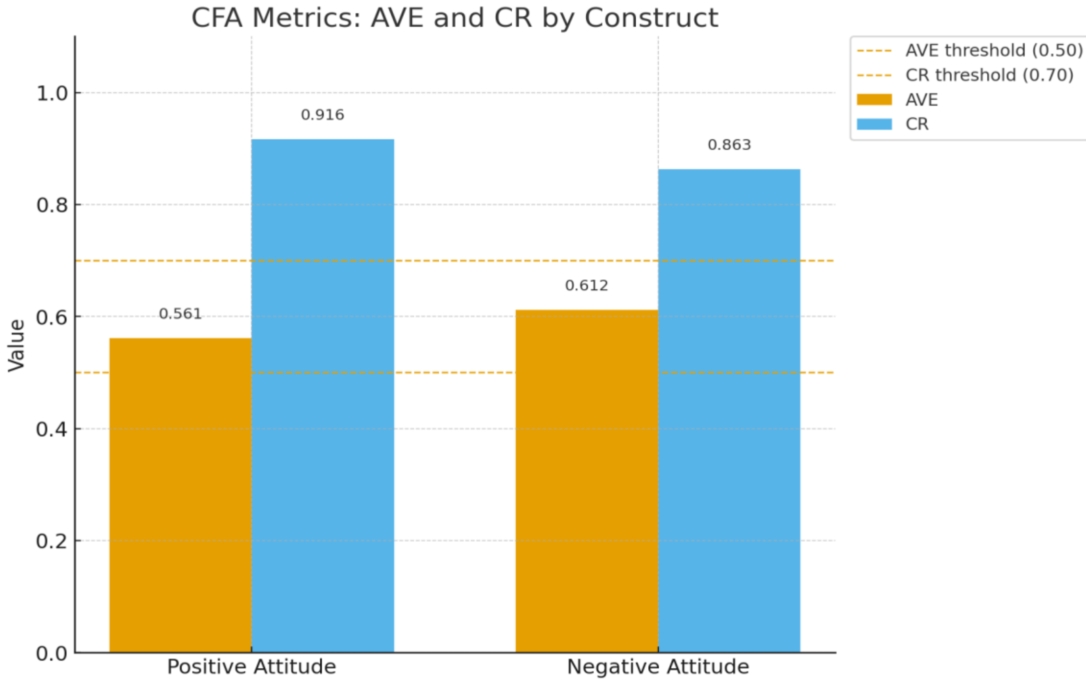

Figure 3: *AVE and CR Values for Positive and Negative Attitude Factors.*

Taken together, these CFA results, combined with the exploratory factor analysis, provide strong evidence of convergent validity and factorial structure. The two-factor model demonstrated adequate factorability (KMO = 0.856, Bartlett's p < 0.001), clear factorial separation (eigenvalues: 5.1 and 2.5), strong convergent validity (AVE > 0.50), and excellent composite reliability (CR > 0.86). Both attitude factors meet or exceed all recommended psychometric thresholds established thus far, supporting the validity of the two-factor structure. Internal consistency reliability is examined in the following section.

Reliability Analysis and Internal Consistency (Cronbach's α)

To further evaluate the reliability of the measurement instrument, Cronbach's α coefficients were computed for the two latent constructs—positive attitude and negative attitude. Cronbach's α is one of the most widely used indices of internal consistency reliability, assessing the degree to which items within a scale are correlated and, therefore, measure the same underlying construct (Cronbach, 1951; DeVellis, 2016). Generally, α values above 0.70 are considered acceptable, values above 0.80 indicate good reliability, and values above 0.90 reflect excellent internal consistency (Nunnally & Bernstein, 1994).

As shown in Table 2, the α coefficient for the positive attitude subscale was 0.707, meeting the conventional cutoff for acceptable reliability. This suggests that items measuring students' favorable perceptions of AI-assisted English learning (e.g., efficiency, motivation, feedback) were moderately correlated and captured a coherent latent construct. The α coefficient for the negative attitude subscale was 0.784, indicating good reliability and stronger inter-item consistency. This finding implies that students' concerns (e.g., dependency, accuracy) formed a relatively stable and internally consistent dimension of the scale.

Table 2: *Cronbach's α Reliability Analysis of Positive and Negative Attitudes.*

Construct	Cronbach's α	Reliability Level	Description
Positive attitude	0.707	Acceptable	Moderate inter-item correlation, relatively stable structure
Negative attitude	0.784	Good	Stronger inter-item consistency

In summary, the comprehensive psychometric evaluation demonstrates that the attitude measurement instrument possesses robust validity and reliability across multiple analytical approaches. The exploratory factor analysis established a clear two-factor structure with strong factorability, while the confirmatory factor analysis validated this structure through adequate model fit, strong convergent validity, and excellent composite reliability. The internal consistency analysis further corroborated these findings, with both attitude dimensions achieving acceptable to good reliability levels. Collectively, these results provide compelling evidence that the two-factor attitude scale is a valid, reliable, and structurally sound instrument for measuring students' attitudes toward AI-assisted English learning, establishing a solid psychometric foundation for subsequent regression analyses examining the relationship between attitudes and major choice intentions.

Descriptive Statistics

To better understand the sample and their use of AI-assisted English learning, this study conducted descriptive statistical analysis in four areas: (1) gender and grade distribution, (2) frequency of AI tool use, (3) types of tools employed, and (4) students' perceptions of advantages and disadvantages. These results not only outline the sample profile but also provide essential context for analyzing the relationship between attitudes and academic major choice.

Gender Distribution

A total of 101 valid questionnaires were collected, including 37 male (36.6%) and 64 female students (63.4%). All were Grade 12 students from Handan No. 3 High School in Hebei Province, sharing similar academic backgrounds, which ensured sample consistency.

Frequency of AI Use

Approximately 62% of students reported having used AI tools for English learning, while 38% had never engaged with them, suggesting moderate adoption but cautious attitudes among high school learners.

Among users, approximately 77% reported occasional use of AI tools for English learning, indicating that AI adoption remains predominantly periodic or supplementary in nature. About 15% reported using AI several times a week, while only 8% used AI daily. Overall, there remains considerable room for improvement in the regularization and deeper integration of AI tools into high school English learning.

AI Tool Usage Patterns

This study analyzed the AI-related tools used by participating Grade 12 students, covering four main categories: ChatGPT, intelligent translation software, intelligent voice assistants, and other AI tools. The results show that a considerable proportion of students reported using ChatGPT. Intelligent translation software was used frequently within the sample, with some students using multiple translation tools (such as Baidu Translate and WeChat translation features). Intelligent voice assistants were used less frequently. In the "other" category, students mentioned various emerging AI applications, including DeepSeek, Kimi, and Doubao.[1] Overall, many students had used at least one AI-assisted learning tool, and some exhibited a pattern of combining multiple tools, indicating that AI technology has achieved a certain degree of penetration in the high school English learning community, alongside a trend toward diverse usage.

Advantages and Disadvantages of AI

The survey indicates that students generally view AI-assisted English learning positively, recognizing its ability to save time, improve efficiency, enhance interactivity, and stimulate interest. Many respondents emphasized that AI fosters autonomous learning, broadens knowledge access, and supports oral practice and grammar correction. Personalized learning plans were considered especially valuable for meeting diverse proficiency levels. As one student explained, "AI helps me practice speaking without feeling embarrassed, and it gives me feedback immediately, which teachers cannot always do." Another noted, "I like how AI can adjust the exercises according to my level. It feels like having a private tutor who understands my weaknesses."

However, students also identified several limitations. AI-generated translations were often criticized for lacking accuracy in conveying subtle emotions or complex contexts. One respondent remarked, "Sometimes AI's translation is correct in grammar but feels very unnatural, especially when it comes to emotional expressions." Concerns about dependency were also evident: "I feel that if I rely too much on AI, I stop thinking by myself and just accept its answers." The interaction process was sometimes described as mechanical, with difficulty handling emotional, contradictory, or metaphorical language. For example, a student observed, "When I tried to ask AI to explain a metaphor in a poem, it gave a very rigid explanation that missed the deeper meaning."

Additionally, some students pointed out weaknesses in logical flow and verbosity: "Sometimes AI writes too much, but the sentences are not very connected, and I cannot learn good structures from it." Such limitations reduced the perceived effectiveness of AI as a learning tool.

Overall, while students acknowledged AI's advantages in efficiency, engagement, and personalized learning, concerns about accuracy, overreliance, and authenticity remain important challenges for its integration into English learning.

Regression Analysis Results

The regression analysis revealed that positive attitude had a significant positive predictive effect on students' intentions to choose a language-related major. The regression coefficient for positive attitude was $\beta = 0.303$, reaching statistical significance ($p = 0.002$). This indicates that the stronger the positive experiences students gained from AI-assisted English learning—such as increased interest, enhanced confidence, and reduced anxiety—the more likely they were to express an intention to choose a language-related major. The coefficient of determination ($R^2 = 0.092$) suggested that positive attitude explained approximately 9.2% of the variance in major choice intentions.

In contrast, negative attitude was not significantly related to language-related major choice intentions. The regression coefficient was $\beta = 0.092$, indicating that each unit increase in negative attitude corresponded to only a slight increase in major choice intention scores. The coefficient of determination ($R^2 = 0.007$) indicated very weak explanatory power, accounting for only 0.7% of the variance, and the relationship was not statistically significant ($p = 0.403$). This suggests that although some students held concerns about potential negative effects of AI in English learning—such as inaccurate expression, increased dependence, and reduced communication skills—these attitudes did not significantly influence their intention to choose a language-related major. Detailed statistics are presented in Table 3.

Table 3: *Combined Regression Analysis Statistics for Positive and Negative Attitudes.*

Regression Item	Positive Attitude Regression	Negative Attitude Regression
Regression Coefficient (β)	0.303	0.092
Coefficient of Determination (R^2)	0.092	0.007
F-Statistic	9.999	0.707
p-Value	0.002	0.403
Intercept	1.332	2.166

These findings indicate that students' perceptions of AI tools as effective are associated with enhanced motivation for English learning and a greater appreciation of language-related majors as viable academic options. The regression results provide preliminary evidence for a psychological linkage between AI-assisted learning experiences and subsequent academic decision-making.

Inclination

Figure 4 presents a positive linear relationship between positive attitude scores and inclination to choose a language-related major. The regression line confirms that higher levels of positive attitude were associated with stronger academic intentions. The data points show considerable dispersion, with notable concentrations at major inclination scores of 1, 2, and 3, alongside several students expressing maximum inclination (score 5) across varying positive attitude levels. Despite this dispersion, the upward trend of the regression line provides support for the hypothesized positive relationship between attitudes and academic choice.

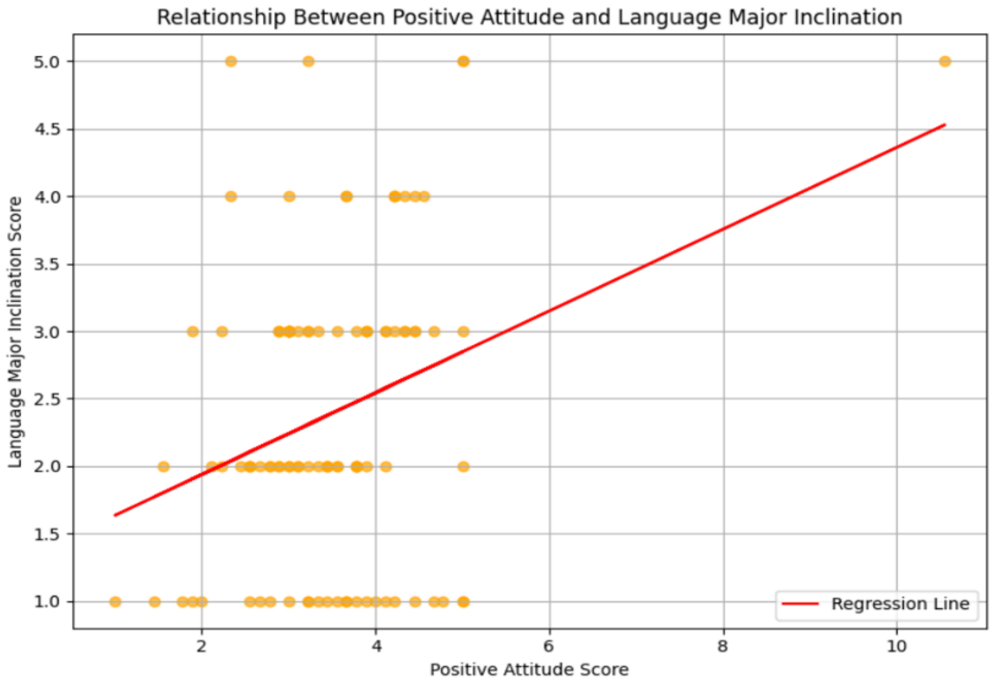

Figure 4: *Scatter Plot and Regression Line for Positive Attitude and Language Major.*

Figure 5 presents the relationship between negative attitude scores and language major inclination. Although the regression line displays a slight positive slope, the wide dispersion of data points and nearly horizontal trajectory indicate only a weak linear association. The data points are distributed across the full range of both variables with no clear pattern, suggesting that students' negative attitudes were not a strong predictor of their inclination to choose a language-related major.

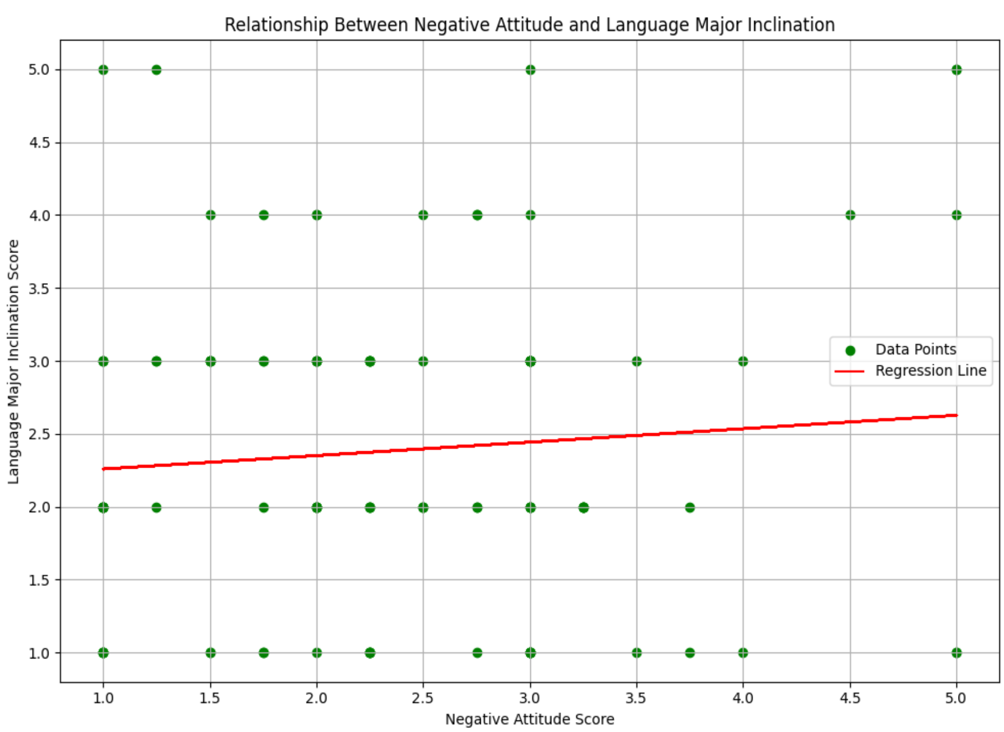

Figure 5: *Scatter Plot and Regression Line for Negative Attitude and Language Major.*

Discussion

Theoretical Interpretation

The results indicate a significant positive relationship between students' positive experiences with AI-assisted English learning and their intention to pursue language-related majors, whereas negative attitudes exerted no significant influence. This asymmetry is theoretically revealing. Qualitative analysis shows that positive attitudes stemmed primarily from psychological experiences—autonomy ("AI adjusts exercises according to my level"), competence ("gives me feedback immediately"), and reduced anxiety ("practice without feeling embarrassed")—reflecting the fulfillment of basic needs identified in Self-Determination Theory. In contrast, negative attitudes focused on technical limitations—accuracy ("unnatural translations"), verbosity ("writes too much"), and rigidity ("rigid explanations")—rather than motivational or psychological barriers. The fact that technical concerns did not predict major choice intentions, while psychological need satisfaction did, suggests that AI's educational impact on academic decision-making operates primarily through motivational mechanisms rather than technological features alone. This interpretation aligns with SDT's proposition that intrinsic motivation arises from need fulfillment (Deci & Ryan, 2000) and SCT's emphasis on self-efficacy as a driver of goal pursuit (Bandura, 2001).

The motivational mechanisms identified above operate through a dual-pathway model. From the SDT perspective, AI-assisted English learning supports learners' basic psychological needs for autonomy, competence, and relatedness. Students experience autonomy when given freedom to decide how and when to engage with AI tools; competence when personalized feedback and adaptive scaffolding make improvement visible; and relatedness when AI-supported reflection and peer collaboration sustain social engagement in learning. These needs collectively strengthen intrinsic motivation, transforming AI from a mechanical tool into a motivational catalyst.

Meanwhile, SCT emphasizes self-efficacy, self-regulation, and observational learning as key determinants of sustained engagement. Continuous AI feedback provides guided mastery experiences that reinforce self-efficacy, while contrastive analysis between AI-generated and human-produced texts enables observational learning. Reflective AI-use journals and justification tasks cultivate self-regulation, helping students monitor, evaluate, and refine their strategies. Together, these mechanisms explain why positive experiences drive stronger academic intentions: students who perceive AI as a tool for mastery rather than a threat develop enduring confidence and agency.

Pedagogical Implications

The theoretical pathways discussed above can be translated into concrete pedagogical practices that strengthen positive motivational mechanisms while transforming negative perceptions into reflective learning opportunities. The following four (04) strategies integrate SDT and SCT principles into AI-assisted language instruction.

Strategy 1: Autonomy-Supported Choice Architecture

To enhance intrinsic motivation and learner agency, teachers should design choice-based learning tasks that allow students to determine when and how to integrate AI tools during writing, speaking, or translation activities (Reeve & Jang, 2006). For example, when assigning a composition task, teachers might offer three approaches: (1) draft independently, then use AI for revision suggestions; (2) use AI for initial brainstorming, then write independently; or (3) alternate between human and AI feedback across multiple drafts.

Critically, students should articulate and justify their chosen approach, then reflect on which pathway felt most supportive of their learning goals. This metacognitive dimension prevents passive tool dependence while honoring learner autonomy (Zimmerman & Schunk, 2011), ensuring that AI functions as adaptive scaffolding rather than a substitute for critical thinking. Research suggests that such autonomy-supportive structures enhance both engagement and achievement outcomes.

Strategy 2: Iterative Micro-Feedback Cycles for Competence Building

Drawing on formative assessment principles (Hattie & Timperley, 2007), teachers can implement micro-feedback cycles in which students draft, receive AI-generated feedback, justify their revisions, and engage in teacher-led or peer-mediated follow-up discussions. This iterative process makes improvement visible and cultivates mastery-based self-efficacy (Bandura, 1997).

A practical implementation sequence might include: (1) student composes a paragraph introducing their hometown; (2) AI tool (e.g., Grammarly, ChatGPT) identifies grammatical or stylistic issues; (3) student revises and articulates the rationale for each correction; (4) peer reviewer evaluates the revised version and suggests communicative improvements the AI overlooked. This cyclical approach not only renders progress tangible but also trains students to distinguish mechanical accuracy from pragmatic effectiveness, thereby deepening metalinguistic awareness (Swain, 2006). The visible trajectory from initial draft to polished product reinforces perceived competence—a key motivational prerequisite identified in SDT (Deci & Ryan, 2000).

Strategy 3: AI-Mediated Collaborative Learning for Social Connectedness

The relatedness dimension of SDT can be preserved through collaborative projects that position AI as a shared analytical object rather than an individual assistant (Johnson & Johnson, 2009). Activities such as comparative translation analysis, argument reconstruction, or collaborative dialogue revision require students to collectively critique AI-generated outputs, negotiate interpretations, and co-construct improved versions.

For instance, small groups might compare multiple AI translations of an idiomatic expression, evaluate their respective strengths and limitations, and synthesize an optimal version that balances accuracy with naturalness. Such tasks foster intellectual community and shared accountability while developing critical language awareness (Kern, 2000). By framing AI as a catalyst for dialogue rather than a replacement for human interaction, these collaborative designs sustain the social fabric of language learning.

Strategy 4: Transforming Concerns into Reflective Learning Objectives

Rather than viewing students' concerns about AI limitations—such as dependency, accuracy, verbosity, or authenticity—as barriers to adoption, educators can reframe these reservations as explicit pedagogical objectives within reflective classroom practice. Carefully designed activities can transform each concern into a learning opportunity that enhances autonomy, competence, and self-regulation.

For example, alternating between AI-supported and independent writing tasks encourages students to compare outputs and thereby strengthen metacognitive awareness and reflective independence. Tasks requiring comparison of AI-generated and human translations foster pragmatic sensitivity and cultural nuance, helping learners identify issues of register, connotation, and contextual appropriateness. Fact-verification exercises, in which students validate AI-generated content against authoritative sources, cultivate critical digital literacy and epistemic vigilance (Wineburg & McGrew, 2019). "AI compression" tasks—requiring students to condense or refine verbose AI responses—train learners to prioritize cohesion, logical flow, and structural clarity (Weigle, 2002).

Collectively, these scaffolded and reflective practices acknowledge students' legitimate concerns while channeling them toward deeper learning. By making AI's limitations pedagogically productive, teachers can address negative attitudes not through dismissal but through critical engagement, ultimately strengthening the very competencies that students fear AI might erode.

Educational Significance

Beyond their immediate classroom implications, these findings have broader significance for the future of humanities education. Integration of AI-assisted English learning into both secondary and tertiary curricula can reposition language education as an interdisciplinary bridge linking communication, culture, and computation. By addressing learners' fundamental psychological needs (SDT) and enhancing self-efficacy (SCT), educators can not only improve language proficiency but also strengthen students' recognition of the academic and professional value of language-related disciplines and, more broadly, humanities fields that depend on sophisticated communication competencies.

These findings suggest that effective AI integration requires systematic teacher preparation. Teacher training programs should emphasize AI pedagogical literacy, scaffolding design, and motivation-based instructional strategies, enabling educators to guide students toward reflective, ethical, and effective use of AI tools. When pedagogical practice aligns with motivational theory, AI-assisted English learning can evolve from a technical supplement into a motivationally coherent and educationally transformative practice—one that cultivates reflective, autonomous, and self-efficacious learners while supporting the continued vitality of humanities education in an increasingly AI-integrated world.

Conclusion

This study demonstrates that high school students' positive attitudes toward AI-assisted English learning significantly predict their intentions to pursue language-related majors, whereas negative attitudes exert no significant influence. Through systematic psychometric validation and regression analysis, we identified a dual-pathway mechanism grounded in Self-Determination Theory and Social Cognitive Theory: positive AI experiences enhance autonomy, competence, and self-efficacy, thereby strengthening academic intentions, while concerns about technical limitations do not undermine motivational pathways when psychological needs are met.

These findings carry important implications for educational practice and policy. At the classroom level, educators should design autonomy-supportive choice architectures, implement iterative micro-feedback cycles, foster AI-mediated collaborative learning, and transform students' legitimate concerns into reflective learning objectives. At the institutional level, teacher preparation programs must cultivate AI pedagogical literacy to ensure that technology integration aligns with motivational principles rather than serving as mere technical supplementation.

While this study advances understanding of how AI-assisted learning shapes academic intentions, several limitations warrant attention. The single-school sample limits regional generalizability; the cross-sectional design precludes causal inference; and reliance on self-reported attitudes may not fully capture actual classroom behaviors. Future research should employ multi-site longitudinal designs with behavioral measures to validate the proposed framework and assess long-term impacts on major enrollment patterns.

Ultimately, when thoughtfully embedded in pedagogical practice, AI-assisted English learning can strengthen students' intrinsic motivation and self-efficacy, informing their academic choices and supporting the ongoing integration of AI and Humanities in language education. As education enters an era of unprecedented AI capabilities, this study demonstrates that the key to effective technology integration lies not in the sophistication of tools but in their alignment with fundamental human motivational needs.

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