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Article

Exploring the effect of demographic characteristics and personality traits on attitude toward AI-assisted second language learning among Chinese college students: A multiple regression analysis

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Abstract: Previous research underscores the pivotal role of AI in advancing second language (L2) learning, yet gaps persist in understanding how individual differences shape L2 learners' perceptions of AI resources. Addressing this gap, this study explored the impact of demographic characteristics (age and gender) and personality traits (extroversion, agreeableness, conscientiousness, neuroticism, and openness) on attitude toward AI-assisted L2 learning. This attitude encompasses the opinions, feelings, and beliefs individuals hold about using AI as a tool to facilitate L2 learning. Data were collected from 493 L2 learners enrolled in Chinese colleges through an online questionnaire using two validated scales. Through SPSS 26, descriptive statistics indicated a moderately high positive attitude among students. Multiple regression analyses revealed that older students and females exhibited more favorable attitude compared to their younger and male counterparts, respectively. Additionally, personality traits—excluding agreeableness—significantly influenced attitude. Besides, extroversion and neuroticism negatively predicted attitude, whereas conscientiousness and openness had positive predictive effects. Moreover, this study discusses theoretical implications and offers educational insights while suggesting avenues for future research.

Keywords: AI-assisted L2 learning; demographic characteristics; personality traits; multiple regression analyses

1. Introduction

Artificial intelligence (AI) is transforming numerous industries by embedding advanced cognitive functions into systems that operate automatically [1]. Recent research indicates that AI is instrumental in improving students' learning outcomes, including knowledge acquisition, emotional health, and skills development necessary for second language (L2) learning [2–4]. The effectiveness of AI in educational spheres is attributed to a suite of technologies, including intelligent chatbots, automated essay scoring, language translation software, and advanced natural language processing capabilities [5,6]. These tools are crucial for delivering personalized educational content, offering real-time responses, and conducting automated evaluations—key components for the successful learning of an L2 [7,8].

Nevertheless, the true potential of AI can only be harnessed when these technologies are not just recognized but actively utilized by learners [9]. While the role of attitude in the adoption of AI technologies is well-established [10], a significant gap exists in understanding whether demographics—specifically age and gender—as well as psychological variables, namely, personality traits shape students' attitudes toward AI in L2 learning contexts. To our best knowledge, this study pioneers the exploration of the impact of these factors on students' attitude toward AI-assisted L2 learning. By identifying these factors, we aim to make a distinct contribution to the field by shedding light on the underexplored dimensions that influence AI acceptance among L2 learners. This focus can provide a detailed insight into how students across different ages, genders, and personality traits perceive and interact with AI tools. Such understanding is essential for crafting pedagogical strategies that align with students' preferences and improve their L2 proficiency. It informs the development of inclusive and effective educational strategies tailored to meet the diverse needs of students.

2. Literature review

2.1. Defining attitude toward AI-assisted L2 learning

The term "attitude" originated with Spencer [11] and has since been elaborated upon by Ajzen and Fishbein [12] who defined it as an evaluative orientation influencing individuals' predispositions toward behaviors. Contemporary psychological discourse maintains a similar perspective, describing attitude as the evaluative stance individuals hold toward people, issues, or objects [13]. This evaluation typically ranges from positive to negative, though it can also include ambivalence. Researchers identify three key dimensions of attitude [14]: cognitive (involving perceptions and beliefs), affective (encompassing likes and dislikes), and behavioral (reflecting actions or intentions toward the object, based on cognitive and affective responses). Initially proposed by Eagly and Chaiken [15], this tripartite model has gained widespread acceptance and continues to be influential in current academic discourse [16]. Applying this model, our study defines attitude toward AI-assisted L2 learning as encompassing learners' perceptions of AI's usefulness, usability, and overall user experience. This comprehensive evaluation reflects the effectiveness of AI technology in facilitating improvements in their L2 proficiency. It includes their affective responses, cognitive beliefs, and behavioral intentions related to incorporating AI in their L2 learning endeavors.

2.2. Attitude as a key construct in AI acceptance for L2 learning

The role of attitude toward AI in people's acceptance of AI can be explored through various theoretical frameworks, including the Technology Acceptance Model (TAM), the Theory of Reasoned Action (TRA), and the Unified Theory of Acceptance and Use of Technology (UTAUT). TAM, introduced by Davis [17], is among the most influential models explaining technology acceptance, emphasizing perceived usefulness and ease of use as pivotal factors. It posits that a favorable attitude toward technology stems from these perceptions, influencing the intention to use it. TRA, developed by Fishbein and Ajzen [18], examines how attitude, subjective norms, and behavioral intentions interrelate. It suggests that intentions directly predict behavior, shaped by attitude toward the behavior and subjective norms. UTAUT, proposed by Venkatesh et al. [19], integrates TAM and TRA along with other models, identifying performance expectancy, effort expectancy, social influence, and facilitating conditions as critical determinants of behavioral intention. In these models, attitude serves as a significant determinant or mediator of AI acceptance. A positive attitude is formed based on beliefs about AI's benefits, ease of use, social influences, and perceived environmental support. This attitude drives the intention to use AI, a robust predictor of actual adoption according to these theories.

Based on TAM, TRA, or UTAUT, recent empirical research has extensively examined how learner attitude impacts the integration of AI in L2 learning [20,21]. For instance, Liu and Ma [22] adapted Attitude toward Behavior Scale from Davis [17] to investigate 405 Chinese college students' perceptions of the generative AI platform ChatGPT, revealing that favorable attitude toward ChatGPT correlated with increased usage in L2 learning. Additionally, drawing on the General Attitudes Towards Artificial Intelligence developed by Schepman and Rodway [23], Wu et al. [24] explored AI adoption among 464 Chinese college students using, finding that attitude directly influenced their intention to use AI for L2 learning. Most recently, Wu et al. [10] created the AI-Assisted Second Language Learning Attitude Scale. They subsequently verified its validity with 429 participants, finding that a more positive attitude toward AI predicted greater AI usage frequency. These studies are valuable as they underscore the pivotal role of attitude in determining AI adoption in L2 learning contexts. However, they predominantly focused on traditional factors like perceived usefulness and ease of use, potentially overlooking other factors that may also shape individuals' attitude toward AI-assisted learning.

2.3. Personality traits in L2 learning

Personality traits are commonly defined as enduring predispositions that shape individuals' thoughts, emotions, and behaviors [25]. Among the prominent models in personality psychology is the Big Five Personality Theory, introduced by Costa and McCrae [26]. The theory posits that five broad dimensions can account for the majority of the variations in human personality: Extroversion, agreeableness, conscientiousness, neuroticism, openness. In detail, extroversion measures the extent to which a person is outgoing and seeks stimulation in the company of others. Extroverts are typically sociable, energetic, and enjoy being in social situations. Agreeableness pertains to a person's cooperation and attunement to others' feelings. High scorers on agreeableness are empathetic and compassionate. Conscientiousness describes the degree to which a person is organized, reliable, and goal-oriented. People with high conscientiousness are dependable and persistent. In contrast, neuroticism is characterized by tendencies toward negative emotions such as anxiety and depression [27,28]. Finally, openness reflects a person's breadth, depth, originality, and openness of thought. Individuals who score high on openness tend to be creative, curious, and appreciate new ideas. These traits have biological foundations, influencing how individuals respond to various situations throughout their lives.

Over the past several decades, researchers have extensively explored individual differences in L2 learning [29–32]. Among these, personality traits have emerged as a potentially influential factor in predicting successful L2 learning [33,34]. Its role is thought to be associated with several factors pertinent to L2 learning [35], including motivation [36], strategic use [37], and willingness to communicate [38]. However, findings regarding the relationship between personality traits and L2 learning outcomes have not been entirely consistent. Some studies suggest that certain personality traits can facilitate L2 learning, while others indicate potential negative impacts of certain traits [39]. For example, Cao and Meng [36] utilized the Chinese Big Five Personality Inventory-Brief Version [40] alongside self-reporting to evaluate the L2 performance of Chinese students in speaking, listening, reading, and writing. Their aim was to investigate whether personality traits could predict L2 proficiency. The study findings suggested that conscientiousness and extraversion positively correlated with L2 proficiency, whereas other personality traits did not show significant effects. In contrast, Khajavy [41] employed Goldberg's Transparent Bipolar Inventory [42] to assess personality traits among Iranian students and utilized a similar self-report method to gauge L2 proficiency. His research indicated that only extraversion and openness positively predicted L2 proficiency, while other personality traits did not have a significant impact. This discrepancy in findings may arise from variations in measurement tools and participant characteristics across the two studies. Drawing from these studies, it can be inferred that personality traits may also influence individuals' attitude toward AI-assisted L2 learning. Further research is necessary to elucidate the interactions between specific personality traits' implications for optimizing L2 learning strategies, including those involving AI technologies.

2.4. Potential link between personality traits and attitude toward AI-assisted L2 learning

While research specifically exploring the relationship between personality traits and attitude toward AI-assisted L2 learning remains scarce, recent sporadic studies in the broader field have begun to shed light on this topic. These studies, however, yield inconsistent findings. For instance, Schepman and Rodway [23] developed the General Attitudes towards Artificial Intelligence Scale (GAAIS), which comprises positive and negative subscales. Through hierarchical regression analyses, they found that extraverted individuals exhibited a less positive attitude toward AI's positive aspects compared to introverted individuals. Surprisingly, none of the other Big Five personality traits significantly predicted positive attitude in the context of other predictor variables. In contrast, Kaya et al. [43], also employing the GAAIS, found that personality traits did not directly impact general positive attitude toward AI. However, they did observe that agreeableness positively predicted negative attitude, while the remaining Big Five traits did not significantly influence negative attitude in relation to other predictors. Despite these inconsistencies, it is evident that personality traits play a pivotal role in shaping individuals' attitude toward AI.

However, attitude toward AI in the L2 learning context may diverge from that in the general sense. As highlighted by Wu et al. [10], general attitude is not inherently aligned with specific learning contexts. A general attitude toward AI encompasses societal perspectives on AI's role and impact across various domains. It combines both anticipation and concerns related to AI development, ethical considerations, privacy implications, and employment dynamics. In contrast, attitude toward AI-assisted L2 learning specifically pertains to perceptions of AI's role in L2 education, emphasizing its potential to customize and enhance the learning experience. To address this distinction, Wu et al. [10] constructed a specialized scale for assessing attitude toward AI-assisted L2 learning. Given that the predictive influence of personality traits in L2 the learning context likely differs from their impact in the general context, exploring the potential effects of personality traits on AI-assisted L2 learning may provide valuable insights to the field of L2 education.

2.5. Context and research questions

Recently, alongside ChatGPT, several other GenAI tools have emerged in China, including Kimi, ERNIE Bot, and iFLYTEK Spark. These tools are freely accessible, contributing to their widespread popularity in the country. Unlike middle and high school students in China who face restrictions on electronic device usage, college students enjoy more freedom in this regard, potentially benefiting more from AI-assisted L2 learning. L2 proficiency, particularly English, holds significant importance for Chinese college students. It is a mandatory component of college curriculum for all majors and aligns with China's globalization strategy, linking its economy closely with numerous other nations. Enhanced L2 proficiency enhances students' competitiveness in the job market, underscoring its relevance. This study aims to achieve two primary objectives: firstly, to explore Chinese college students' attitude toward AI-assisted L2 learning; secondly, to investigate the influence of personality traits on this attitude. Furthermore, demographic variables commonly exert influences on outcome variables. Therefore, we also investigated the impact of age and gender on attitude in this context. Specifically, the study addresses the following three research questions:

RQ1: How is the general tendency of Chinese college students' attitude toward AI-assisted L2 learning?

RQ2: Do age and gender predict attitude toward AI-assisted L2 learning? If so, what is the extent of their predictive power?

RQ3: Do personality traits predict attitude toward AI-assisted L2 learning? If so, what is the extent of their predictive power?

3. Methodology

3.1. Participants

In this study, convenience sampling was employed to enlist 538 college students from multiple provinces across China, including Hunan, Zhejiang, and Henan, using an online questionnaire survey. Participants were instructed to complete a self-reported online questionnaire comprising two main sections: demographic information (e.g., university, age, gender, and grade) and two scales assessing personality traits and attitudes toward AI-assisted L2 learning. Subsequently, 45 participants (10.27%) were excluded from the analysis due to either providing identical responses across all items or failing to complete the questionnaire. The final sample comprised 493 participants, whose demographic characteristics are detailed in **Table 1**. Before commencing the survey, participants were informed about its objectives, provided instructions on questionnaire completion, and assured of confidentiality and anonymity. They were also given the opportunity to seek clarification about the survey and voluntarily consented to participate.

Table 1. Demographic information of participants (n = 493).

Age	Mean	19.72
	Range	18—25
	SD	1.073
Gender	Male	156
	Female	337
Grade	Freshman	236
	Sophomore	136
	Junior	112
	Senior	9

Note: SD = standard deviation.

To ensure the validity of the self-report scales measuring personality traits and attitude toward AI, a rigorous translation and back-translation procedure was employed. Initially, the scales were translated from English to Chinese and subsequently back-translated into English by three bilingual researchers. Following this, a psychology expert specializing in translation reviewed and refined the phrasing of items to maximize semantic consistency between the English and Chinese versions. Participants were instructed to complete the scales in Chinese, with the English versions provided for reference to ensure understanding of the original item meanings when necessary.

3.2. Instruments

3.2.1. The ten-item personality inventory

The Ten-Item Personality Inventory [44] was employed in this study to assess the Big Five personality traits. This inventory consists of 10 items distributed across five factors, with each factor containing two items. We calculated the average scores to assess each personality trait. Responses are recorded using a 7-point Likert-type scale ranging from 1 (strongly disagree) to 7 (strongly agree). To ascertain the reliability of the instrument, consisting of two items each, Eisinga et al. [45] recommended the use of the Spearman-Brown Correlation Coefficient. In our study, the Spearman-Brown Correlation Coefficient was utilized to compute the split-half reliability of the inventory. Analysis of our sample data revealed satisfactory split-half reliability coefficients (cutoff > 0.7): r = 0.703 for openness, r = 0.726 for conscientiousness, r = 0.818 for extroversion, r = 0.855 for agreeableness, and r = 0.758 for neuroticism. In our study, we assessed the construct validity of the inventory using AMOS 24, yielding acceptable results: χ^2/df = 3.846 (excellent: < 3; acceptable: 3–5), CFI = 0.924 (acceptable: > 0.9; excellent: > 0.95), TLI = 0.906 (acceptable: > 0.9; excellent: > 0.95), RMSEA = 0.078 (excellent: < 0.06; acceptable: < 0.08), SRMR = 0.072 (excellent: < 0.06; acceptable: < 0.08) [46].

3.2.2. The AI-Assisted L2 learning attitude scale

The AI-Assisted L2 Learning Attitude Scale developed by Wu et al. [10] was employed to evaluate the attitude of Chinese college students toward AI-assisted L2 learning. This scale consists of 12 items categorized into two components: Behavioral and Cognitive. Responses were collected using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). We calculated the average scores to assess the overall attitude. Higher total scores show a more positive attitude toward AI-assisted L2 learning. The scale demonstrated strong reliability in our sample, with Cronbach's α coefficients of 0.890 for the overall scale, 0.839 for the Behavioral component, and 0.779 for the Cognitive component. In our study, we assessed the construct validity of the scale using AMOS 24, yielding excellent results: χ^2/df = 2.774 (excellent: < 3; acceptable: 3–5), CFI = 0.964 (acceptable: > 0.9; excellent: > 0.95), TLI = 0.951 (acceptable: > 0.9; excellent: > 0.95), RMSEA = 0.060 (excellent: < 0.06; acceptable: < 0.08), SRMR = 0.039 (excellent: < 0.06; acceptable: < 0.08) [46].

3.3. Data analysis

All statistical analyses were conducted using SPSS 26, chosen for its robust capabilities and user-friendly interface, which facilitate efficient data exploration and summarization. Descriptive analyses were employed to address RQ1, while multiple regression analyses were utilized for RQ2. In these regressions, personality traits and demographic characteristics served as predictor variables, with attitude toward AI-assisted L2 learning as the outcome variable. In our data analysis, significance was determined at $p < 0.05$.

Before conducting ordinary least-square (OLS) regression analyses, several assumptions were checked. Firstly, normality of the data was assessed based on standardized skewness and kurtosis values recommended by Field [47], with values falling between −2.0 and +2.0 considered indicative of normal distribution. Additionally, correlations between predictor and outcome variables were examined to ensure the suitability of the data for regression analysis.

We also checked the fit of our regression model using several criteria. Initially, we evaluated the multicollinearity assumption by examining relationships between predictor variables, considering variance inflation factors (VIF). According to Field [47], VIF values should be below 5. Then, we tested for heteroskedasticity in our data using the White test, $p > 0.05$ indicates that there is no heteroskedasticity in our data. We did not verify every assumption of regression models, and there is a possibility that some have been breached. Nevertheless, OLS regressions are generally resilient in the face of such breaches [48].

4. Results

4.1. Common method bias

Common method variance (CMV) refers to the variance that arises due to the measurement method itself rather than being reflective of the construct intended to be measured [49]. This issue is particularly pertinent in research where both independent and dependent variables are assessed using self-reported data from the same source, potentially leading to problematic variations [49]. The likelihood of common method variance is heightened when data collection relies exclusively on responses from a single respondent.

Harman's single-factor test is a method used to detect CMB [50]. This approach assesses whether there is a single factor in the data that can account for a large portion of the variance through Exploratory Factor Analysis (EFA), thereby determining the presence of CMB. This study conducted a CMB test on the data in the following steps: First, a non-rotated EFA was performed. This involved including all questionnaire items, which comprised 10 items for personality traits and 16 items related to attitudes toward AI-assisted L2 learning (excluding demographic characteristics), in order to observe the inherent structure of the data. Second, the number of factors and eigenvalues were checked: The analysis should determine how many factors have eigenvalues greater than 1. Finally, the explained variance of the first factor was assessed: The proportion of variance explained by the first factor was observed; if this proportion exceeds half of the total variance (commonly using 50% as the standard), it may indicate the presence of CMB.

The results are shown in **Table 2**, where the explained variance of the first factor is 26.923, not exceeding half of the total variance explained, so it can be concluded that our data does not exhibit a situation where a single factor explains the vast majority of the variance, indicating that CMB is not severe.

Table 2. Total variance explained (n = 493).

Component	Initial eigenvalues			Extraction sums of squared loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.923	26.923	26.923	5.923	26.923	26.923
2	2.678	12.173	39.096	2.678	12.173	39.096
3	1.604	7.291	46.387	1.604	7.291	46.387
4	1.473	6.697	53.084	1.473	6.697	53.084
5	1.265	5.751	58.834	1.265	5.751	58.834

Note: Extraction method: Principal component analysis.

4.2. Descriptive statistics

The initial research inquiry examined the attitude of Chinese college students toward AI-assisted L2 learning. To explore this, descriptive statistics were employed, encompassing measures such as the mean, range, standard deviation, and median. The Attitude toward AI-assisted L2 Learning Scale, utilizing a 5-point Likert scale, indicates that values approximating 3 reflect a moderate attitude, around 1 indicate a low attitude, and near 5 signify a high attitude. As presented in **Table 3**, the calculated mean attitude score was 3.985 (>3), suggesting that Chinese college students hold a moderately high positive attitude toward AI-assisted L2 learning. This conclusion is supported by the median values as well.

Furthermore, the normality of the data was verified through the examination of Skewness and Kurtosis values, as detailed in **Table 3**. This validation established that the data adhered to the requisite assumptions for conducting subsequent multiple regression analyses in the forthcoming sections.

Another prerequisite for conducting multiple regression analyses is the presence of significant correlations between predictor variables and outcome variables. To address this, we conducted a correlation analysis examining the relationship between age, gender, personality traits, and attitude toward AI-assisted L2 learning.

Table 3. Descriptive statistics for AI attitude and personality traits (n = 493).

	Attitude	**Extroversion**	**Agreeableness**	**Conscientiousness**	**Neuroticism**	**Openness**
Mean	3.985	4.059	3.874	4.134	4.470	4.705
Median	4.083	4.000	4.000	4.000	4.500	4.500
SD	0.746	1.267	1.000	0.970	1.072	0.939
Skewness	−0.561	−0.078	−0.286	0.408	0.191	0.517
SE of Skewness	0.110	0.110	0.110	0.110	0.110	0.110
Kurtosis	−0.028	0.121	−0.827	1.320	0.487	−0.168
SE of Kurtosis	0.220	0.220	0.220	0.220	0.220	0.220
Minimum	1.0	1.0	1.0	1.0	1.0	2.0
Maximum	5.0	7.0	5.5	7.0	7.0	7.0

Note: SD = standard deviation; SE = standard error.

Table 4 illustrates that age, gender, and the five personality traits exhibit significant correlations with attitude toward AI-assisted L2 learning. Thus, these findings confirm that the data satisfy the necessary assumptions for conducting multiple regression analyses.

Table 4. Correlations between AI attitude and personality traits (n = 493).

Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1. Age	-							
2. Gender	−0.042	-						
3. Attitude	0.118**	−0.142**	-					
4. Extroversion	−0.007	−0.067	−0.212**	-		*		
5. Agreeableness	0.005	−0.085	−0.196**	−0.039	-	*		
6. Conscientiousness	0.011	0.141**	0.218**	−0.243**	−0.254**	-		
7. Neuroticism	−0.031	−0.200**	−0.207**	0.160**	−0.452**	−0.494**	-	
8. Openness	0.023	0.070	0.226**	−0.375**	0.401**	0.387**	−0.379**	-

Note: **. Correlation is significant at the 0.01 level (2-tailed); male = 1, female = 0.

4.3 Multiple regression analyses

To investigate the second and third research questions pertaining to the prediction of attitude toward AI-assisted L2 learning by age, gender, and personality traits, we conducted a multiple regression analysis. Age, gender, and various personality traits were employed as predictor variables, while attitude toward AI-assisted L2 learning served as the outcome variable.

Before delving into the interpretation of the findings, we first evaluated how well our model fits the data. The model summary for the multiple regression analysis, as depicted in **Table 5**, discloses an R-squared value of 0.167. This signifies that, when considered together, the predictor variables explained 16.7% of the variability in attitudes towards AI-assisted L2 learning. Furthermore, to examine the presence of heteroskedasticity in our dataset, we performed the White test. The outcome of this test indicated a p-value greater than 0.05, which leads to the conclusion that our data did not exhibit any significant heteroskedasticity.

Table 5. Summary of the multiple regression model (n = 493).

Model fit					**White Test for Heteroskedasticity**[a,b]		
Model	***R***	***R* Square**	**Adjusted *R* Square**	**SE of the Estimate**	**Chi-Square**	**df**	***p***
	0.326	0.167	0.093	0.710	34.028	34	0.466

Note: R = correlation coefficient; R Square = coefficient of determination; Adjusted R Square = adjusted coefficient of determination; df = degrees of freedom; p = significance probability; a. Dependent variable: Attitude; b. Tests the null hypothesis that the variance of the errors does not depend on the values of the independent variables.

Multicollinearity refers to a statistical phenomenon in multiple regression analysis and econometrics where two or more predictor variables demonstrate high correlation. This correlation can result in inflated standard errors, potentially influencing hypothesis testing outcomes. Low t-statistics for regression coefficients may occur, increasing the risk of failing to reject a false null hypothesis (Type II error). Hence, we assessed multicollinearity within our regression model. The findings presented in **Table 6** indicate that the VIF for all variables was below 5Therefore, it can be concluded that multicollinearity was not present in our regression model.

Table 6. Results of multiple regression analyses (n = 493).

Model	***β***	***t***	***p***	**SE**	**Collinearity Statistics**	
					Tolerance	**VIF**
Gender	−0.161	−3.589	0.000	0.069	0.915	1.092
Age	0.109	2.527	0.012	0.015	0.996	1.004
Extroversion	−0.129	−2.685	0.009	0.028	0.829	1.206
Agreeableness	−0.086	−1.664	0.097	0.039	0.688	1.453
Conscientiousness	0.143	2.715	0.008	0.040	0.697	1.434
Neuroticism	−0.104	−2.473	0.032	0.038	0.603	1.658
Openness	0.145	2.734	0.006	0.042	0.655	1.527

Note: β = standardized coefficient; t = t-value; p = significance probability; SE = standard error; VIF = variance inflation factor.

Following confirmation of the fit of our regression model fit, formal analysis of the multiple regression results commenced. As depicted in **Table 6**, except for agreeableness, all other predictor variables exhibited statistically significant effects on attitude toward AI-assisted L2 learning. For the purpose of graphically representing the outcomes, **Figure 1** was employed to provide a visual synthesis of the data.

Specifically, addressing the second research question, gender was found to have a significant negative predictive effect on attitude (β = −0.161, p < 0.05), accounting for 2.59% of the total variance. Additionally, age showed a significant positive predictive effect on attitude (β = 0.109, p < 0.05), explaining 1.18% of the total variance.

Regarding the third research question, extroversion exhibited a significant negative prediction of attitude (β = −0.129, p < 0.05), accounting for 1.66% of the total variance. Conscientiousness, on the other hand, demonstrated a significant positive prediction of attitude (β = 0.143, p < 0.05), explaining 2.04% of the total variance. Additionally, neuroticism negatively predicted attitude (β = −0.104, p < 0.05), contributing to 1.08% of the total variance, while openness positively predicted attitude (β = 0.145, p < 0.05), explaining 2.10% of the total variance.

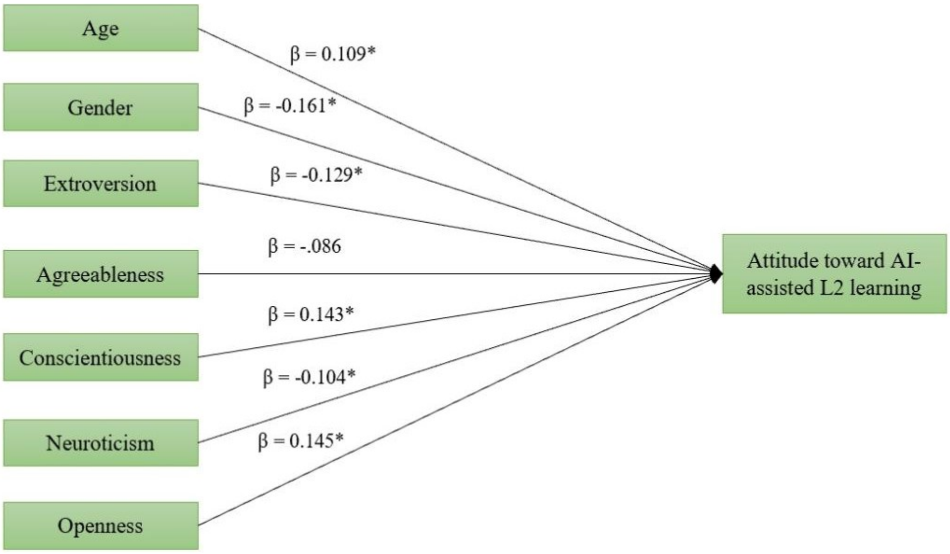

Figure 1. Results of multiple regression analyses.

Note: *. Correlation is significant at the 0.05 level (2-tailed).

5. Discussion

Given the significant potential benefits of AI in L2 learning and the pivotal role of attitude in its adoption, understanding the factors that influence this attitude is paramount. Personality traits emerge as a key determinant among these factors. Therefore, this study aims to achieve three specific objectives: first, to investigate the prevailing attitude of Chinese college students toward AI-assisted L2 learning; second, to examine the impact of gender and age on this attitude; and third, to further scrutinize the influence of personality traits on this attitude.

RQ1: The general tendency of Chinese college students' attitude toward AI-assisted L2 learning.

Regarding the first research question, descriptive analyses unveiled that Chinese college students generally held a moderately high positive attitude toward AI-assisted L2 learning (M = 3.985). This finding contrasts somewhat with Wu et al. [10], who utilized the same scale to assess attitude among 808 Chinese college students and found a moderate positive attitude (M = 3.539). The discrepancy between these results is not unexpected nor unreasonable. Wu et al. [10] gathered their data in 2023, whereas our data were collected in June 2024, representing a six-month interval. Significant developments have occurred during this period; for instance, Moonshot, a Chinese company, officially introduced Kimi as a GenAI in October 2023, mirroring functionalities akin to ChatGPT 4, contributing to its burgeoning popularity over the past six months. Likewise, Baidu, another prominent technology firm in China, released a new ChatGPT-comparable version known as ERNIE Bot in October 2023. These robust GenAI tools are freely accessible, bolstering their adoption and likely contributing to the heightened positive attitude observed among Chinese college students recently.

RQ2: The predictive role of demographics on Chinese college students' attitude toward AI-assisted L2 learning.

In addressing the second research question, the multiple regression analyses revealed that age positively predicted attitude toward AI-assisted L2 learning, explaining 1.18% of its total variance. Specifically, older students tended to hold a more favorable attitude. This finding contrasts with previous research that has explored the impact of age on attitude toward AI in broader contexts, where older individuals exhibit more negative attitude [23,43,51]. The observed inconsistency can be attributed to differences in participants and contexts. For instance, studies by Kaya et al. [43] and Schepman and Rodway [23] encompassed participants spanning a wider age range (18–51 and 18–76 years, respectively), including multiple generational perspectives. Older generations may be less exposed to new technologies like AI, causing their cautious attitude. In contrast, our study focuses on attitude in the L2 learning context among college students, where AI is tended to be perceived as a tool to enhance L2 proficiency. Besides, older students' more positive attitude observed in our study is possible due to their diverse learning experiences, which fosters greater openness to adopting new technologies, including AI, for enhancing learning efficiency [52].

In addition, our study identified a negative impact of gender on attitude toward AI-assisted L2 learning, explaining 2.59% of its total variance. This indicates that female college students generally exhibited more favorable attitude toward AI in this specific educational context compared to their male counterparts. This finding is contradictory to the research by Kaya et al. [43] and Schepman and Rodway [23], where gender did not significantly influence attitude toward AI in a general sense. Several factors may explain this discrepancy. Firstly, the contextual application of AI, particularly in L2 learning, may magnify gender-based differences due to distinct educational needs, interests, or learning styles that may not manifest as prominently in broader contexts. Moreover, female students' heightened positivity toward AI-assisted L2 learning tools in our study could stem from their perceived utility in enhancing their language learning experiences. Previous studies have indicated that female L2 learners often exhibit greater motivation and adopt diverse learning strategies [37,53], which might further contribute to their more favorable attitude toward AI in educational settings. To our best knowledge, our study is the first one that explores the effect of demographics on attitude toward AI in the L2 learning context.

RQ3: The predictive role of personality traits on Chinese college students' attitude toward AI-assisted L2 learning.

As for the third research question, our multiple regression analyses indicate that, except for agreeableness, the other four personality traits significantly predicted attitude toward AI-assisted L2 learning among Chinese college students. This study represents the initial exploration of the relationship between personality traits and attitude toward AI in the L2 learning context. Agreeableness, characterized by traits such as friendliness, generosity, and consideration for others' feelings, does not appear to relate to attitude toward AI-assisted L2 learning, Extroversion was found to negatively predicted this attitude, explaining 1.66% of the total variance. This finding was consistent with Schepman and Rodway's [23] observation that extroversion negatively predicted attitude toward AI more broadly. However, the underlying reasons for this congruence likely differ. In our study, extroverted individuals may prefer learning environments that emphasize interpersonal communication and interaction [37,39]. Consequently, they might perceive AI-assisted learning as lacking the personal engagement and authentic communicative experiences they value, thereby fostering a negative attitude toward this mode of learning.

Similarly, it was found that neuroticism significantly dampened attitude toward AI-assisted L2 learning, explaining 1.08% of the total variance. This trend can be attributed to the typical traits associated with neurotic personalities, characterized by emotional instability and anxiety [54]. When confronted with innovative tools such as AI applications for L2 support, individuals exhibiting neurotic tendencies may experience heightened anxiety due to unfamiliarity. Consequently, this anxiety could impede their adoption of such technologies. Conversely, conscientiousness and openness emerged as significant predictors of a positive attitude, accounting for 2.04% and 2.10% of the total variance, respectively. A possible reason is that conscientious individuals, driven by a strong sense of self-discipline, tend to favor autonomous learning and self-regulation [55]. AI-assisted systems, offering personalized learning experiences aligned with their individual pace, are tended to be perceived as valuable aids in their educational journey [3]. In term of openness' positive effect, it might be because individuals high in openness demonstrate a receptiveness to technologies. Accordingly, they are more inclined to embrace AI-driven tools for L2 learning. Moreover, prior research indicates that highly open students often exhibit greater self-efficacy [56], which may make them believe in their capacity to effectively leverage AI tools to enhance their foreign language learning outcomes.

6. Implications and limitations

This study contributes both theoretically and practically in several ways. Theoretically, our findings extend the application of the Big Five personality theory to attitude toward AI in education. Specifically, we provide a nuanced understanding of how specific traits relate to AI acceptance in the L2 learning context. Additionally, our research highlights the influence of age and gender on attitude, adding a demographic dimension to the study of AI acceptance. Lastly, the identification of personality traits—such as extroversion and neuroticism with negative predictive effects, and conscientiousness and openness with positive effects—enriches our theoretical understanding of the intricate interplay between personality and AI adoption in L2 learning.

Our study also offers practical implications. In detail, we found that older college students exhibited a more positive attitude toward AI-assisted L2 learning compared to their younger counterparts, and females were more enthusiastic than males. When designing courses, these differences should inform customized learning materials and methods for diverse age groups and genders. Additionally, personality traits played a significant role: extroversion and neuroticism negatively impacted attitude, while conscientiousness and openness had a positive influence. Educators can assess students' personality traits and tailor support accordingly. For instance, students with higher neuroticism may benefit from emotional management strategies when using AI for L2 learning. Conversely, conscientious and open students are adept at utilizing AI tools, making them valuable advocates for promoting AI adoption and sharing positive experiences with peers.

This study is subject to several limitations that warrant acknowledgment. Initially, the inclusion of exclusively Chinese samples raises questions about the generalizability of our findings to other cultural contexts. Future research could address this limitation through cross-national comparative studies to explore the effect of demographics and personality traits on college students' attitude towards AI-assisted L2 learning. Besides, the relatively small sample size, drawn solely from three provinces in China, may limit the broader applicability of our results across the diverse population of Chinese college students. Thus, future studies could include larger and more diverse samples to improve the reliability of findings. Thirdly, the exclusive use of a quantitative approach in this study may not fully capture individual differences. Future research could benefit from employing a mixed-methods design to provide deeper insights into the complex interplay between personality traits and attitude toward AI-assisted L2 learning.

Moreover, the scale for attitude toward AI-assisted L2 learning ranges from 1 to 5, with a mean close to 4, indicating a tendency for most participants to rate their attitude toward the higher end of the scale. The SD was notably low, at 0.746, suggesting a tight clustering of participant scores and a narrow distribution range. This concentration implies a prevalent highly positive attitude among participants regarding AI-assisted L2 learning, thereby limiting variability in the outcome measurement. To capture a more nuanced attitude, future research might consider employing a broader scoring method, such as a scale ranging from 1 to 7 or 1 to 10, to avoid ceiling effect and enable participants to express their attitude with greater precision. Finally, it is crucial to recognize that the personality questionnaire with only 10 items may not fully capture the complexity of personality traits. While such a concise instrument offers a brief overview, it may lack the depth necessary for a thorough understanding of an individual's personality dimensions. To mitigate this limitation, employing a more extensive personality scale with a greater number of items is recommended.

7. Conclusion

Through investigating Chinese college students' attitude toward AI-assisted L2 learning, this study revealed several key insights. First, students exhibited a moderately high positive attitude. Second, older students displayed a more positive attitude than younger ones, and females were more positive than males. Finally, personality traits—except for agreeableness—significantly influenced this attitude. Specifically, extroversion and neuroticism had a negative predictive effect, while conscientiousness and openness positively predicted it.

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