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ISSUES

DECODING the HUMAN-AI RELATIONSHIP USING the AIDUA MODEL: APPRAISAL OUTCOMES and EFL STUDENTS' INTENTIONS

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The rapid growth of artificial intelligence (AI) has impacted diverse sectors, including language education, highlighting the critical importance of user acceptance and key factors that facilitate AI adoption. This study employs a quantitative approach to investigate the factors influencing English as a Foreign Language (EFL) students' willingness and objections to using AI in English language learning, utilizing the AIDUA framework. An online survey was sent to EFL Vietnamese students, and 1,118 valid responses were analyzed using SmartPLS 4.0.9.8. The findings revealed that although all the factors in primary appraisal significantly influenced students' willingness to accept AI, they had little impact on students' objections. Surprisingly, while affective attitude significantly influences students' willingness to use AI for English learning, it also triggers emotional resistance, revealing a complex emotional dynamic. Conversely, cognitive attitude marginally softens hesitance yet exerts a more substantial influence on students' willingness. The study provides insights into the application of AI in English learning, highlighting the cognitive and affective aspects of students' learning experiences.

1. Introduction

AI technology has developed rapidly across various industries, including transportation, healthcare, and customer service (Kumar et al., 2023; Song et al., 2022; Xia et al., 2020). Traditional teaching and learning methods are being transformed in education through technology-driven automated evaluation systems, personalized learning systems, and AI tutors (Chaudhry & Kazim, 2021).

As traditional language teaching approaches face practical challenges of class sizes and limited resources (Fatima et al., 2024), English language education has progressively integrated technology-driven methods. The emergence of Computer-Assisted Language Learning (CALL) has provided students with access to interactive assignments and multimedia content through real-time feedback systems. However, CALL systems do not offer customized educational experiences (Bahari et al., 2025). Recent advances in artificial intelligence (AI) offer more sophisticated solutions by analyzing learner data, adapting content, adjusting instruction, and customizing experiences, thereby enabling individualized and context-responsive learning in English as a

Foreign Language (EFL) education (Wei, 2023). Moreover, educational technology has advanced from rule-based systems to Generative AI (GenAI) for interactive content delivery, including writing suggestions, speaking feedback, and automated task generation (AbuSa'aleek & Alenizi, 2024; Samala et al., 2025). The appeal of advanced technologies, such as AI, has motivated learners' engagement, resulting in improved learning outcomes. However, the study by Hwang et al. (2020) suggests that further research is needed to exploit the potential of AI in language learning applications.

There are two popular theoretical frameworks for technology acceptance: the technology acceptance model (TAM), developed by Davis (1989), and the unified theory of acceptance and use of technology (UTAUT), introduced by Venkatesh et al. (2003). However, these models examine general technology rather than AI-based technology. As AI benefits society through advances in various fields, it is essential to understand the factors that facilitate user acceptance and adoption of this technology, enabling its practical use. In 2019, Gursoy et al. promoted the artificially intelligent device use acceptance (AIDUA) model, which offers a framework for AI acceptance. AIDUA contrasts its approach from earlier models through three assessment stages: primary appraisal, secondary appraisal, and outcome stage (Gursoy et al., 2019). Ma and Huo (2023) further developed the model, adding novelty value to the primary appraisal and incorporating cognitive and affective attitude into the secondary appraisal.

Despite growing research on AI in education, studies specifically addressing EFL students' attitudes toward AI acceptance remain scarce. As AI integration in English learning increases, further investigation is needed to assess students' readiness for AI and the attitudinal factors influencing their acceptance. This study examines key acceptance factors based on Ma and Huo's (2023) modified AIDUA model, thereby enhancing the understanding of technology acceptance theories within the context of AI-supported English as a Foreign Language (EFL) learning.

2. Literature review

2.1. Theoretical background and hypothesis development

Technology acceptance models have been developed and extended by researchers to explain users' behaviors or intentions to use or reject technologies. The technology acceptance model (TAM) (Davis, 1989) and the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003) were among these models originally developed to help explore how users accept non-AI technology. However, these models primarily focus on measuring functional benefits, overlooking the emotional responses that users experience when interacting with AI platforms (Gursoy et al., 2019; Ma & Huo, 2023). As Gursoy et al. (2019) posit that emotional factors significantly influence users' behavioral intentions toward AI service devices, they highlight the central role of emotions in the acceptance process (Alzyoud et al., 2024). In contrast to these classic technology acceptance models, the AIDUA model is extended by acknowledging the emotional bonds users form with AI.

Although the original AIDUA model by Gursoy (2019) produced valuable findings, it lacks an essential cognitive attitude when examining users' rational evaluations of AI utility. The AIDUA framework was enhanced by Ma and Huo (2023), who substituted cognitive attitude and affective attitude for emotions as the primary determinants of user acceptance of AI systems. Their model features perceived humanness and novelty value, cognitive attitude, and affective attitude as new constructs. The updated AIDUA model by Ma and Huo (2023) comprises primary appraisal (social influence, novelty value, perceived humanness, and hedonic motivation), secondary appraisal (performance expectancy, effort expectancy, cognitive attitude, and affective attitude), and the outcome stage (willingness to accept and objection to use). In this study, we adopt the AIDUA model proposed by Ma and Huo (2023) to investigate EFL students' willingness and objections to using AI in English learning.

2.2. Primary appraisal

SOCIAL INFLUENCE

Social influence (SI) describes the extent to which a person, influenced by others, perceives they should adopt a particular technology (Venkatesh et al., 2003). When people plan to adopt new technologies, they generally take advice from their family members and friends (He et al., 2022). They also consider the posts of celebrities and influencers on social media when evaluating technology adoption (Ma & Huo, 2023). Recent studies have identified SI as a key factor influencing university students' behavioral intentions and acceptance of AI tools (Supianto et al., 2024; Tam & Kataoka, 2024). Given these insights, we propose the following hypotheses:

> **H1a**: Social influence (SI) significantly affects students' performance expectancy (PE) of AI in English learning.
>
> **H1b**: Social influence (SI) significantly affects students' effort expectancy (EE) of AI in English learning.

NOVELTY VALUE

Novelty value (NV) is defined as the degree to which a product is perceived as fresh, original, and distinct from existing alternatives (Im et al., 2015). Users who perceive technology as a new experience tend to derive greater enjoyment from it, resulting in increased perceived enjoyment and task utility. Alzyoud et al. (2024) found that NV was positively associated with performance expectancy (PE) but had a negative relationship with effort expectancy (EE).

These results suggest that users may expect highly novel technologies to function intuitively and require minimal effort to operate. Building on these findings, this study proposes the following hypotheses:

> **H2a**: Novelty value (NV) significantly influences students' performance expectancy (PE) of AI in English learning.
>
> **H2b**: Novelty value (NV) significantly influences students' effort expectancy (EE) of AI in English learning.

PERCEIVED HUMANNESS

Perceived humanness (PH) refers to how AI technologies exhibit human-like qualities. Specifically, AI systems can communicate with humans by using natural language, engaging in coherent conversations, and exhibiting emotional sensitivity (Hsu & Lin, 2023). Educational tools with human-like characteristics can enhance communication skills and foster emotional connection, increasing learner engagement and motivation (Ebadi & Rahimi, 2024). Perceived humanness also contributes to users' satisfaction and enjoyment, reinforcing expectations regarding the AI's usefulness and ease of use, highlighting its positive influence on performance and effort expectancies (Ma & Huo, 2023). Hence, the following hypotheses are proposed:

> **H3a**: Perceived humanness (PH) significantly influences students' performance expectancy (PE) of AI in English learning.
>
> **H3b**: Perceived humanness (PH) significantly influences students' effort expectancy (EE) of AI in English learning.

HEDONIC MOTIVATION

According to Venkatesh et al. (2012), hedonic motivation (HM) is the enjoyment or pleasure derived from using technology. Individuals with high hedonic motivation enjoy the interactive experience and are driven by the playfulness and enjoyment that technology provides. According to Strzelecki (2024), hedonic motivation involves how entertaining and enjoyable students find AI tools, as well as how much they like exploring new ones. Previous studies indicate that HM factors, such as focused immersion, boredom, joy, and a sense of control, significantly influence university students' behavioral intention to use AI for English learning (Qu & Wu, 2024; Zhou et al., 2024). However, there were contradictory findings. Ma and Huo (2023) found no significant link between hedonic motivation and performance expectancy in the use of AI chatbots, whereas Cai et al. (2024) identified a positive relationship. This contrast highlights the need for further investigation. The following hypotheses are, therefore, proposed.

> **H4a**: Hedonic motivation (HM) significantly influences AI users' performance expectancy (PE) of AI in English learning.

H4b: Hedonic motivation (HM) significantly influences AI users' effort expectancy (EE) of AI in English learning.

2.3. Secondary appraisal

PERFORMANCE EXPECTANCY

For the technology to be considered high performing, its functions must meet the user's expectations. Gerlich (2023) posited that performance expectancy (PE) refers to an individual's belief that the use of AI technology can enhance productivity and efficiency, contributing to improved performance outcomes. Factors influencing PE include perceived usefulness of a chatbot, task compatibility, task completion, job performance impact, sense of accomplishment, and engagement (Menon & Shilpa, 2023). Some studies have found a favorable attitude towards AI among EFL learners, particularly in its support for vocabulary building, reading comprehension, and pronunciation (Nguyen, 2024; Pham et al., 2023). These results suggest that PE has a significant contribution to forming students' positive attitudes toward AI tools for English language learning. The hypotheses are proposed as follows:

H5a: Performance expectancy (PE) significantly affects users' cognitive attitude (CA) toward AI in English learning.

H5b: Performance expectancy (PE) significantly affects users' affective attitude (AA) toward AI in English learning.

EFFORT EXPECTANCY

Effort expectancy (EE) indicates the ease of use of technology (Venkatesh et al., 2012). Users are less likely to reject integrating AI tools into their daily tasks when they are straightforward, easy to use, and intuitive (Emon et al., 2023). Perceived ease of use is important in language learning because students are more likely to use AI technologies that are simple and require minimal effort (Gupta et al., 2024). Cai et al. (2024) proposed a similar idea, finding that AI chatbots offer smooth and adaptive feedback, which in turn enhances motivation and learning effectiveness. Based on these insights, the following hypotheses are proposed:

H6a: Effort expectancy (EE) significantly influences EFL students' cognitive attitude (CA) toward AI in English learning.

H6b: Effort expectancy (EE) significantly influences EFL students' affective attitude (AA) toward AI in English learning.

COGNITIVE ATTITUDE

Cognitive attitude (CA) denotes the beliefs about the context in which something exists (Garrett et al., 2003), the ideas or opinions about a particular subject (Zulfikar et al., 2019), or the thoughts and knowledge an individual holds about a specific object (Dogan & Tuncer, 2020). It demonstrates how a subject is evaluated based on its practical aspects, which usually depend on its usefulness. In the context of AI, cognitive appraisals refer to how users perceive the effectiveness of AI in supporting their tasks or providing information (Ma & Huo, 2023). Svenningsson et al. (2022) found that cognitive and affective attitudes significantly influence users' behavioral intentions, which in turn motivate actual behavior. Based on these insights, the following hypotheses are proposed:

> **H7a**: Cognitive attitude (CA) significantly influences students' willingness to accept AI in English learning (WTA).

> **H7b**: Cognitive attitude (CA) significantly influences students' objections to use AI in English learning (O).

AFFECTIVE ATTITUDE

Affective attitude (AA), also referred to as the emotional dimension, represents the feelings experienced toward something, such as liking or disliking it (Zulfikar et al., 2019). Emotions, sentiments, and instinctive responses influence affective assessments related to the hedonic component of attitude. Studies have shown that students generally hold favorable perceptions of integrating AI into their learning experiences (Kairu, 2020; Pande et al., 2023). In language learning, socially active individuals who are willing to take risks and engage in communication are more likely to develop positive attitudes toward the language (Dogan & Tuncer, 2020). Ma and Huo (2023) found that cognitive attitude had a strong influence on users' willingness to adopt AI tools, whereas affective attitude had a limited impact on acceptance. However, positive emotion did help reduce resistance, suggesting that it eases rejection rather than drives adoption. Based on these insights, the following hypotheses are proposed:

> **H8a**: Affective attitude (AA) significantly influences students' willingness to accept AI in English learning (WTA).

> **H8b**: Affective attitude (AA) significantly influences students' objections to use AI in English learning (O).

3. Methodology

3.1. Instrument

The questionnaire items were adapted from existing literature scales and developed into the initial list. The questionnaire was bilingual (English and Vietnamese) to ensure clarity and comprehension for students. The questionnaire consisted of four parts. Part 1 collected demographic information, including age, major, purposes and frequency of using AI tools. Part 2 addressed the primary appraisal and comprised four constructs: Social Influence (SI), Novelty Value (NV), Perceived Humanness (PH), and

Hedonic Motivation (HM). Part 3 investigated secondary appraisal and covered four constructs: Performance Expectancy (PE), Effort Expectancy (EE), Cognitive Attitudes (CA), and Affective Attitudes (AA). Part 4 aimed to collect the outcomes using two constructs: Willingness to Accept AI for English Learning (WTA) and Objection to Use AI in English Learning (O). A pilot test was conducted with 109 students to assess the reliability, validity, and intelligibility of the scale before formal data collection. A five-point Likert scale from 1 'Strongly disagree' to 5 'Strongly agree' was used from Part 2 to Part 4.

3.2. Ethics considerations and responsible AI

At the beginning of the online survey, students were asked to read the consent form for the study, which was in the introduction section of Google Forms. This section outlines the study's aim, the voluntary nature of participation, and students' rights to withdraw at any time. The survey took place in the second semester, and students were required to acknowledge that they were 18 or older to be eligible to participate in the study. There were two options in Google Forms: if students agreed to participate, they clicked 'I understand the aims of the survey and agree to participate'; if they refused to participate, they clicked 'I do not agree' and the survey closed.

To safeguard data privacy, no personal information (e.g., name, class, student ID) was collected. All responses were anonymized and stored on a secure platform accessible only to the research team. Data will be retained for three years and then permanently deleted.

AI tools were utilized for survey item translation support and to check the grammar and expressions of the manuscript. Survey items were pilot-tested and revised to ensure intelligibility and neutrality. The researchers cross-checked the linguistic support of AI tools to avoid unintended bias or misrepresentation.

Ethical approval for the research was obtained from the SLT - Scientific and Ethics Committee under protocol number SLT-EC/2025/AI-079. All procedures were conducted in accordance with institutional guidelines and responsible AI practices.

3.3. Data collection and cleaning

The target population of this study is approximately 7,000 undergraduate students across all year levels and seven majors. The survey link (Google Forms) was distributed through lecturers of the seven majors, who shared it with their classes. Participation was voluntary, and no incentives were offered. A total of 2,055 students were invited through their lecturers, and 2,406 responses were received, of which 60 respondents declined to participate, leaving 2,346 cases for data cleaning.

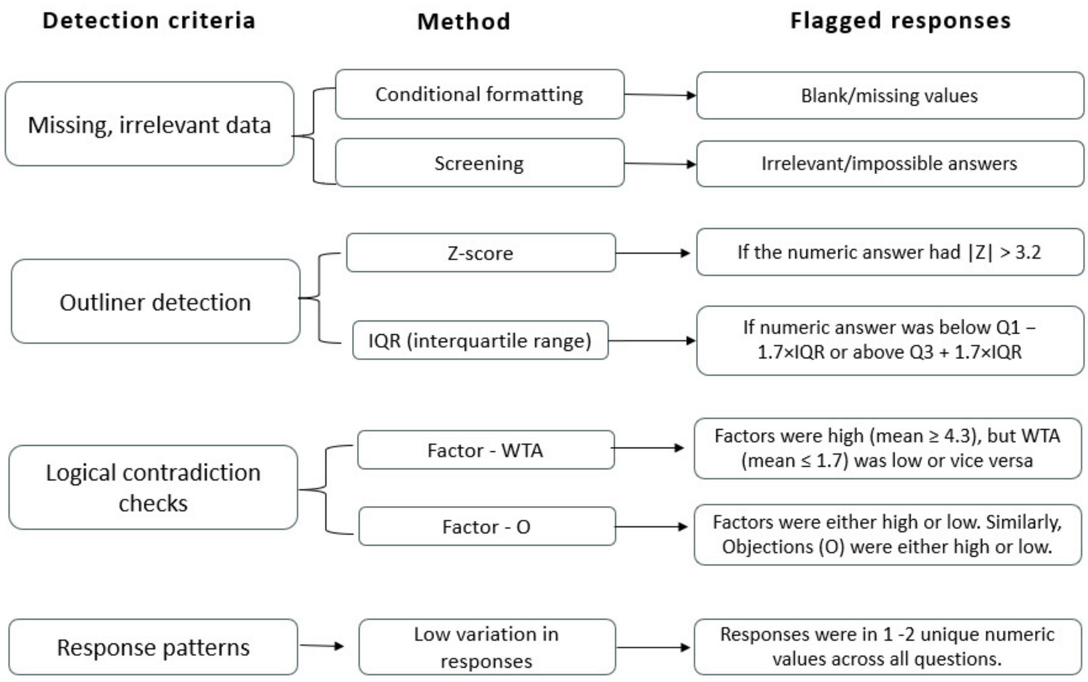

Figure 1. Data cleaning protocol

The data cleaning protocol (Figure 1) was applied to remove missing data, and inconsistent, unreliable, or extreme responses. Cases were excluded if they showed missing or irrelevant data (n =539), extreme outlier detected by Z-score (n=172), interquartile range (IQR) method (n=532), failed logical checks for WTA or O responses (n=369), or showed very low variation in answers (n=36). Because some responses were flagged by more than one criterion, the total number of excluded cases was 1,228. Only responses that passed all these quality control criteria were retained for analysis, and 1,118 valid responses remained for analysis using SmartPLS 4.0.9.8 software. The final sample represents roughly 46.5% of the total sampling. The sample size of 1,118 surpasses the required 160 for PLS-SEM analysis, as proposed by Kock and Hadaya (2018).

A total of 1,118 students were majoring in Business and Finance (30.95%), Tourism (14.85%), Electrical and Electronic Engineering (11.72%), Information Technology (25.85%), and other majors accounted for 16.63%, as presented in Table 1.

Students reported using AI chatbots (79.34%), language translation tools (54.38%), English learning apps (39.27%), grammar checker tools (29.79%), and other types, as shown in Table 2. Students revealed that they used AI to learn grammar and vocabulary (77.55%), translate and do reading tasks (61.99%), brainstorm and get feedback for the writing process (57.16%), subtitle and do the listening tasks (35.24%), practice speaking (33.01%), and other goals. AI tools were also a source of relaxation, as 37.21% confirmed that they used AI to make their English learning more fun and exciting.

Table 1. Demographic information

Item	Values	Frequency	%
Gender	Male	640	57.25
	Female	478	42.75
	Other	0	0
Age	18	161	14.4
	19 - 20	641	57.33
	Above 20	316	28.26
Major	Business and Finance	346	30.95
	Information Technology	289	25.85
	Tourism and Hospitality	166	14.85
	Electrical and Electronic Engineering	131	11.72
	Mechanical Engineering	103	9.21
	Automotive Engineering	55	4.92
	Chemical, Environmental and Food Technology	28	2.50

Table 2. Use of AI

Item	Values	Frequency	%
Types of AI tools	AI chatbots (e.g., ChatGPT, Google Gemini, Copilot)	887	79.34
	Language translation tools (e.g., Google Translate, Microsoft Translator)	608	54.38
	English learning apps (e.g., Duolingo, Elsa)	439	39.27
	Virtual assistants (e.g., Google Assistant, Siri)	354	31.66
	Grammar Checker tools (e.g., Grammarly, QuillBot)	333	29.79
	Paraphrasing tools (e.g., Grammarly, Paraphraser.io)	233	20.84
	Language learning games (e.g., Wordwall, Kahoot!)	186	16.64
Aims of using AI	Learn grammar and vocabulary	867	77.55
	Translate and do reading tasks	693	61.99
	Brainstorm, get feedback, and edit in the writing process	639	57.16
	Make English learning exciting and fun	416	37.21
	Subtitle and do the listening tasks	394	35.24
	Practice speaking through interaction, pronunciation, and error correction	369	33.01
	Make quizzes, presentations	258	23.08

3.4. Data analysis

This research employed the Partial Least Squares Structural Equation Model (PLS-SEM), utilizing SmartPLS version 4.0.9.8 for model assessment. Because this study is exploratory, applying SEM enables the evaluation of relationships among multiple variables (J. Hair & Alamer, 2022), thereby facilitating the prediction and explanation of target outcomes (J. F. Hair et al., 2019).

According to Hair et al. (2019), there are two stages of assessment. The first stage involves assessing the reflective constructs, where the loadings should be no less than 0.70 with a p-value of 0.05 or below, and indicator values of 0.50 are acceptable. Internal consistency reliability is confirmed if the cut-off values of Cronbach's alpha and composite reliability (CR) are between 0.70 and 0.95 (J. F. Hair Jr. et al., 2021). The average variance extracted

(AVE) values should be 0.50 or higher, and the cut-off value for discriminant validity through HTMT is less than 0.90 (J. F. Hair Jr. et al., 2021). The second stage assesses the structural model. The structural model is examined for collinearity, with VIF values ideally being lower than 5 (J. F. Hair Jr. et al., 2021). Then, the size and path coefficients are evaluated. According to Hair and Alamer (2022), the path coefficients range from 0 to 0.10 (weak), 0.11 to 0.30 (modest), 0.31 to 0.50 (moderate), and higher than 0.50 (strong). The final step is the coefficient of determination (R^2) for in-sample predictive power. R^2 values can range from 0.10 to higher than 0.50, indicating weak to strong explanatory power (J. F. Hair et al., 2019).

4. Results

4.1. Measurement model

Table 3 presents the construct items, loadings, Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). O3 was removed because it inflated the VIF, indicating potential multicollinearity. All remaining loadings exceeded 0.70. Cronbach's alpha and composite reliability ranged from 0.78 to 0.91, and AVE values were higher than 0.5. Therefore, the convergent validity of the construct was established.

The discriminant validity was evaluated using the Heterotrait-Monotrait Ratio (HTMT). The threshold of 0.9 was proposed by Hair et al. (2021). Bootstrapping with 10,000 subsamples was used to examine the empirical 95% confidence interval. Table 4 shows that all constructs were below 0.9, demonstrating sufficient discriminant validity.

4.2. Structural model assessment

The structural model was examined for collinearity, with VIF values ideally being lower than 5 (J. F. Hair Jr. et al., 2021). To assess potential common-method bias, full collinearity VIFs were examined. All values ranged from 1.345 to 2.922, which were well under the threshold of 3.3, confirming the absence of substantial bias (J. F. Hair Jr. et al., 2021; Kock, 2015). The results assure the model's quality and collinearity are not a concern. The structural model was then evaluated for both the direct and indirect effects of the latent variables, as well as the percentage of variation predicted by the research model. The coefficients of determination (R^2) and predictive relevance (Q^2) were assessed (Table 5). Most endogenous constructs exhibit moderate and strong predictive power, with Q^2 values ranging from 0.039 to 0.429. However, the construct of Objection to use AI in English learning (O) has a low Q^2 (0.039), suggesting a weak predictive relevance. The overall model demonstrates satisfactory predictive power, with all Q^2 values higher than 0.

Table 3. Item reliability and convergent validity

Constructs	Items	Loadings	Cronbach's alpha	CR	AVE
Social influence	SI1	0.781	0.863	0.867	0.646
	SI2	0.787			
	SI3	0.825			
	SI4	0.787			
	SI5	0.838			
Novelty value	NV1	0.811	0.892	0.895	0.755
	NV2	0.893			
	NV3	0.886			
	NV4	0.883			
Perceived humanness	PH1	0.845	0.897	0.900	0.765
	PH2	0.898			
	PH3	0.892			
	PH4	0.863			
Hedonic motivation	HM1	0.772	0.874	0.886	0.726
	HM2	0.895			
	HM3	0.872			
	HM4	0.821			
Performance expectancy	PE1	0.838	0.887	0.887	0.746
	PE2	0.882			
	PE3	0.875			
	PE4	0.860			
Effort expectancy	EE1	0.867	0.857	0.858	0.778
	EE2	0.899			
	EE3	0.880			
Cognitive attitude	CA1	0.845	0.882	0.883	0.739
	CA2	0.874			
	CA3	0.864			
	CA4	0.856			
Affective attitude	AA1	0.879	0.887	0.890	0.747
	AA2	0.880			
	AA3	0.864			
	AA4	0.833			
Objection to use AI in English learning	O1	0.741	0.786	0.797	0.704
	O2	0.869			
	O4	0.899			
Willingness to accept AI in English learning	WTA1	0.829	0.910	0.911	0.690
	WTA2	0.784			
	WTA3	0.828			
	WTA4	0.851			
	WTA5	0.838			
	WTA6	0.853			

Table 6 presents that 15 out of 16 hypotheses were supported. The effect size (f^2) analysis was conducted to complement the structural model results. According to Cohen's (2013) guidelines, f^2 equals or is higher than 0.02, 0.15, and 0.35, representing small, medium, and large effect sizes, respectively. For the primary appraisal constructs, the findings demonstrated that Social

Table 4. Heterotrait-Monotrait Ratio results

	AA	CA	EE	HM	NV	O	PE	PH	SI	WTA
AA										
CA	0.800									
EE	0.646	0.790								
HM	0.565	0.599	0.594							
NV	0.412	0.459	0.498	0.679						
O	0.268	0.160	0.152	0.125	0.109					
PE	0.702	0.791	0.735	0.629	0.517	0.139				
PH	0.447	0.442	0.423	0.634	0.505	0.136	0.507			
SI	0.469	0.436	0.374	0.567	0.562	0.154	0.492	0.496		
WTA	0.662	0.707	0.579	0.534	0.439	0.247	0.686	0.410	0.485	

Table 5. R^2 and Q^2 results

Constructs	R^2	Q^2
AA	0.438	0.322
CA	0.587	0.429
EE	0.299	0.230
PE	0.370	0.273
O	0.058	0.039
WTA	0.444	0.304

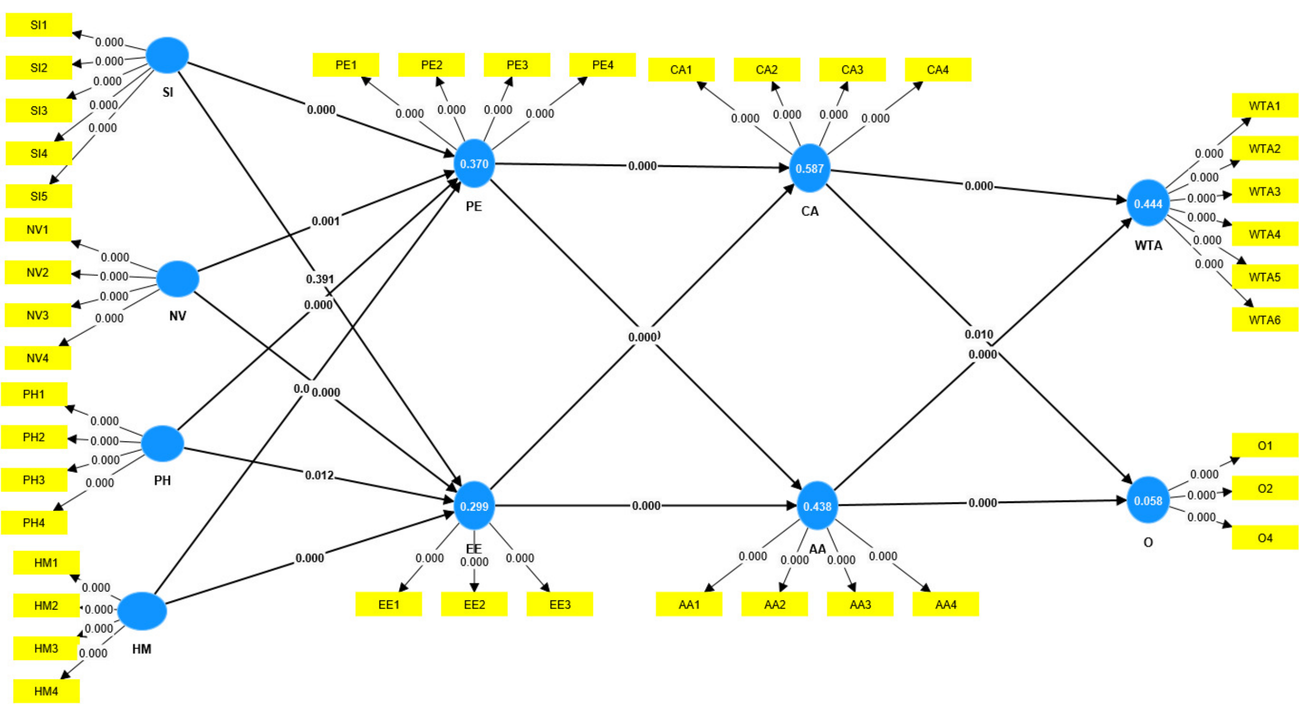

Figure 2. Path analysis results

Influence (SI) only influenced Performance Expectancy (PE) ($\beta = 0.143$, $p < 0.01$, $f^2 = 0.022$, small), thereby supporting Hypothesis 1a. However, SI did not significantly influence Effort Expectancy (EE) ($p > 0.05$, $f^2 = 0.001$, negligible), which did not support Hypothesis H1b. The outcomes

Table 6. Hypothesis results

Hypothesis	Path	Coefficient	p-value	f^2	Effect size	Results
H1a	SI > PE	0.143	0.000	0.022	Small	Support
H1b	SI > EE	0.028	**0.384**	**0.001**	Negligible	**Reject**
H2a	NV > PE	0.123	0.000	0.014	Negligible	Support
H2b	NV> EE	0.168	0.000	0.023	Small	Support
H3a	PH > PE	0.151	0.000	0.023	Small	Support
H3b	PH > EE	0.083	0.012	0.006	Negligible	Support
H4a	HM > PE	0.329	0.000	0.088	Small	Support
H4b	HM > EE	0.358	0.000	0.094	Small	Support
H5a	PE > CA	0.440	0.000	0.277	Medium	Support
H5b	PE > AA	0.443	0.000	0.206	Medium	Support
H6a	EE > CA	0.405	0.000	0.234	Medium	Support
H6b	EE > AA	0.284	0.000	0.084	Small	Support
H7a	CA > WTA	0.429	0.000	0.163	Medium	Support
H7b	CA > O	-0.167	0.009	0.015	Negligible	Support
H8a	AA > WTA	0.289	0.000	0.074	Small	Support
H8b	AA > O	0.330	0.000	0.057	Small	Support

of the path analysis revealed that Novelty Value (NV), Perceived Humanness (PH), and Hedonic Motivation (HM) significantly influence Performance Expectancy (PE) ($\beta = 0.123$, $p < 0.01$, $f^2 = 0.014$, negligible; $\beta = 0.151$, $p < 0.01$, $f^2 = 0.023$, small; $\beta = 0.329$, $p < 0.01$, $f^2 = 0.088$, small) and Effort Expectancy (EE) ($\beta = 0.168$, $p < 0.01$, $f^2 = 0.023$, small; $\beta = 0.083$, $p < 0.01$, $f^2 = 0.006$, negligible; $\beta = 0.358$, $p < 0.01$, $f^2 = 0.094$, small), respectively. Consequently, H2a, H2b, H3a, H3b, H4a, and H4b were supported.

For the secondary appraisal constructs, Performance Expectancy (PE) and Effort Expectancy (EE) were found to influence Cognitive Attitude (CA) significantly ($\beta = 0.440$, $p < 0.01$, $f^2 = 0.277$, medium; $\beta = 0.405$, $p < 0.01$, $f^2 = 0.234$, medium) and Affective Attitude (AA) ($\beta = 0.443$, $p < 0.01$, $f^2 = 0.206$, medium; $\beta = 0.284$, $p < 0.01$, $f^2 = 0.084$, small). As a result, H5a, H5b, H6a, H6b were supported.

For the outcome stage, the results revealed that Cognitive Attitude (CA) and Affective Attitude (AA) both statistically influence the willingness to accept AI in English learning (WTA) ($\beta = 0.429$, $p < 0.01$, $f^2 = 0.163$, medium; $\beta = 0.289$, $p < 0.01$, $f^2 = 0.074$, small), confirming H7a and H8a. For the Objection to Use (O), Hypotheses H7b and H8b were supported. AA influenced O ($\beta = 0.330$, $p < 0.01$, $f^2 = 0.057$, small) significantly. There was a noticeable result of the impact of CA on O ($\beta = -0.167$, $p < 0.01$, $f^2 = 0.015$, negligible). The negative path coefficient from Cognitive Attitude (CA) to Objection to Use (O) indicated a reverse relationship, i.e., a higher level of CA was associated with a lower level of O (Figure 2).

In this study, the model specified the indirect pathways from primary appraisal (SI, NV, PH, HM) to WTA and O through secondary appraisal (PE, EE, CA, AA) (Table 7). The primary appraisal variables' direct effect on WTA and O was not modeled; hence, mediation was not assessed.

The total effect of SI on WTA was significant ($\beta = 0.053$, $p < 0.01$), indicating a positive impact. Significant specific indirect effects were observed along the paths SI > PE > AA > WTA ($\beta = 0.018$, $p < 0.01$) and SI > PE > CA > WTA ($\beta = 0.027$, $p < 0.01$), implying that SI indirectly influences WTA through PE via AA and CA. Conversely, indirect effects involving Effort Expectancy (EE) were insignificant, such as SI > EE > AA > WTA ($\beta = 0.002$, $p = 0.406$) and SI > EE > CA > WTA ($\beta = 0.005$, $p = 0.388$), indicating no mediation through EE, AA, and CA. Regarding objection to use (O), the total effect of SI was significant ($\beta = 0.011$, $p = 0.013$). Likewise, SI exerted significant indirect effects on O via PE through AA ($\beta = 0.021$, $p < 0.01$) and CA ($\beta =- 0.011$, $p < 0.05$). The indirect paths through EE (SI > EE > AA > O and SI > EE > CA > O) were not significant. Overall, while SI's total effect on O was significant, it only influenced O indirectly through PE, AA, and CA.

The analysis revealed that the total effect of NV on WTA was significant ($\beta = 0.082$, $p < 0.01$), with all paths from NV through PE and EE, via AA and CA, being statistically significant. These findings confirmed the indirect influence of NV on WTA through the secondary appraisal constructs. Likewise, the total effect of NV on O was significant ($\beta = 0.013$, $p < 0.05$). Notably, all the specific indirect effect paths were significant, with the indirect effects of NV > PE > CA > O ($\beta = -0.009$, $p < 0.05$) and NV > EE > CA > O ($\beta = -0.011$, $p < 0.05$) being negative. These findings suggested that both the total effect and the indirect effect were significant. NV exerted its influence on O via indirect pathways through PE, EE, AA, and CA, where some pathways facilitated and others inhibited the outcomes.

Similarly, the total effect of PH on WTA was significant ($\beta = 0.069$, $p < 0.01$), with all specific indirect effects via PE, EE through AA, and CA. The total effect of PH on O was significant; however, the specific indirect path PH > EE > CA > O ($\beta = -0.006$, $p =0.089$) was insignificant and demonstrated negative effects.

Hedonic Motivation (HM) showed a similar pattern to NV and PH. Its total effect on WTA was significant ($\beta = 0.196$, $p < 0.01$), and all specific indirect paths via PE and EE, through AA and CA, were also statistically significant. In addition, HM's total effect on O was significant ($\beta = 0.033$, $p < 0.05$). Likewise, all specific indirect paths were statistically significant, with two paths HM > PE > CA > O ($\beta = -0.024$, $p < 0.05$) and HM > EE > CA > O ($\beta = -0.024$, $p < 0.05$), showing negative coefficients. These findings highlight that higher levels of CA are consistently associated with lower levels of O, reinforcing the inverse relationship between CA and O.

Table 7. Total and indirect effect

	Path	Coefficient	p-value
Total effect	SI > WTA	0.053	0.000
Specific indirect effect	SI > PE > AA > WTA	0.018	0.000
	SI > PE > CA > WTA	0.027	0.000
	SI > EE > AA > WTA	0.002	0.406
	SI > EE > CA > WTA	0.005	0.388
Total effect	SI > O	0.011	0.013
Specific indirect effect	SI > PE > AA > O	0.021	0.000
	SI > PE > CA > O	-0.011	0.031
	SI > EE > AA > O	0.003	0.403
	SI > EE > CA > O	-0.002	0.449
Total effect	NV > WTA	0.082	0.000
Specific indirect effect	NV > PE > AA > WTA	0.016	0.001
	NV > PE > CA > WTA	0.023	0.001
	NV > EE > AA > WTA	0.014	0.000
	NV > EE > CA > WTA	0.029	0.000
Total effect	NV > O	0.013	0.036
Specific indirect effect	NV > PE > AA > O	0.018	0.002
	NV > PE > CA > O	-0.009	0.041
	NV > EE > AA > O	0.016	0.000
	NV > EE > CA > O	-0.011	0.029
Total effect	PH > WTA	0.069	0.000
Specific indirect effect	PH > PE > AA > WTA	0.019	0.000
	PH > PE > CA > WTA	0.029	0.000
	PH > EE > AA > WTA	0.007	0.026
	PH > EE > CA > WTA	0.014	0.016
Total effect	PH> O	0.013	0.016
Specific indirect effect	PH > PE > AA > O	0.022	0.000
	PH > PE > CA > O	-0.011	0.027
	PH > EE > AA > O	0.008	0.025
	PH > EE > CA > O	-0.006	0.089
Total effect	HM > WTA	0.196	0.000
Specific indirect effect	HM > PE > AA > WTA	0.042	0.000
	HM > PE > CA > WTA	0.062	0.000
	HM > EE > AA > WTA	0.029	0.000
	HM > EE > CA > WTA	0.062	0.000
Total effect	HM > O	0.033	0.014
Specific indirect effect	HM > PE > AA > O	0.048	0.000
	HM > PE > CA > O	-0.024	0.018
	HM > EE > AA > O	0.033	0.000
	HM > EE > CA > O	-0.024	0.018

5. Discussion

5.1. Frequency of AI usage

The findings reveal that students actively utilize AI as part of their English learning, and 79.34% of the students reported using GenAI tools (e.g., ChatGPT and Gemini) to assist with translation and reading tasks.

Additionally, over half of the students (57.16%) reported relying on these tools during the writing process for brainstorming, receiving feedback, and editing their text. The results demonstrate a high interest in GenAI applications, offering real-time feedback, personalized assistance, and opportunities for independent learning, particularly in reading and writing. Hence, these tools can offer benefits, including fostering more efficient and effective learning environments, reducing exam-related anxiety, and promoting greater learner autonomy. At the same time, these tools are designed to deliver personalized feedback, create adaptive learning pathways, and encourage engagement through interactive features that nurture motivation and support long-term academic performance (Holmes & Tuomi, 2022). More than one-third of the students (37.21%) reported using AI to make learning more stimulating, indicating that AI serves both academic and motivational purposes. The findings suggest that students appreciate AI's functionality and its potential to make learning more engaging and autonomous.

5.2. Primary appraisal

Regarding primary appraisal factors, the results revealed that hedonic motivation had a potent effect on both performance expectancy and effort expectancy, highlighting that when the experience is enjoyable and meaningful, students perceive AI as helpful and easy to use. This underscores the critical factor behind hedonic motivation value in the initial AI assessment, especially important in language learning, when positive emotional activity can strengthen perceptions of effectiveness. This view aligns with the findings of Qu and Wu (2024), who argue that emotional bonding is necessary for AI user acceptance.

Another interesting finding in the primary appraisal stage is that social influence had limited impacts on students' behavioral intentions through its effects on performance expectancy, but not on effort expectancy. The absence of social influence effects on effort expectancy suggests that EFL learners rely more on their individual, direct experiences with technology than on social influence in determining its usability. It also supports Valle et al.'s (2024) finding that learners prefer to be independent in navigating digital tools and are more likely to trust their interactions over feedback from peers and social networks.

Finally, novelty value, perceived humanness, and hedonic motivation proved to be the three most influential factors in producing a meaningful willingness to accept AI predictions, exerting indirect effects through performance expectancy and effort expectancy, as well as cognitive and affective attitudes. The finding suggests that EFL students utilize AI tools that provide helpful support and foster a sense of emotional connection. The influence of novelty value shows that students are motivated not only by the utility of AI but also by its newness and innovative character. This sense of novelty creates curiosity and encourages learners to experiment with AI tools, offering a fresh learning experience that traditional resources may not provide. The high impact of perceived humanness suggests that students perceive AI systems as valuable when they imitate human-like interaction, especially in language learning contexts, where communication and social presence play a crucial role. Similarly, the effects of hedonic motivation also make it clear that enjoyment and motivation play a crucial role in sustaining learners' interest and engagement.

5.3. Secondary appraisal and outcome stage

The study's results highlight the direct impact of performance expectancy and effort expectancy on both cognitive and affective attitudes. Notably, the effects of effort expectancy on affective attitude suggest that if learners perceive AI tools as user-friendly, they will feel more emotionally comfortable, which can be particularly beneficial in settings where technological anxiety hinders successful language learning. This finding is consistent with recent studies (Sobaih et al., 2024; Strzelecki & ElArabawy, 2024) that emphasize that both performance expectancy and effort expectancy substantially influence attitudes and behavioral intentions toward adopting AI tools in language learning.

The results indicate that cognitive attitude has a medium effect on WTA, whereas its effect on O is negative and negligible. This suggests that how students perceive the usefulness and value of AI tools has a direct influence on their willingness to adopt them. EFL students who possess some knowledge of AI tend to be less hesitant and more willing to try out these technologies. In language learning, this finding is important because unfamiliar digital tools often cause anxiety or resistance. The result aligns with Ma and Huo (2023), who underscored the role of cognitive attitude in encouraging technology acceptance. In the present study, however, its influence was limited, affecting WTA rather than extending to other behavioral outcomes.

A noteworthy finding is a positive relationship between affective attitude and objections to use, which contradicts Ma and Huo's (2023) study, which reported a negative association. This suggests that positive emotions alone are insufficient predictors of behavior, as users may express favorable attitudes while still exhibiting hesitation. Emotional attachment to traditional methods, such as teacher interaction, may make students reluctant to use AI tools, as they may perceive these tools as impersonal and emotionally unresponsive. Additionally, concerns about the validity of AI-generated content, privacy, ethical risks, and potential misuse also contribute to students' resistance to embracing AI in language learning.

Recent AIDUA-ChatGPT studies suggest that both cognitive and emotional attitudes explain why students accept or resist AI (Cai et al., 2024; Sobaih et al., 2024; Supianto et al., 2024). The present study, however, reveals a different pattern in which cognitive attitude affects students' willingness to use AI and negatively impacts their objections to using AI, while affective attitude both encourages acceptance and contributes to objections. This difference can be understood through cognitive appraisal theory (Lazarus, 1991), which explains that people's feelings stem from their evaluation of whether something matters to their goals, whether it helps or harms them, and whether they feel capable of dealing with it. From this perspective, rational judgments may give students enough confidence to try AI, but they do not remove the mixed feelings caused by worries about risks, ethics, or losing control. Emotional reactions, therefore, play a dual role, creating curiosity and motivation on the one hand, while also adding doubt and hesitation on the other. This emotional-ambivalence pathway highlights the research gap by showing that AI adoption in EFL is not simply a rational decision but a process shaped by ongoing judgments that mix both thought and emotion.

6. Conclusion and implications

The study's findings show that the AIDUA model is effective in explaining EFL students' intention to use AI in English learning, with an explanatory power of 44.4% for willingness to accept AI (WTA) and 5.8% for objection to use (O). Hedonic motivation emerged as the primary predictor of both performance expectancy and effort expectancy, indicating the importance of enjoyment in forming positive perceptions of AI. Likewise, Perceived humanness, though weaker, also contributed to shaping these perceptions, indicating that students value human-like qualities when deciding whether to use these tools. Novelty value played a small yet notable role, suggesting that students are drawn not only to what AI can do functionally but also to its new and appealing features. In contrast, social influence exerted limited impacts, implying that students tend to prioritize personal judgment over external recommendations. Finally, affective attitude increases both AI acceptance and hesitation, suggesting a complex relationship between emotions and AI adoption.

This study contributes to the expanding research on AI adoption in education by exploring how EFL students' cognitive and affective attitudes shape their willingness to accept AI and their objections to its use. The findings offer a more nuanced understanding of the AIDUA framework. Unlike recent ChatGPT-related studies, which often treat cognitive and affective attitudes as parallel predictors of acceptance and resistance, this study shows that cognitive attitude influences willingness to accept AI and exerts a statistically significant, though marginal, negative influence on objection to use. This result suggests that rational evaluation can buffer against resistance. In contrast, affective attitude shows an ambivalent role, simultaneously encouraging adoption and fueling objections. This pattern highlights an emotional-ambivalence pathway, suggesting that AI adoption in EFL contexts is not simply a matter of rational evaluation, but rather a negotiation of conflicting emotions, such as curiosity, enjoyment, anxiety, and doubt. By integrating insights from cognitive appraisal theory (Lazarus, 1991), the study extends existing models of technology acceptance and offers a theoretical framework for understanding why learners may embrace AI's novelty while still resisting its use.

Beyond its theoretical contribution, the study has practical implications for classroom practices. For EFL teachers, AI can be incorporated as a supportive resource for vocabulary development, grammar reinforcement, writing feedback, and speaking practice, thereby reducing learner anxiety while fostering greater autonomy. Teachers also play a crucial role in helping students critically engage with AI outputs by questioning accuracy, identifying potential bias, and acknowledging limitations. Professional development through training and workshops can further prepare teachers to design lessons, activities, and ethical discussions that integrate AI in meaningful and responsible ways. For AI developers, the findings highlight the need to design tools that align with students' actual learning practices. Since most learners use GenAI for translation, reading, and writing support, developers should focus on features that provide real-time feedback, adaptive pathways, and personalized assistance, which can boost motivation and reduce exam-related anxiety. Personalized pathways and adjustable difficulty levels are crucial for supporting independent learning and accommodating diverse proficiency levels. Finally, collaboration with educators is crucial to ensure AI complements classroom instruction without undermining teachers' roles or the learning process.

Overall, the study provides insight into the theoretical understanding of AI adoption and offers suggestions for both educators and AI designers. The study thus positions emotional ambivalence not as a barrier to be overcome but as a dynamic pathway that must be acknowledged to foster a more balanced, practical, and ethical use of AI in English language learning.

6.1. Limitations and future research

This study has several limitations, despite its contributions. First, the survey sample comprises EFL students at the university level, which limits generalizability of the results. Second, the cross-sectional design and reliance on self-reported data may not fully capture changes over time and control for response biases. Future studies can employ a longitudinal design to track changes in students' attitudes toward AI and language learning, incorporating interviews and observations to gain insights into the emotional and ethical challenges associated with applying AI to English education.

Data and code availability

The anonymised dataset, bilingual survey instrument, and SmartPLS project file (.splms) are openly available in the Open Science Framework (OSF) at: https://doi.org/10.17605/OSF.IO/R2XAP

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Conflict of interest

The authors declare no conflict of interest.

Ethics approval

The study received ethical clearance from the SLT - Scientific and Ethics Committee (Decision No: SLT-EC/2025/AI-079). Participation in the survey is voluntary. Informed consent was obtained from all participants prior to their participation in the survey, and they had the right to withdraw their data/consent at any time during the study. Their data were treated anonymously, stored securely, and processed in accordance with applicable data protection laws (GDPR).

Author contributions

Conceptualization, Nga Thuy Nguyen; Methodology, Nga Thuy Nguyen; Literature review, Hue Thi Kim Tran, and Ha Hoang Thi Bui; Ethical approval submission, Hue Thi Kim Tran and Ha Hoang Thi Bui; Data planning and variable selection, Huong Thi Thu Le and Hue Thi Kim Duong; Task and consent form design, Nga Thuy Nguyen; Communication with external evaluator, Nga Thuy Nguyen; Data collection, Huong Thi Thu Le, Hue Thi Kim Duong, Hue Thi Kim Tran, and Ha Hoang Thi Bui; Data entry, analysis, and visualization, Nga Thuy Nguyen; Proofreading, Nga Thuy Nguyen; Writing – original draft, Nga Thuy Nguyen, Huong Thi Thu Le, Hue Thi Kim Duong, Hue Thi Kim Tran, and Ha Hoang Thi Bui; Writing – review and editing, Nga Thuy Nguyen, Huong Thi Thu Le, Hue Thi Kim Duong, Hue Thi Kim Tran, and Ha Hoang Thi Bui; Project administration, Nga Thuy Nguyen. All authors contributed equally to the development and finalization of the manuscript.

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