TPM Vol. 32, No. R2, 2025
ISSN: 1972-6325
https://www.tpmap.org/

Open Access

MODELING UNIVERSITY STUDENTS' ADOPTION OF ARTIFICIAL INTELLIGENCE FOR SECOND LANGUAGE ACQUISITION: THE MEDIATING ROLE OF ATTITUDE

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ABSTRACT: As artificial intelligence (AI) becomes increasingly embedded in educational environments, understanding the factors that influence students' adoption of AI technologies for second language (L2) learning has become critical. This study investigates the relationships among AI self-efficacy, attitudes toward AI, and the actual use of AI tools among university students engaged in L2 acquisition. A structural equation model was developed and tested using survey data from 312 undergraduates. The results revealed that AI self-efficacy significantly predicted both attitudes toward AI and actual use behavior, while attitude also served as a significant mediator between self-efficacy and use. These findings suggest that confidence alone does not lead to technology adoption unless accompanied by a favorable emotional orientation toward AI. Moreover, while gender did not influence usage behavior, academic major (STEM vs. non-STEM) showed a marginal effect, indicating potential disciplinary differences in AI engagement. The findings offer practical implications for language educators, EdTech designers, and institutions seeking to implement AI tools in pedagogically meaningful ways.
Keywords: Artificial intelligence, self-efficacy, attitude, second language learning, AI adoption, structural equation modeling

INTRODUCTION

In recent years, the integration of artificial intelligence (AI) into educational contexts has reshaped the landscape of language learning and teaching. AI-driven tools such as automated writing evaluators, intelligent chatbots, machine translation systems, and personalized learning assistants are increasingly being adopted in second language (L2) classrooms, offering learners adaptive feedback, real-time interaction, and individualized learning pathways. These affordances hold particular promise for improving learner autonomy, engagement, and proficiency in L2 acquisition (Chun, 2016; Zawodniak & Kruk, 2022). However, the mere availability of AI technologies does not guarantee their pedagogical effectiveness. Learners' willingness and ability to engage with such tools are shaped by a complex set of psychological, cognitive, and contextual factors, which remain insufficiently understood.

Among the emerging research on technology-enhanced language learning, increasing attention has been paid to the roles of self-efficacy and attitude in determining learners' acceptance and use of educational technologies (Liaw, 2008; Reinders & White, 2011). Drawing on Bandura's (2006) social cognitive theory, AI self-efficacy refers to learners' beliefs in their ability to effectively use AI-based tools in the language learning process. Numerous studies have shown that learners with higher digital or technological self-efficacy tend to approach new tools with more confidence and are more likely to persist in using them (Avgousti, 2018). In parallel, attitudes toward technology—including perceived usefulness, enjoyment, and trust—have long been recognized as central to technology acceptance models (Davis, 1989; Venkatesh et al., 2003). While both variables have been studied independently, few studies have explored how they interact to shape actual use behavior in the specific context of AI-assisted second language learning.

Furthermore, existing models such as the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) have been widely applied in general educational technology research but have yet to be fully adapted to the affordances and challenges of AI in L2 learning. Unlike traditional digital tools, AI systems often involve degrees of autonomy, unpredictability, and opaque feedback processes, which can influence learner trust and perceived control (Godwin-Jones, 2020). These affective-cognitive dynamics necessitate a refined understanding of how learners interpret and respond to AI systems in linguistically and cognitively demanding environments.

To address this gap, the present study proposes and tests a structural equation model that examines the interrelationships among AI self-efficacy, attitude toward AI, and actual use of AI among university students engaged in second language learning. In addition to testing direct effects, the study investigates the mediating role of attitude, offering insight into whether learners' beliefs about their ability to use AI translate into behavior via positive or negative affective dispositions. Gender and academic discipline are also included as control variables to account for potential background influences.

LITERATURE REVIEW

AI self-efficacy

Self-efficacy is a fundamental notion in educational theory (Alotaibi, 2016). Initially established by Bandura (1977) within the framework of social cognitive theory, it pertains to individuals' overarching views of their talents and competencies in managing stressful situations. In addition to general self-efficacy, task-specific self-efficacy assesses an individual's confidence in a particular activity or circumstance (Sherer & Maddux, 1982).

General and task-specific self-efficacy both pertain to an individual's confidence in achieving desired results; however, task-specific self-efficacy is more susceptible to contextual influences than general self-efficacy (Lu et al., 2023). Within the realm of AI, this notion has been tailored to a distinct form of self-efficacy: AI self-efficacy. In contrast to generic self-efficacy, AI self-efficacy evaluates an individual's confidence in a particular activity or scenario related to artificial intelligence. Hong (2022) defined AI self-efficacy as individuals' overarching belief in their capability to utilise and engage with AI.

In education research, there is considerable interest in examining the influence of AI self-efficacy and attitudes towards AI on its practical use (Bergdahl & Sjöberg, 2025). The exact nature of the association between AI self-efficacy and attitude towards AI remains unclear. Conversely, empirical research from the wider educational sector consistently demonstrates a favourable association between technical self-efficacy and attitudes towards technology. Pan (2020) noted that in a cohort of 332 college students, individuals with elevated technological self-efficacy demonstrated a more positive attitude towards technology-enhanced self-directed learning. Bai et al. (2024) found a substantial impact of technological self-efficacy on the attitudes of 314 in-service primary and secondary school teachers regarding technology. Based on the above mentioned findings, it is plausible to suggest that AI self-efficacy may likewise influence attitudes towards AI in the second language acquisition environment.

AI anxiety

The introduction of AI technology has created numerous challenges in various aspects of life. These challenges include job displacement, privacy and transparency concerns, algorithmic biases, socioeconomic disparities, and unethical actions (Ammah et al., 2024; Turchin & Denkenberger, 2020). These challenges can cause anxiety (Wang, & Wang, 2024). The phenomenon known as "AI anxiety," is characterised by extreme dread about AI-induced changes in personal or societal life. According to Wang & Wang (2022), "AI anxiety" has four subcategories: "job replacement anxiety," "sociotechnical blindness," "AI configuration anxiety," and "AI learning anxiety." Huo et al. (2023) found that AI fear, a new field of study, influences the adoption of AI technologies. However, the literature lacks information on how English major students' AI anxiety affects their AI self-efficacy, attitude towards AI, and usage of AI in English major learning. Alternatively, research consistently links self-efficacy to reduced anxiety in general education (Mensah et al., 2023). Lei et al. (2021) found that academic self-efficacy mitigated test anxiety in 560 high school students. Using these antecedents, it is hypothesised that AI self-efficacy may also impact AI anxiety.

METHODOLOGY

RESEARCH DESIGN

This study adopts a quantitative research design utilizing Structural Equation Modeling (SEM) to explore the factors influencing university students' actual use of AI. The research is grounded in a theoretical framework that integrates psychological constructs (AI self-efficacy and attitude toward AI) and sociodemographic factors (gender and academic major) to model their direct and indirect effects on AI usage behavior. The study follows a cross-sectional, correlational survey design, wherein all constructs are measured using a structured questionnaire. The relationships among constructs are evaluated based on their path coefficients, model fit indices, and indirect effects, with attention to the mediating and moderating roles within the model. This design is suitable for assessing both measurement validity and structural relationships among latent variables.

Participants

The participants of this study were undergraduate students enrolled at several comprehensive universities, selected to represent a diverse range of academic backgrounds. The study targeted students from various disciplines, including science, technology, engineering, and mathematics (STEM), humanities, social sciences, arts, language, and medical-related majors. Totally 362 participants were recruited through online academic platforms, university mailing lists, and classroom announcements. Participation was voluntary and anonymous, with informed consent obtained prior to the administration of the questionnaire. The recruitment strategy ensured an inclusive approach across gender and major, reflecting the demographic characteristics commonly found in higher education institutions. To ensure the relevance of responses, participants were required to have had some prior exposure to AI tools or applications, whether through formal coursework, informal experimentation, or daily technology use. This inclusion criterion ensured that respondents could meaningfully reflect on their self-efficacy, attitudes, and behaviors related to AI. Both male and female students were included, and gender was considered as a potential explanatory variable in the model due to its known influence in technology acceptance and education research.

Instruments

The AI self-efficacy scale

The self-efficacy of participants in utilising AI-assisted L2 learning was evaluated using the Artificial Intelligence Self-efficacy Scale (AISES), which was devised by Wang and Chuang (2023). The scale is a 22-item instrument that assesses four components of self-efficacy: Assistance, Anthropomorphic Interaction, Comfort with AI, and Technological Skills. The items are evaluated on a 7-point Likert scale, with 1 representing "strongly disagree" and 7 representing "strongly agree." An example item for Assistance is "Some AI technologies/products facilitate the learning of second languages." The individual's self-efficacy in utilising AI-assisted L2 learning is reflected in the total score, with greater scores indicating stronger self-efficacy. The scale's Cronbach's α was 0.842 in this investigation.

The AI anxiety scale

The criterion was the AI Anxiety Scale (AIAS) developed by Wang and Wang (2022). The 21 items are categorised into four factors: learning, AI configuration, job replacement, and sociotechnical blindness. A 7-point Likert scale was employed, with a range of 1 (strongly disagree) to 7 (strongly concur). "I experience anxiety when learning to use AI techniques/products for L2 learning." is an example of a learning item. An individual's aggregate AI anxiety is represented by the sum of the items' scores, with higher scores suggesting a greater degree of AI anxiety. The scale's Cronbach's α was 0.921 in this study.

Self-reported frequency of using AI for L2 learning

The participants' utilisation of AI for L2 learning was assessed using the item "How often do you use AI technology/applications for English learning?" employing a 5-point Likert scale from 1 (never) to 5 (often). An elevated score signified an increased frequency of utilisation.

Data Analysis

Data analysis for this study was conducted using a two-step approach consistent with best practices in SEM. The first step involved assessing the measurement model to ensure the reliability and validity of the latent constructs, while the second step evaluated the structural model to test the hypothesized relationships among variables. Before model estimation, the dataset was screened for missing values, outliers, and normality. Cases with significant missing data or outlier patterns were excluded from the final analysis. All items were assessed for univariate and multivariate normality to confirm suitability for SEM using maximum likelihood estimation. Descriptive statistics were calculated to provide an overview of the sample's demographic profile and the distribution of key study variables.

The measurement model was tested using confirmatory factor analysis (CFA) to evaluate the psychometric properties of the latent variables. Convergent validity was assessed based on factor loadings, average variance extracted (AVE), and composite reliability (CR). Discriminant validity was established by comparing the square roots of the AVE values with inter-construct correlations. Cronbach's alpha was also reported to confirm internal consistency. Following confirmation of the measurement model, the structural model was tested to examine the hypothesized direct and indirect relationships among the constructs. Path coefficients

were estimated, and their statistical significance was assessed using standardized regression weights and associated p-values. The overall model fit was evaluated using multiple fit indices, including the Chi-square to degrees of freedom ratio (χ^2/df), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). Thresholds recommended by Hu and Bentler (1999) were used to interpret model fit, with CFI and TLI values above 0.90, RMSEA below 0.08, and SRMR below 0.08 considered indicative of acceptable model fit.
In addition to evaluating the structural paths, mediation effects were tested using bootstrapping procedures with 5,000 resamples to generate bias-corrected confidence intervals. This allowed for the identification of indirect effects through mediating variables such as AIA and Major. Furthermore, subgroup analyses were conducted where appropriate to explore potential moderating effects of gender or academic major on selected paths.

RESULTS

Descriptive Statistics and Preliminary Analysis

A total of 312 valid responses were obtained from undergraduate students across a variety of academic disciplines. The demographic characteristics of the sample are presented in Table 1. Of the participants, 58.7% identified as female and 41.3% as male. Students were relatively evenly distributed across academic years, with 26.0% in Year 1, 24.4% in Year 2, 27.9% in Year 3, and 21.8% in Year 4. In terms of academic major, the majority of participants were from non-STEM fields (58.3%), while 41.7% were from STEM-related programs. Descriptive statistics of means and standard deviations were calculated for the three key latent variables: AI self-efficacy (AISE), attitude toward AI (AIA), and actual use of AI (AUAI).

TABLE 1 Demographic Characteristics of Participants

Items	Category	Frequency	Percentage (%)
Gender	Male	129	41.30%
	Female	183	58.70%
Year of Study	Year 1	81	26.00%
	Year 2	76	24.40%
	Year 3	87	27.90%
	Year 4	68	21.80%
	4.21		
AISE (Mean/SD)	0.71		
	4.05		
AIA (Mean/SD)	0.66		
	3.98		
AUAI (Mean/SD)	0.77		

Measurement Model

To evaluate the adequacy of the latent constructs in the proposed model, a CFA was conducted prior to structural modeling. All standardized factor loadings were statistically significant and exceeded the recommended threshold of 0.60, indicating satisfactory item reliability. As summarized in Table 2, the constructs demonstrated adequate internal consistency, with Cronbach's alpha values ranging from 0.80 to 0.87. The CR values were between 0.83 and 0.88, exceeding the benchmark of 0.70. Additionally, AVE values ranged from 0.56 to 0.65, supporting convergent validity (Fornell & Larcker, 1981). According to Table 3, the measurement model demonstrated good fit to the data, with χ^2/df = 1.97, CFI = .958, TLI = .942, RMSEA = .056, and SRMR = .043. These indices are within the recommended cutoffs suggested by Hu and Bentler (1999). Pearson correlation was established by verifying that the square root of each construct's AVE exceeded its correlations with other constructs (see Table 4). No evidence of multicollinearity was observed. The overall fit of the measurement model was satisfactory based on multiple fit indices. These results support the validity and reliability of the measurement model and provide a strong foundation for subsequent structural path analysis.

TABLE 2 Factor Loadings, Reliability, and Validity Statistics

Construct	Cronbach's α	CR	AVE
AISE	0.84	0.86	0.61
AIA	0.8	0.83	0.56
AUAI	0.87	0.88	0.65

TABLE 3 Statistics Model Fit Indices for the Measurement Model

Fit Index	Value	Recommended Threshold
χ^2/df	1.97	< 3.00 (acceptable)
CFI	0.958	> 0.90 (good), > 0.95 (excellent)
TLI	0.942	> 0.90 (acceptable)
RMSEA	0.056	< 0.08 (acceptable), < 0.06 (good)
SRMR	0.043	< 0.08

TABLE 4 Pearson Correlation

Variable	1	2	3
1. AISE	—		
2. AIA	.62***	—	
3. AUAI	.55***	.60***	—

NOTE: * $p \leq 0.05$; ** $p \leq 0.01$; ***$p \leq 0.001$

Structural Model

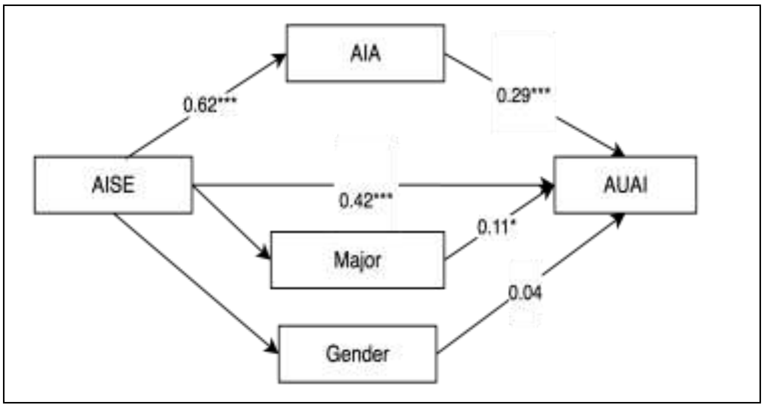
Following the validation of the measurement model, the hypothesized structural model was tested to examine the direct and indirect relationships among AISE, attitude toward AIA, and actual use of AUAI, with gender and academic major included as control variables. Structural path coefficients were estimated using maximum likelihood estimation, and their significance was assessed via standardized regression weights and corresponding p-values. Table 5 summarizes the standardized path coefficients and significance levels. AISE had a significant positive effect on both attitude toward AI (β = .62, p < .001) and actual use of AI (β = .29, p < .001), supporting H1 and H2. Attitude toward AI (AIA) also had a significant direct effect on actual use of AI (β = .42, p < .001), supporting H3. The indirect effect of AISE on AUAI through AIA was significant (β = .26, p < .001), suggesting a partial mediation, consistent with H4. The effects of control variables were also examined. Gender had no significant direct effect on AUAI (β = –.04, p = .29), while academic major (STEM vs. non-STEM) was marginally significant (β = .11, p = .046), suggesting that students from STEM fields may be slightly more inclined to use AI tools.

The hypothesized structural relationships among the latent variables are illustrated in Figure 1, which presents the proposed model including direct and indirect paths from AISE to actual use of AUAI, with attitude toward AIA as a mediating variable. Gender and academic major were included as control variables.

TABLE 5 Standardized Path Coefficients and Hypothesis Testing Results

Hypothesized Path	β	SE	*p*-value	Supported
H1: AISE → AIA	0.62	0.05	< .001***	Yes
H2: AISE → AUAI	0.29	0.07	< .001***	Yes
H3: AIA → AUAI	0.42	0.06	< .001***	Yes
H4: AISE → AIA → AUAI	0.26 (indirect)	—	< .001***	Yes
Gender → AUAI	–0.04	0.04	0.29	No
Major → AUAI	0.11	0.05	0.046**	Yes

FIGURE 1 Hypothesized Structural Equation Model



DISCUSSION

This study explored how university students' self-efficacy and attitudes toward artificial intelligence (AI) influence their actual use of AI tools in the context of L2 acquisition. The findings provide valuable insight into the psychological and affective mechanisms underlying AI adoption among language learners, enriching the growing body of research on technology-assisted language learning.

The positive association between AI self-efficacy and learners' attitudes toward AI reflects the foundational role of confidence in shaping openness to new technologies, particularly in language learning environments. This is consistent with prior studies in Computer-Assisted Language Learning (CALL), which show that learners with higher perceived competence in using digital tools are more likely to hold positive beliefs about their value for language development (Chun, 2016; Reinders & Benson, 2017). In the specific context of AI-enhanced L2 learning—such as intelligent writing assistants, AI chatbots, or speech feedback tools—this study confirms that students' belief in their ability to use such tools meaningfully shapes how they evaluate them.

The findings also reaffirm the central role of attitude as a predictor of actual use behavior, a relationship well-documented in models like the Technology Acceptance Model (Davis, 1989) and extended into language learning through frameworks such as CALL acceptance (Stockwell, 2007; Godwin-Jones, 2011). Students who perceived AI as useful, trustworthy, and relevant to their language learning goals were more likely to engage with AI-powered platforms and tools. This supports the view that affective factors—such as trust, motivation, and openness—are key determinants of sustained technology use in L2 learning contexts (Golonka et al., 2014).

Notably, the study found that attitude mediates the relationship between AI self-efficacy and actual AI use, offering empirical support for a layered process of adoption. This implies that even confident students may not use AI in practice unless they also perceive it positively—pointing to the importance of shaping both cognitive and emotional orientations toward technology. This is particularly relevant in L2 learning, where the use of AI often requires learners to trust machine-generated feedback, tolerate ambiguity, and integrate automated assistance into their language development strategies (Dewaele & Li, 2021). The mediating role of attitude thus suggests that fostering positive experiences and reducing anxiety around AI tools may be as crucial as improving digital competence.

Regarding individual differences, the results also highlight that disciplinary background (STEM vs. non-STEM) may influence students' willingness to integrate AI into language learning routines. This aligns with findings from broader CALL studies indicating that familiarity with technology-rich environments enhances learner agency in using digital tools (Reinders & White, 2011). On the other hand, the lack of significant gender differences supports emerging literature that suggests the gender gap in technology adoption may be narrowing, especially in digitally embedded educational contexts (Bailey & Lee, 2020).

CONCLUSION

This study investigated the relationships among AI self-efficacy, attitudes toward AI, and actual use of AI technologies among university students engaged in second language (L2) learning. Through structural equation modeling, the findings offer a theoretically grounded and empirically validated model that reveals how

psychological and contextual factors jointly influence students' engagement with AI tools in language acquisition contexts. The findings carry practical implications for language educators, curriculum designers, and EdTech developers. First, institutions should not only provide technical training to improve students' AI-related competencies but also cultivate positive attitudes through reflective practices, learner-centered design, and transparency around how AI functions. Embedding AI tools meaningfully into classroom activities—rather than offering them as optional add-ons—can normalize their use and reduce resistance.
Several limitations should be acknowledged. First, the study relied on self-reported data, which may be subject to social desirability bias and cannot fully capture the quality or depth of AI use. Future research should incorporate behavioral trace data or platform usage logs to triangulate findings. Second, the cross-sectional design limits causal inference. Longitudinal or experimental studies could better examine how changes in self-efficacy or attitude influence behavior over time.

FUNDINGS: N/A

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